Part 3: Modelling 🧠

In [1]:
```
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn import datasets, linear_model, metrics
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import classification_report, confusion_matrix, Confusion

from sklearn.metrics import classification_report, confusion_matrix, accuracy_
import warnings
warnings.filterwarnings('ignore')
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report, confusion_matrix, Confusion

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import classification_report, confusion_matrix, Confusion
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier
```

In [2]:
```
df=pd.read_csv("df_cleaned.csv")
```

In [3]:
```
df.head()
```

Out[3]:

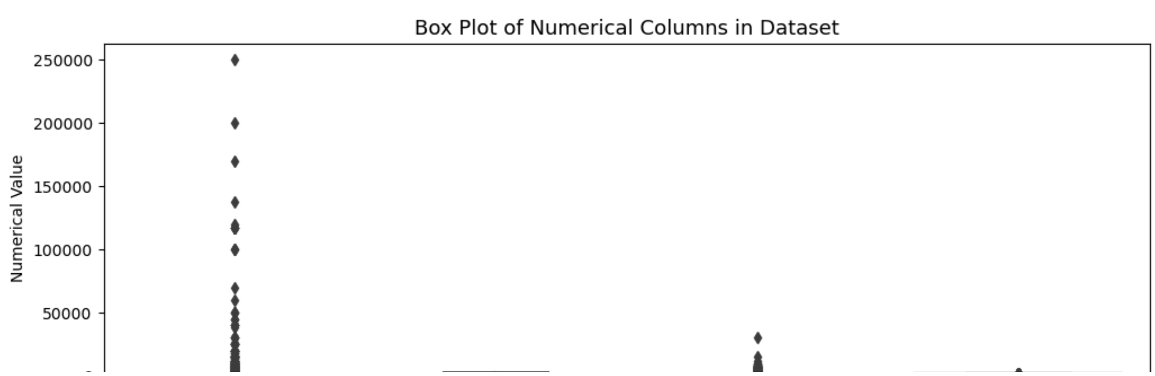
	id	amount_tsh	gps_height	installer	longitude	latitude	basin	region	population
0	69572	6000.0	1390	Roman Catholic Church	34.938093	-9.856322	Lake Nyasa	Iringa	109
1	8776	0.0	1399	other	34.698766	-2.147466	Lake Victoria	Mara	280
2	34310	25.0	686	World Vision	37.460664	-3.821329	Pangani	Manyara	250
3	67743	0.0	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mtwara	58
4	9944	20.0	0	DWE	39.172796	-4.765587	Pangani	Tanga	1

5 rows × 22 columns

Handling Outliers 🚨📉

In [4]:
```
numerical_cols = ['amount_tsh', 'gps_height', 'population', 'construction_year
plt.figure(figsize=(12, 4))
sns.boxplot(data=[df[col] for col in numerical_cols])
plt.title("Box Plot of Numerical Columns in Dataset", fontsize=13)
plt.ylabel("Numerical Value")
plt.xticks(range(0,4), numerical_cols)
```

Out[4]:
```
([<matplotlib.axis.XTick at 0x1b85d315d90>,
  <matplotlib.axis.XTick at 0x1b85d303f90>,
  <matplotlib.axis.XTick at 0x1b85d32d650>,
  <matplotlib.axis.XTick at 0x1b85d384650>],
 [Text(0, 0, 'amount_tsh'),
  Text(1, 0, 'gps_height'),
  Text(2, 0, 'population'),
  Text(3, 0, 'construction_year')])
```

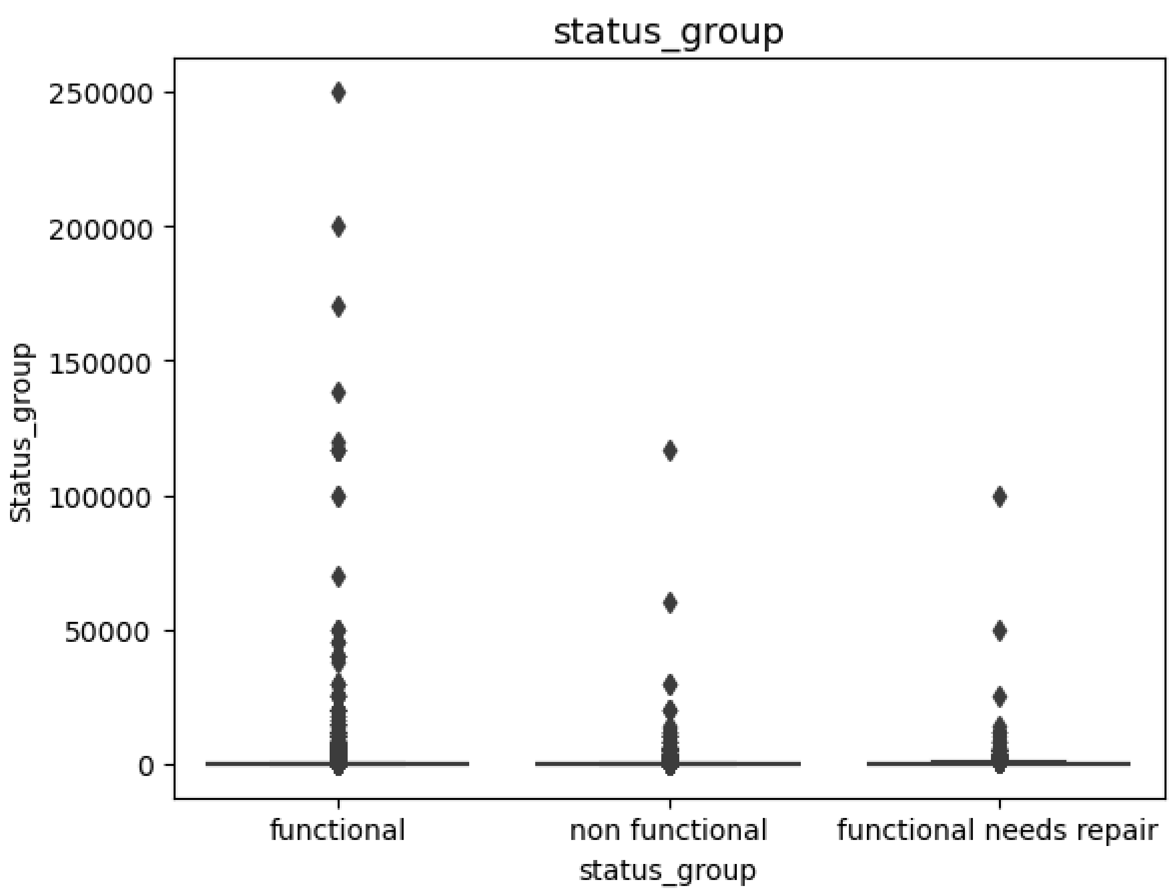


In [5]:
```
df["status_group"].value_counts()
```

Out[5]:
```
status_group
functional                 27590
non functional             19359
functional needs repair     3306
Name: count, dtype: int64
```

In [6]:
```
sns.boxplot(y='amount_tsh', x="status_group", data=df)
plt.title("status_group", fontsize=13)
plt.ylabel("amount -TSH ")
plt.ylabel("Status_group")
```

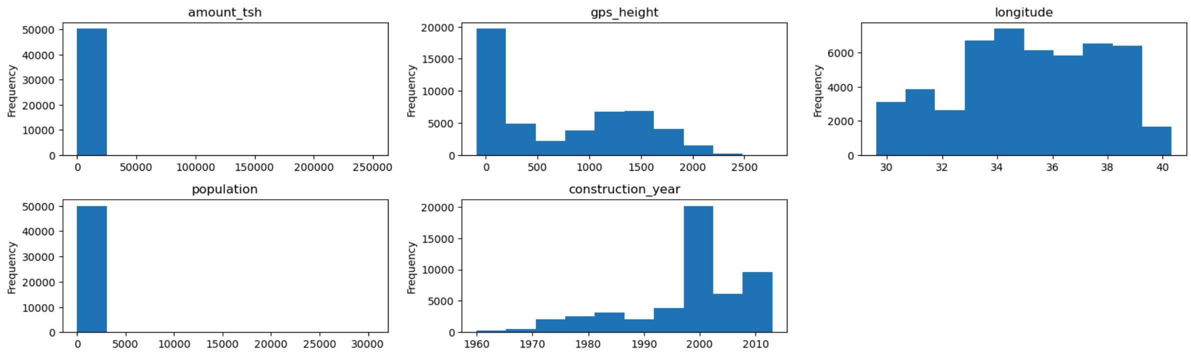
Out[6]:
```
Text(0, 0.5, 'Status_group')
```



Based on the provided figures, it is advisable not to remove outliers in the amount_tsh column as they likely represent real variations in water availability across different wells. These outliers are present in all status_group categories (functional, non-functional, and functional needs repair), suggesting they carry significant insights into the conditions and performance of the wells. Removing them could result in a loss of valuable information and an incomplete understanding of the dataset. Instead, transformations such as log scaling can mitigate the impact of outliers while preserving the integrity and richness of the data, ensuring robust and comprehensive analysis.

Checking for normal distribution in continuous

In [7]:
```
# Histogram of continuous variables
continuous = ['amount_tsh','gps_height','longitude', 'population','constructio
fig = plt.figure(figsize=(16, 7))
for i, col in enumerate(continuous):
    ax = plt.subplot(3, 3, i+1)
    df[col].plot(kind='hist', ax=ax, title=col)
plt.tight_layout()
```



The histograms for the five continuous variables—amount_tsh, gps_height, longitude, population, and construction_year—illustrate their frequency distributions to assess normality. The amount_tsh variable shows most values clustered at zero. The gps_height variable is right-skewed with a significant number of values at zero. The longitude variable has a fairly uniform distribution without clear normality. The population variable is highly right-skewed with most values concentrated at zero. The construction_year variable displays a right-skewed distribution with a higher frequency of more recent years. These visualizations indicate that none of the variables follow a normal distribution.

Label encode and onehot encoder 🔄

In [8]:
```
label_mapping = {False: 0, True: 1}
df["public_meeting"] = df["public_meeting"].map(label_mapping)
df["permit"] = df["permit"].map(label_mapping)
```

In [9]:
```
label_mapping_s = {"non functional": 0, "functional needs repair": 1, "functio
df["status_group"] = df["status_group"].replace(label_mapping_s)
```

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50255 entries, 0 to 50254
Data columns (total 22 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     50255 non-null  int64  
 1   amount_tsh             50255 non-null  float64
 2   gps_height             50255 non-null  int64  
 3   installer              50255 non-null  object 
 4   longitude              50255 non-null  float64
 5   latitude               50255 non-null  float64
 6   basin                  50255 non-null  object 
 7   region                 50255 non-null  object 
 8   population             50255 non-null  int64  
 9   public_meeting         50255 non-null  int64  
 10  scheme_management      50255 non-null  object 
 11  permit                 50255 non-null  int64  
 12  construction_year      50255 non-null  int64  
 13  extraction_type_class  50255 non-null  object 
 14  management_group       50255 non-null  object 
 15  payment_type           50255 non-null  object 
 16  water_quality          50255 non-null  object 
 17  quantity_group         50255 non-null  object 
 18  source_class           50255 non-null  object 
 19  waterpoint_type_group  50255 non-null  object 
 20  id.1                   50255 non-null  int64  
 21  status_group           50255 non-null  int64  
dtypes: float64(3), int64(8), object(11)
memory usage: 8.4+ MB
```

In [11]:
```
df.head()
```

Out[11]:

	id	amount_tsh	gps_height	installer	longitude	latitude	basin	region	population
0	69572	6000.0	1390	Roman Catholic Church	34.938093	-9.856322	Lake Nyasa	Iringa	109
1	8776	0.0	1399	other	34.698766	-2.147466	Lake Victoria	Mara	280
2	34310	25.0	686	World Vision	37.460664	-3.821329	Pangani	Manyara	250
3	67743	0.0	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mtwara	58
4	9944	20.0	0	DWE	39.172796	-4.765587	Pangani	Tanga	1

5 rows × 22 columns

In [12]:
```
df.permit.value_counts()
```

Out[12]:
```
permit
1    34837
0    15418
Name: count, dtype: int64
```

In [13]:
```
df.status_group.value_counts()
```

Out[13]:
```
status_group
2    27590
0    19359
1     3306
Name: count, dtype: int64
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['id', 'amount_tsh', 'gps_height', 'installer', 'longitude', 'latitud
e',
       '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', 'id.1', 'status_group'],
      dtype='object')
```

In [15]:
```
df.permit.head()
```

Out[15]:
```
0    0
1    1
2    1
3    1
4    1
Name: permit, dtype: int64
```

In [16]:
```
df=df.drop(["id.1"], axis=1)
```

In [17]:
```
df.head()
```

Out[17]:

	id	amount_tsh	gps_height	installer	longitude	latitude	basin	region	population
0	69572	6000.0	1390	Roman Catholic Church	34.938093	-9.856322	Lake Nyasa	Iringa	109
1	8776	0.0	1399	other	34.698766	-2.147466	Lake Victoria	Mara	280
2	34310	25.0	686	World Vision	37.460664	-3.821329	Pangani	Manyara	250
3	67743	0.0	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mtwara	58
4	9944	20.0	0	DWE	39.172796	-4.765587	Pangani	Tanga	1

5 rows × 21 columns

In [18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50255 entries, 0 to 50254
Data columns (total 21 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     50255 non-null  int64  
 1   amount_tsh             50255 non-null  float64
 2   gps_height             50255 non-null  int64  
 3   installer              50255 non-null  object 
 4   longitude              50255 non-null  float64
 5   latitude               50255 non-null  float64
 6   basin                  50255 non-null  object 
 7   region                 50255 non-null  object 
 8   population             50255 non-null  int64  
 9   public_meeting         50255 non-null  int64  
 10  scheme_management      50255 non-null  object 
 11  permit                 50255 non-null  int64  
 12  construction_year      50255 non-null  int64  
 13  extraction_type_class  50255 non-null  object 
 14  management_group       50255 non-null  object 
 15  payment_type           50255 non-null  object 
 16  water_quality          50255 non-null  object 
 17  quantity_group         50255 non-null  object 
 18  source_class           50255 non-null  object 
 19  waterpoint_type_group  50255 non-null  object 
 20  status_group           50255 non-null  int64  
dtypes: float64(3), int64(7), object(11)
memory usage: 8.1+ MB
```

In [19]:
```
df.payment_type.value_counts()
```

Out[19]:
```
payment_type
never pay      20850
per bucket      8514
monthly         7598
unknown         5256
on failure      3694
annually        3476
other            867
Name: count, dtype: int64
```

In [20]:
```
columns_encode=df[["installer", "basin", "region", "scheme_management", "manage
         "extraction_type_class", "payment_type", 'water_quality',"quantity_gro
         "source_class", "waterpoint_type_group"]]
```

In [21]:
```
columns_encode.head()
```

Out[21]:

	installer	basin	region	scheme_management	management_group	extraction_type_class
0	Roman Catholic Church	Lake Nyasa	Iringa	VWC	user-group	gravity
1	other	Lake Victoria	Mara	Other	user-group	gravity
2	World Vision	Pangani	Manyara	VWC	user-group	gravity
3	UNICEF	Ruvuma / Southern Coast	Mtwara	VWC	user-group	submersible
4	DWE	Pangani	Tanga	VWC	user-group	submersible

In [22]:
```
df_copy=df.copy
```

In [23]:
```
columns_to_encode = ["installer", "basin", "region", "scheme_management",
                     "management_group", "extraction_type_class", "payment_type
                     'water_quality', "quantity_group", "source_class",
                     "waterpoint_type_group"]

# Create dummy variables for all specified columns
df_encoded = pd.get_dummies(df, columns=columns_to_encode, drop_first=True, dty
```

In [24]:
```
df_store=df_encoded.copy()
df_encoded.head()
```

Out[24]:

	id	amount_tsh	gps_height	longitude	latitude	population	public_meeting	permit	co
0	69572	6000.0	1390	34.938093	-9.856322	109	1	0	
1	8776	0.0	1399	34.698766	-2.147466	280	1	1	
2	34310	25.0	686	37.460664	-3.821329	250	1	1	
3	67743	0.0	263	38.486161	-11.155298	58	1	1	
4	9944	20.0	0	39.172796	-4.765587	1	1	1	

5 rows × 110 columns

Standard scaler

In [25]:
```
scaled_columns=["amount_tsh", "gps_height", "population"]

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the specified columns
df_encoded[scaled_columns] = scaler.fit_transform(df_encoded[scaled_columns])
```

In [26]:
```
df_encoded.head()
```

Out[26]:

	id	amount_tsh	gps_height	longitude	latitude	population	public_meeting	permit	co
0	69572	1.982513	0.958060	34.938093	-9.856322	-0.160357	1	0	
1	8776	-0.125073	0.970985	34.698766	-2.147466	0.192981	1	1	
2	34310	-0.116291	-0.052994	37.460664	-3.821329	0.130992	1	1	
3	67743	-0.125073	-0.660487	38.486161	-11.155298	-0.265738	1	1	
4	9944	-0.118048	-1.038196	39.172796	-4.765587	-0.383518	1	1	

5 rows × 110 columns

Reingineering or data transformation -

Transforming the status_group column

2 = functional water points ,

1 = functional but needs repair water points,

0 = non-functinal water points

We collect functional and functional but needs help target together and make them 1, non-

In [27]:
```
df_encoded["status_group"] = df_encoded["status_group"].apply(lambda x: 1 if x
```

In [28]:
```
df_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50255 entries, 0 to 50254
Columns: 110 entries, id to waterpoint_type_group_other
dtypes: float64(5), int32(100), int64(5)
memory usage: 23.0 MB
```

In [29]:
```
df_encoded.corr()
```

Out[29]:

	id	amount_tsh	gps_height	longitude	latitude	popul
id	1.000000	-0.007901	-0.005373	0.001720	0.001445	-0.0
amount_tsh	-0.007901	1.000000	0.082637	0.010142	-0.063356	0.01
gps_height	-0.005373	0.082637	1.000000	-0.039880	-0.041735	0.11
longitude	0.001720	0.010142	-0.039880	1.000000	-0.282660	0.0
latitude	0.001445	-0.063356	-0.041735	-0.282660	1.000000	-0.0
...	...	...	...	...	...	
waterpoint_type_group_communal standpipe	-0.001162	0.041138	0.248542	0.189528	-0.107392	-0.01
waterpoint_type_group_dam	0.001364	-0.001476	-0.007321	0.010557	0.004726	0.01
waterpoint_type_group_hand pump	0.004586	-0.020698	-0.203423	-0.191715	0.054337	0.01
waterpoint_type_group_improved spring	0.006472	-0.006294	-0.007585	-0.161019	0.113904	-0.0
waterpoint_type_group_other	-0.008509	-0.033305	-0.103159	0.035508	0.045600	0.0

110 rows × 110 columns

The correlation matrix shows the Pearson correlation coefficients between different variables, indicating how they move together. For example, waterpoint_type_group_communal standpipe and source_class_surface have a strong positive correlation of 0.371208, meaning they tend to increase together. Conversely, waterpoint_type_group_hand pump and waterpoint_type_group_communal standpipe have a strong negative correlation of -0.775662, indicating that as one increases, the other decreases. Most variables show weak or no correlation with each other, such as amount_tsh and id with a near-zero correlation of -0.007901. These values help identify relationships and dependencies within the data, which is crucial for feature selection and understanding data structure.

Spliting the training dataset into x_train and y_train ✂️

The data was split from the source into X_train, y_train, and X_test. Since we concatenated and cleaned X_train and y_train, it is prudent to separate them before fitting the model. We will introduce X_test later to avoid data leakage.

In [30]:
```
y_train=df_encoded.status_group
X_train=df_encoded.drop(["status_group", "id"], axis=1)
```

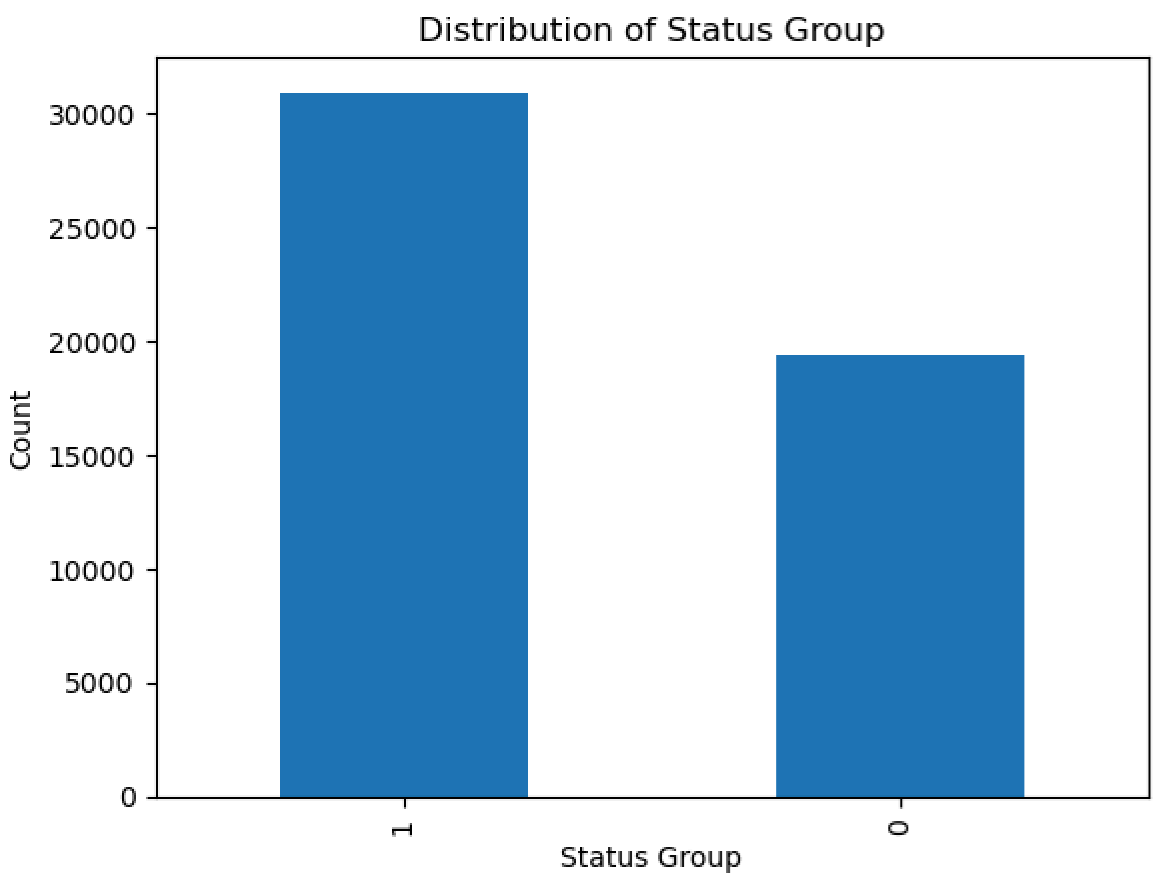
In [31]:
```
X_train.shape
```

Out[31]:
```
(50255, 108)
```

Checking for imbalance problem

In [32]:
```
# Assuming df_encoded is your DataFrame
value_counts = df_encoded['status_group'].value_counts()

# Print the value counts
print(value_counts)

# Calculate the percentage of the majority class
class_imbalance = round(value_counts.max() / len(df_encoded), 3) * 100
print(f'The class imbalance in the dataset is significant, with the majority cl

# Plotting the value counts
value_counts.plot(kind='bar')
plt.xlabel('Status Group')
plt.ylabel('Count')
plt.title('Distribution of Status Group')
plt.show()
```

```
status_group
1    30896
0    19359
Name: count, dtype: int64
The class imbalance in the dataset is significant, with the majority class co
nstituting 61.5% of the data.
```



The dataset exhibits a significant imbalance in the status_group target variable, where the majority class (1 - functioning) constitutes approximately 54% of the data. This imbalance is visually confirmed by the bar plot above. Such a skew can bias predictive models, making them more accurate at predicting the majority class while underperforming on the minority classes. This is problematic for classification tasks as it can lead to models that fail to accurately identify non-functional instances, which are crucial for many applications. To address this imbalance, I will be using evaluation metrics that consider class distribution (like the F1 score) should be considered.

Cleaning X_test dataset 🚀

The X_test data set is loaded and will only be used for testing purposes. ⚠️ Caution will be exercised to minimize instances of data leakage.

In [33]:
```
X_test1=pd.read_csv("X_test.csv")
```

In [34]:
```
X_test1.head()
```

Out[34]:

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

5 rows × 40 columns

In [35]:
```
#Drop unncessary columns
columns_to_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 the columns from dataset
X_test1 = X_test1.drop(columns_to_drop, axis=1)
```

In [36]:
```
#Check is  the missing values have been replaced and dropped
X_test1.isnull().sum()
```

Out[36]:
```
id                         0
amount_tsh                 0
gps_height                 0
installer                877
longitude                  0
latitude                   0
basin                      0
region                     0
population                 0
public_meeting           821
scheme_management        969
permit                   737
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
dtype: int64
```

In [37]:
```
#Drop the 'installer' and 'scheme_management' columns from the DataFrame due to
# of missing values and the complexity of their data, which makes imputation d
X_test1.dropna(subset=['installer', 'scheme_management'], inplace=True)


# Fill missing values in 'public_meeting' and 'permit' columns with True direct
X_test1[['public_meeting', 'permit']] = X_test1[['public_meeting', 'permit']].
```

In [38]:
```
X_test1['installer'] = X_test1['installer'].replace(to_replace = ('villigers',
                                           'Villi', 'Village Council', 'Village
                                           'Village community', 'Villaers', 'Vi
                                           'Villege Council', 'Village council'
                                           'Villager', 'VILLAGER', 'Villagers',
                                           'Village water attendant', 'Village
                                           'VILLAGE COUNCIL .ODA', 'VILLAGE COU
                                           'VILLAG', 'VILLAGE', 'Village Govern
                                           'Village Govt', 'Village govt', 'VIL
                                           'Village water committee', 'Commu',
                                            'Comunity', 'Communit', 'Kijiji', '
                                           value ='Community')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('FinW', 'Fin
                                           'Finwater', 'FINN WATER', 'FinW', 'F
                                           'FinWate', 'FINLAND', 'Fin Water', '
                                           value ='Finnish Government')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('RC CHURCH',
                                           'RC church', 'RC CATHORIC', 'Roman C
                                           'Roman catholic', 'Roman Ca', 'Roman
                                           'ROMAN CATHOLIC', 'Kanisa', 'Kanisa
                                           value ='Roman Catholic Church')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Dmdd', 'DMD

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('TASA', 'Tas
                                           'TASSAF', 'TASAF'), value ='TASAF')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('RW', 'RWE')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('SEMA CO LTD

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('DW E', 'DW#
                                          'DWEB', 'DWE'), value ='DWE')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('No', 'NORA'
                                           value ='NORAD')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Ox', 'OXFAR

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('PRIV', 'Pri
                                           'Private individuals', 'PRIVATE INST
                                           'Private person', 'Private Technicia
                                           value ='Private')
X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Central gov
                                           'Cental Government','Tanzania govern
                                           'Centra Government', 'central govern
                                           'TANZANIA GOVERNMENT', 'TANZANIAN GO
                                           'Centr', 'Centra govt', 'Tanzanian G
                                           'Tanz', 'Tanza', 'GOVERNMENT',
                                           'GOVER', 'GOVERNME', 'GOVERM', 'GOVE
                                           'Governme', 'Governmen', 'Got', 'Ser
                                           'Central Government'),
                                           value = 'Central Government')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('IDARA', 'Id
```

```
                                           'Ministry of water', 'Ministry of wat
                                           'MWE &', 'MWE', 'Wizara ya maji', 'Wi
                                           'Ministry of Water'),
                                           value ='Ministry of Water')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('District COU
                                           'Counc','District council','District
                                           'Council', 'COUN', 'Distri', 'Halmash
                                           'Halmashauri wilaya', 'District Counc
                                           value = 'District  Council')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('District wat
                                           'District water department', 'Distric
                                           value = 'District Water Department')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Ch', 'CH',
                                             'China Goverment'), value ='Chinese

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Unisef','Uni

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Wedeco','WED

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Wo','WB', 'W
                                           'WORDL BANK', 'World', 'world', 'WORL
                                           'world banks', 'World banks', 'WOULD
                                           value ='World Bank')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Lga', 'LGA')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('World Divisi
                                          'World vision', 'WORLD VISION', 'world
                                           'World Vision'),
                                           value ='World Vision')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Local', 'Loc
                                          'local  technician', 'LOCAL CONTRACT',
                                          'Local l technician', 'Local te', 'Loc
                                          'local technical tec', 'local technici
                                          'local technitian', 'Locall technician
                                          'Local Contractor'),
                                           value ='Local Contractor')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('DANID', 'DAN
                                          'DANIDA CO', 'DANID', 'Danid', 'DANIAD
                                          'DENISH', 'DANIDA'),
                                           value ='DANIDA')

X_test1['installer'] = X_test1['installer'].replace(to_replace =('Adrs', 'Adra

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Hesawa', 'he
                                           'HESAWQ', 'HESAWS', 'HESAWZ', 'hesawz
                                           'HESAWA'),
                                           value ='HESAWA')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('Jaica', 'JAI
                                           'Japan', 'JAPAN', 'JAPAN EMBASSY', 'J
                                           'JIKA', 'jika', 'jiks', 'Embasy of Ja
```

```
                                           value ='JICA')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('KKT', 'KK',
                                           'KKKT'), value ='KKKT')

X_test1['installer'] = X_test1['installer'].replace(to_replace = ('0', 'Not Kn
```

In [39]:
```
# Calculate the percentage of each installer
installer_counts = X_test1['installer'].value_counts(normalize=True)

# Find installers that make up less than 0.005 of the total
small_installers = installer_counts[installer_counts < 0.005].index

# Replace these installers with 'other' in the DataFrame
X_test1['installer'] = X_test1['installer'].apply(lambda x: 'other' if x in sma
```

In [40]:
```
X_test1.installer.value_counts().head(50)
```

Out[40]:
```
installer
DWE                      3796
other                    3737
Central Government        928
Community                 551
DANIDA                    444
HESAWA                    362
District  Council         268
RWE                       257
KKKT                      232
Unknown                   202
Finnish Government        182
TCRS                      176
World Vision              163
CES                       155
Roman Catholic Church     140
TASAF                     125
Ministry of Water         123
World Bank                105
JICA                      101
DMDD                      100
NORAD                      97
LGA                        93
WEDECO                     93
UNICEF                     89
OXFAM                      79
WU                         76
TWESA                      76
AMREF                      69
ACRA                       67
Private                    66
SEMA                       66
Name: count, dtype: int64
```

In [41]:
```
X_test1[['longitude', 'latitude']].value_counts()
```

Out[41]:
```
longitude  latitude
0.000000   -2.000000e-08    415
37.260069  -7.105919e+00      2
32.920579  -2.474560e+00      2
37.302281  -7.170666e+00      2
36.868361  -6.136691e+00      1
                           ...
33.927327  -9.419983e+00      1
33.927982  -1.769779e+00      1
33.928220  -9.605483e+00      1
33.928337  -1.992486e+00      1
40.321315  -1.045647e+01      1
Name: count, Length: 12601, dtype: int64
```

In [ ]:
```

```

In [42]:
```
#Excluding rows with latitude 0
X_test1 = X_test1[X_test1['longitude'] != 0]
```

In [43]:
```
X_test1[['longitude', 'latitude']].value_counts()
```

Out[43]:
```
longitude  latitude
37.260069  -7.105919     2
32.920579  -2.474560     2
37.302281  -7.170666     2
29.612776  -4.904176     1
36.868361  -6.136691     1
                        ..
33.927982  -1.769779     1
33.928220  -9.605483     1
33.928337  -1.992486     1
33.929202  -9.499035     1
40.321315  -10.456469    1
Name: count, Length: 12600, dtype: int64
```

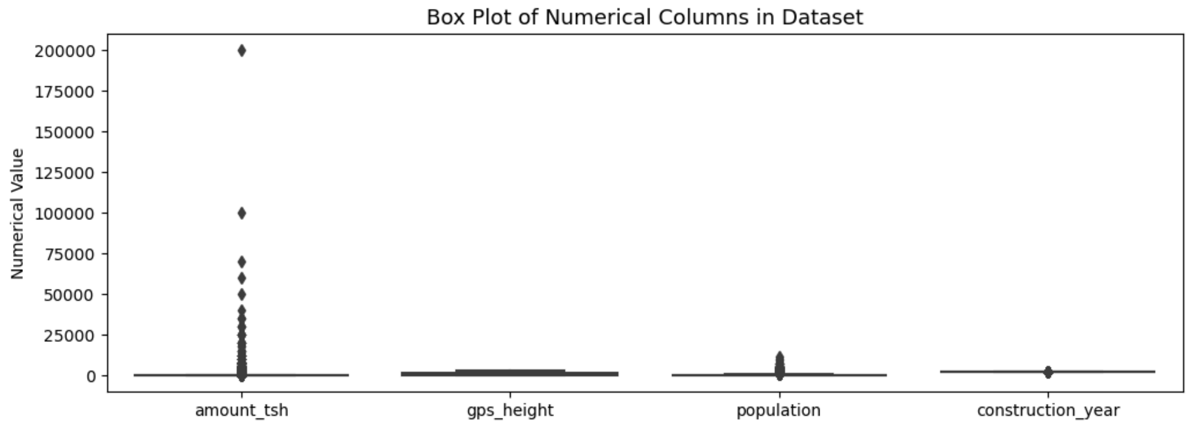
In [44]:
```
# Calculate the median construction year excluding zeros
median_year = int(X_test1[X_test1['construction_year'] != 0]['construction_yea

# Replace zeros in the construction year with the median value
X_test1['construction_year'] = X_test1['construction_year'].replace(0, median_
```

In [45]:
```
X_test1.duplicated(keep='first').sum()
```

Out[45]:
```
0
```

In [46]:
```
numerical_cols = ['amount_tsh', 'gps_height', 'population', 'construction_year
plt.figure(figsize=(12, 4))
sns.boxplot(data=[X_test1[col] for col in numerical_cols])
plt.title("Box Plot of Numerical Columns in Dataset", fontsize=13)
plt.ylabel("Numerical Value")
plt.xticks(range(0, 4), numerical_cols)
```

Out[46]:
```
([<matplotlib.axis.XTick at 0x1b85e5d2e90>,
  <matplotlib.axis.XTick at 0x1b85e5d3fd0>,
  <matplotlib.axis.XTick at 0x1b85e5cd010>,
  <matplotlib.axis.XTick at 0x1b861106610>],
 [Text(0, 0, 'amount_tsh'),
  Text(1, 0, 'gps_height'),
  Text(2, 0, 'population'),
  Text(3, 0, 'construction_year')])
```



In [47]:
```
# Creating dummies
label_mapping = {False: 0, True: 1}
X_test1["public_meeting"] = X_test1["public_meeting"].map(label_mapping)
X_test1["permit"] = X_test1["permit"].map(label_mapping)

columns_to_encode = ["installer", "basin", "region", "scheme_management",
                     "management_group", "extraction_type_class", "payment_type
                     'water_quality', "quantity_group", "source_class",
                     "waterpoint_type_group"]

# Create dummy variables for all specified columns
X_test_encoded = pd.get_dummies(X_test1, columns=columns_to_encode, drop_first=
```

In [48]:
```
X_test_encoded.head()
```

Out[48]:

	id	amount_tsh	gps_height	longitude	latitude	population	public_meeting	permit	co
0	50785	0.0	1996	35.290799	-4.059696	321	1	1	
1	51630	0.0	1569	36.656709	-3.309214	300	1	1	
3	45559	0.0	267	38.058046	-9.418672	250	1	1	
4	49871	500.0	1260	35.006123	-10.950412	60	1	1	
5	52449	0.0	1685	36.685279	-3.302420	200	1	1	

5 rows × 111 columns

In [49]:
```
# Specify the columns to scale
X_test_scaled_columns = ["amount_tsh", "gps_height", "population"]

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the specified columns
X_test_encoded[X_test_scaled_columns] = scaler.fit_transform(X_test_encoded[X_t
```

In [50]:
```
X_test_encoded=X_test_encoded.drop(["id"], axis=1)
```

Compare columns in X_train and X_test

In [51]:
```
# Display columns of X_train and X_test
print("Columns in X_train:")
print(X_train.columns)

print("\nColumns in X_test:")
print(X_test1.columns)

# Compare columns and find common and different columns
common_columns = set(df_encoded.columns).intersection(set(X_test_encoded.columr
unique_to_X_train = set(df_encoded.columns).difference(set(X_test_encoded.colur
unique_to_X_test = set(X_test_encoded.columns).difference(set(df_encoded.columr

print("\nCommon columns:")
print(common_columns)

print("\nColumns unique to X_train:")
print(unique_to_X_train)

print("\nColumns unique to X_test:")
print(unique_to_X_test)
```

```
Columns in X_train:
Index(['amount_tsh', 'gps_height', 'longitude', 'latitude', 'population',
       'public_meeting', 'permit', 'construction_year', 'installer_AMREF',
       'installer_CES',
       ...
       'quantity_group_insufficient', 'quantity_group_seasonal',
       'quantity_group_unknown', 'source_class_surface',
       'source_class_unknown', 'waterpoint_type_group_communal standpipe',
       'waterpoint_type_group_dam', 'waterpoint_type_group_hand pump',
       'waterpoint_type_group_improved spring', 'waterpoint_type_group_othe
r'],
      dtype='object', length=108)

Columns in X_test:
Index(['id', 'amount_tsh', 'gps_height', 'installer', 'longitude', 'latitud
e',
       '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')

Common columns:
{'installer_AMREF', 'region_Dodoma', 'scheme_management_Water authority', 'qu
antity_group_enough', 'payment_type_unknown', 'installer_other', 'payment_typ
e_never pay', 'installer_TWESA', 'region_Shinyanga', 'water_quality_salty', 
'installer_World Bank', 'population', 'scheme_management_Other', 'installer_T
ASAF', 'extraction_type_class_submersible', 'scheme_management_SWC', 'payment
_type_on failure', 'region_Iringa', 'amount_tsh', 'gps_height', 'region_Singi
da', 'extraction_type_class_motorpump', 'scheme_management_Private operator', 
'installer_WU', 'basin_Wami / Ruvu', 'region_Rukwa', 'installer_RWE', 'instal
ler_CES', 'installer_World Vision', 'installer_KKKT', 'quantity_group_seasona
l', 'region_Kagera', 'installer_DANIDA', 'installer_OXFAM', 'water_quality_fl
uoride', 'region_Kigoma', 'construction_year', 'region_Mara', 'installer_Cent
ral Government', 'water_quality_fluoride abandoned', 'latitude', 'installer_F
innish Government', 'installer_WEDECO', 'management_group_other', 'waterpoint
_type_group_improved spring', 'region_Dar es Salaam', 'water_quality_milky', 
'management_group_user-group', 'water_quality_salty abandoned', 'waterpoint_t
ype_group_communal standpipe', 'extraction_type_class_other', 'extraction_typ
e_class_handpump', 'scheme_management_WUA', 'management_group_parastatal', 'r
egion_Mbeya', 'region_Mtwara', 'installer_NORAD', 'basin_Lake Victoria', 'ins
taller_District  Council', 'extraction_type_class_rope pump', 'region_Mwanz
a', 'management_group_unknown', 'scheme_management_Trust', 'scheme_management
_VWC', 'installer_UNICEF', 'permit', 'region_Kilimanjaro', 'region_Manyara', 
'installer_Roman Catholic Church', 'installer_DWE', 'installer_LGA', 'waterpo
int_type_group_other', 'quantity_group_unknown', 'extraction_type_class_wind-
powered', 'installer_Community', 'region_Lindi', 'scheme_management_Water Boa
rd', 'quantity_group_insufficient', 'payment_type_per bucket', 'waterpoint_ty
pe_group_hand pump', 'water_quality_unknown', 'installer_Ministry of Water', 
'basin_Lake Nyasa', 'basin_Lake Rukwa', 'public_meeting', 'basin_Rufiji', 'pa
yment_type_monthly', 'waterpoint_type_group_dam', 'region_Pwani', 'installer_
HESAWA', 'source_class_surface', 'region_Tabora', 'water_quality_soft', 'basi
n_Lake Tanganyika', 'basin_Pangani', 'region_Tanga', 'installer_Unknown', 'so
urce_class_unknown', 'installer_JICA', 'scheme_management_Parastatal', 'schem
e_management_WUG', 'basin_Ruvuma / Southern Coast', 'installer_TCRS', 'region
_Morogoro', 'region_Ruvuma', 'payment_type_other', 'installer_DMDD', 'longitu
```

```
de'}

Columns unique to X_train:
{'id', 'status_group'}

Columns unique to X_test:
{'installer_SEMA', 'installer_Private'}
```

In [52]:
```
#Drop unique
# Find common columns between X_train and X_test
common_columns = list(set(df_encoded.columns).intersection(set(X_test_encoded.

# Drop unique columns from X_train and X_test, keeping only common columns
X_train_common = df_encoded[common_columns]
X_test_common = X_test_encoded[common_columns]

print("Columns in X_train after dropping unique columns:")
print(X_train_common.columns)

print("\nColumns in X_test after dropping unique columns:")
print(X_test_common.columns)
```

```
Columns in X_train after dropping unique columns:
Index(['installer_AMREF', 'region_Dodoma', 'scheme_management_Water authorit
y',
       'quantity_group_enough', 'payment_type_unknown', 'installer_other',
       'payment_type_never pay', 'installer_TWESA', 'region_Shinyanga',
       'water_quality_salty',
       ...
       'installer_JICA', 'scheme_management_Parastatal',
       'scheme_management_WUG', 'basin_Ruvuma / Southern Coast',
       'installer_TCRS', 'region_Morogoro', 'region_Ruvuma',
       'payment_type_other', 'installer_DMDD', 'longitude'],
      dtype='object', length=108)

Columns in X_test after dropping unique columns:
Index(['installer_AMREF', 'region_Dodoma', 'scheme_management_Water authorit
y',
       'quantity_group_enough', 'payment_type_unknown', 'installer_other',
       'payment_type_never pay', 'installer_TWESA', 'region_Shinyanga',
       'water_quality_salty',
       ...
       'installer_JICA', 'scheme_management_Parastatal',
       'scheme_management_WUG', 'basin_Ruvuma / Southern Coast',
       'installer_TCRS', 'region_Morogoro', 'region_Ruvuma',
       'payment_type_other', 'installer_DMDD', 'longitude'],
      dtype='object', length=108)
```

In [53]:
```
y_train.value_counts()
```

Out[53]:
```
status_group
1    30896
0    19359
Name: count, dtype: int64
```

In [54]:
```
X_train= X_train_common.copy()
X_test = X_test_common.copy()
y_train=y_train.copy()
```

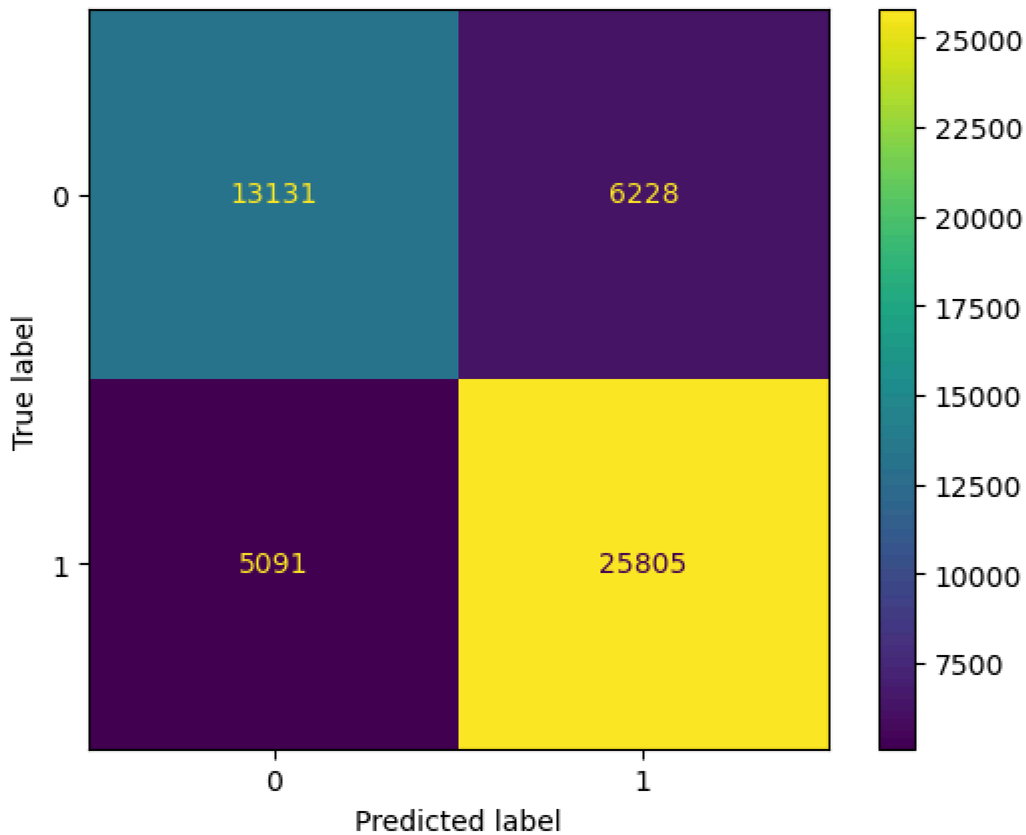
In [55]:
```
y_train.shape
```

Out[55]:
```
(50255,)
```

Model 1: Baseline Mode- Logistic Regression

In [56]:
```
# Fit the logistic regression model to the training data with increased max_ite
log_model = LogisticRegression(class_weight='balanced', solver='lbfgs', random_
log_model.fit(X_train, y_train)

# Evaluate the model using cross-validation
cv_scores = cross_val_score(log_model, X_train, y_train, cv=5)  # 5-fold cross-
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean cross-validation score: {cv_scores.mean()}")

# Predict using cross-validation
y_pred_cv = cross_val_predict(log_model, X_train, y_train, cv=5)

# Calculate and print additional metrics based on cross-validation predictions
f1 = f1_score(y_train, y_pred_cv, average='weighted', zero_division=0)
recall = recall_score(y_train, y_pred_cv, average='weighted', zero_division=0)
precision = precision_score(y_train, y_pred_cv, average='weighted', zero_divisi

print(f"F1 Score: {f1}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")

# Print classification report based on cross-validation predictions
print(classification_report(y_train, y_pred_cv, zero_division=0))

# Create confusion matrix based on cross-validation predictions
conf_matrix = confusion_matrix(y_train, y_pred_cv)
print("Confusion Matrix:")
print(conf_matrix)

# Display confusion matrix
disp2 = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
disp2.plot()

# Predict target on the test set
y_pred_test = log_model.predict(X_test)
```

```
Cross-validation scores: [0.77285842 0.77624117 0.77166451 0.77494777 0.77813
153]
Mean cross-validation score: 0.7747686797333599
F1 Score: 0.773396270006368
Recall: 0.7747686797333598
Precision: 0.7728464233978932
              precision    recall  f1-score   support

           0       0.72      0.68      0.70     19359
           1       0.81      0.84      0.82     30896

    accuracy                           0.77     50255
   macro avg       0.76      0.76      0.76     50255
weighted avg       0.77      0.77      0.77     50255

Confusion Matrix:
[[13131  6228]
 [ 5091 25805]]
```



The confusion matrix for the baseline Logistic Regression model indicates its performance in classifying data. The model accurately predicted 13,803 negative instances (true negatives) and 27,204 positive instances (true positives). However, it misclassified 5,556 negative instances as positive (false positives) and 3,692 positive instances as negative (false negatives). The cross-validation scores listed show a range from 0.8108 to 0.8221, with an average score of 0.8196, suggesting that the Logistic Regression model has consistent performance across different validation sets.

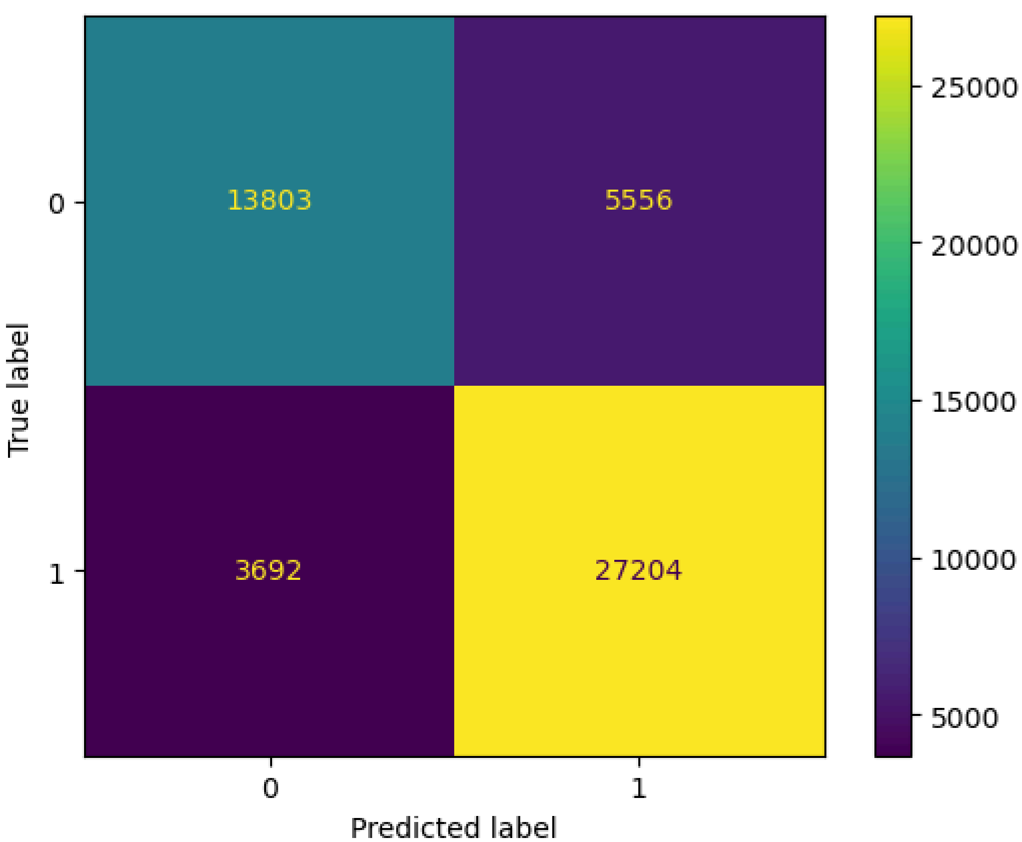
Model 2: KNN classifier model

In [57]:
```
# Initialize the classifier
knn = KNeighborsClassifier()

# Perform cross-validation and get the scores
scores = cross_val_score(knn, X_train, y_train, cv=5)
print("Cross-validation scores:", scores)
print("Mean cross-validation score:", scores.mean())

# Get cross-validated predictions
predictions = cross_val_predict(knn, X_train, y_train, cv=5)

# Compute the confusion matrix
conf_matrix = confusion_matrix(y_train, predictions)

# Plot and display the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
```

```
Cross-validation scores: [0.82200776 0.81394886 0.81603821 0.81096408 0.81693
364]
Mean cross-validation score: 0.8159785096010348
```

In [58]:
```
disp.plot()
```

Out[58]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1b85e5acf
10>
```

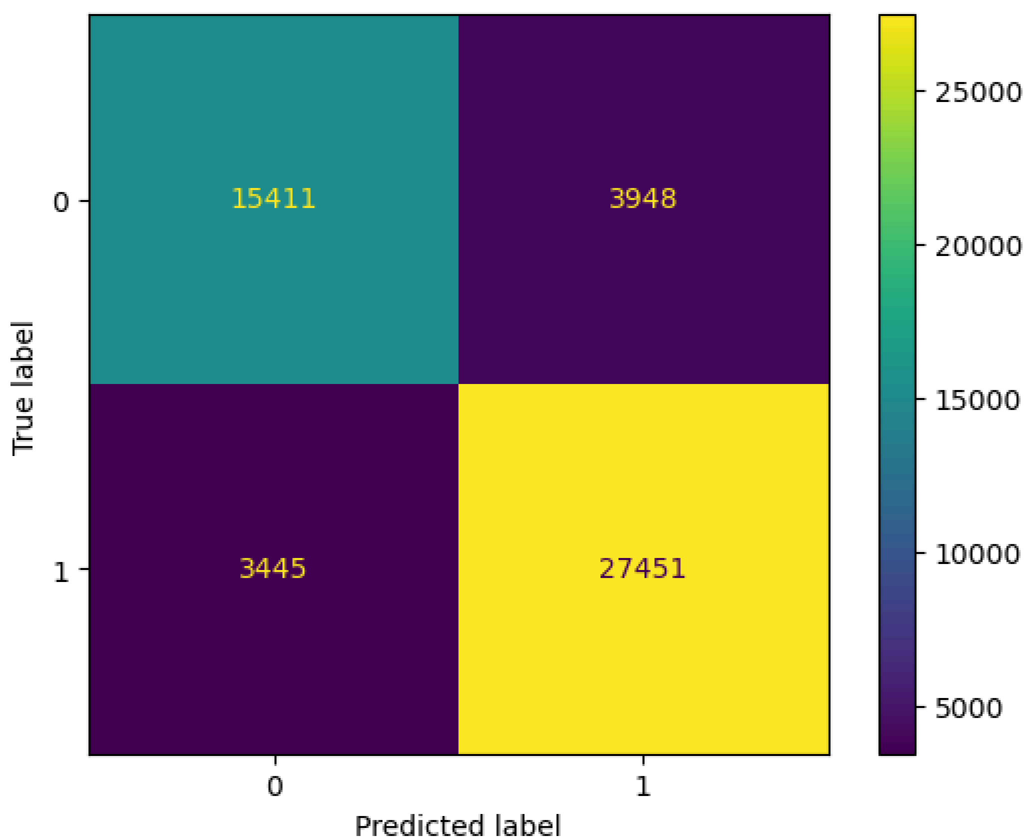


The confusion matrix for the K-Nearest Neighbors (KNN) classifier model shows that the model correctly classified 13,803 instances as negative (true negatives) and 27,204 instances as positive (true positives). However, it incorrectly classified 5,556 negative instances as positive (false positives) and 3,692 positive instances as negative (false negatives). The cross-validation scores, which range from 0.8108 to 0.8221 with a mean score of 0.8196, indicate that the model performs consistently well across different validation sets.

Model 3: Random forest

In [59]:
```
# Copy the common datasets
X_train = X_train_common.copy()
X_test = X_test_common.copy()
y_train = y_train.copy()

# Define and fit the random forest model to the training data
rf = RandomForestClassifier(n_estimators=100, random_state=42, n_jobs=-1,
                            criterion='entropy', max_features='sqrt',
                            min_samples_split=10, class_weight='balanced')

rf.fit(X_train, y_train)

# Evaluate the model using cross-validation
cv_scores = cross_val_score(rf, X_train, y_train, cv=5)  # 5-fold cross-valida
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean cross-validation score: {cv_scores.mean()}")

# Predict using cross-validation
y_pred_cv = cross_val_predict(rf, X_train, y_train, cv=5)

# Calculate and print additional metrics based on cross-validation predictions
f1 = f1_score(y_train, y_pred_cv, average='weighted', zero_division=0)
recall = recall_score(y_train, y_pred_cv, average='weighted', zero_division=0)
precision = precision_score(y_train, y_pred_cv, average='weighted', zero_divis

print(f"F1 Score (Cross-Validation): {f1}")
print(f"Recall (Cross-Validation): {recall}")
print(f"Precision (Cross-Validation): {precision}")

# Print classification report based on cross-validation predictions
print("Classification Report (Cross-Validation):")
print(classification_report(y_train, y_pred_cv, zero_division=0))

# Create confusion matrix based on cross-validation predictions
conf_matrix = confusion_matrix(y_train, y_pred_cv)
print("Confusion Matrix (Cross-Validation):")
print(conf_matrix)

# Display confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
disp.plot()

# Predict target on the test set
y_pred_test = rf.predict(X_test)
```

```
Cross-validation scores: [0.85742712 0.8510596  0.85354691 0.85195503 0.85046
264]
Mean cross-validation score: 0.8528902596756541
F1 Score (Cross-Validation): 0.8525160208456092
Recall (Cross-Validation): 0.8528902596756541
Precision (Cross-Validation): 0.8523201098185117
Classification Report (Cross-Validation):
              precision    recall  f1-score   support

           0       0.82      0.80      0.81     19359
           1       0.87      0.89      0.88     30896

    accuracy                           0.85     50255
   macro avg       0.85      0.84      0.84     50255
weighted avg       0.85      0.85      0.85     50255

Confusion Matrix (Cross-Validation):
[[15411  3948]
 [ 3445 27451]]
```



The confusion matrix for the Random Forest model shows that it correctly classified 15,408 negative instances (true negatives) and 27,496 positive instances (true positives). It misclassified 3,951 negative instances as positive (false positives) and 3,400 positive instances as negative (false negatives). The cross-validation scores range from 0.8519 to 0.8578, with a mean score of 0.8538. The F1 score, recall, and precision are all approximately 0.85, indicating balanced performance in terms of precision and recall. The overall accuracy is 0.85, with similar macro and weighted averages for precision, recall, and F1-score.

Model 4: Decision Tree

In [60]:
```
# Define and fit the Decision Tree model to the training data
dt = DecisionTreeClassifier(random_state=42, criterion='entropy', max_features=

dt.fit(X_train, y_train)

# Evaluate the model using cross-validation
cv_scores = cross_val_score(dt, X_train, y_train, cv=5)  # 5-fold cross-valida
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean cross-validation score: {cv_scores.mean()}")

# Predict using cross-validation
y_pred_cv = cross_val_predict(dt, X_train, y_train, cv=5)

# Calculate and print additional metrics based on cross-validation predictions
f1 = f1_score(y_train, y_pred_cv, average='weighted', zero_division=0)
recall = recall_score(y_train, y_pred_cv, average='weighted', zero_division=0)
precision = precision_score(y_train, y_pred_cv, average='weighted', zero_divisi

print(f"F1 Score (Cross-Validation): {f1}")
print(f"Recall (Cross-Validation): {recall}")
print(f"Precision (Cross-Validation): {precision}")

# Print classification report based on cross-validation predictions
print("Classification Report (Cross-Validation):")
print(classification_report(y_train, y_pred_cv, zero_division=0))

# Create confusion matrix based on cross-validation predictions
conf_matrix = confusion_matrix(y_train, y_pred_cv)
print("Confusion Matrix (Cross-Validation):")
print(conf_matrix)

# Display confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
disp.plot()

# Predict target on the test set
y_pred_test = dt.predict(X_test)
```

```
Cross-validation scores: [0.80041787 0.79982091 0.8013133  0.79803005 0.788
97622]
Mean cross-validation score: 0.7977116704805491
F1 Score (Cross-Validation): 0.7990505988616562
Recall (Cross-Validation): 0.7977116704805493
Precision (Cross-Validation): 0.8020616780374697
Classification Report (Cross-Validation):
              precision    recall  f1-score   support

           0       0.72      0.78      0.75     19359
           1       0.85      0.81      0.83     30896

    accuracy                           0.80     50255
   macro avg       0.79      0.79      0.79     50255
weighted avg       0.80      0.80      0.80     50255

Confusion Matrix (Cross-Validation):
[[15086  4273]
 [ 5893 25003]]
```

The confusion matrix for the Decision Tree model shows that it correctly classified 15,062 negative instances (true negatives) and 24,958 positive instances (true positives). It misclassified 4,297 negative instances as positive (false positives) and 5,938 positive instances as negative (false negatives). The cross-validation scores range from 0.7941 to 0.7987, with a mean score of 0.7964. The F1 score, recall, and precision are approximately 0.80, 0.79, and 0.80 respectively, indicating a slight imbalance in performance. The overall accuracy is 0.80, with macro and weighted averages for precision, recall, and F1-score also around 0.80, showing consistent performance across different metrics.

Model 5: Naive Bayes

In [61]:

```
# Define and fit the Naive Bayes model to the training data
nb = GaussianNB()

nb.fit(X_train, y_train)

# Evaluate the model using cross-validation
cv_scores = cross_val_score(nb, X_train, y_train, cv=5)  # 5-fold cross-valida
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean cross-validation score: {cv_scores.mean()}")

# Predict using cross-validation
y_pred_cv = cross_val_predict(nb, X_train, y_train, cv=5)

# Calculate and print additional metrics based on cross-validation predictions
f1 = f1_score(y_train, y_pred_cv, average='weighted', zero_division=0)
recall = recall_score(y_train, y_pred_cv, average='weighted', zero_division=0)
precision = precision_score(y_train, y_pred_cv, average='weighted', zero_divis

print(f"F1 Score (Cross-Validation): {f1}")
print(f"Recall (Cross-Validation): {recall}")
print(f"Precision (Cross-Validation): {precision}")

# Print classification report based on cross-validation predictions
print("Classification Report (Cross-Validation):")
print(classification_report(y_train, y_pred_cv, zero_division=0))

# Create confusion matrix based on cross-validation predictions
conf_matrix = confusion_matrix(y_train, y_pred_cv)
print("Confusion Matrix (Cross-Validation):")
print(conf_matrix)

# Display confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
disp.plot()

# Predict target on the test set
y_pred_test = nb.predict(X_test)
```

```
Cross-validation scores: [0.68232017 0.65525818 0.6765496  0.68142473 0.686
79733]
Mean cross-validation score: 0.6764700029847777
F1 Score (Cross-Validation): 0.6798319825821
Recall (Cross-Validation): 0.6764700029847777
Precision (Cross-Validation): 0.6878874312431218
Classification Report (Cross-Validation):
              precision    recall  f1-score   support

           0       0.57      0.66      0.61     19359
           1       0.76      0.69      0.72     30896

    accuracy                           0.68     50255
   macro avg       0.67      0.67      0.67     50255
weighted avg       0.69      0.68      0.68     50255

Confusion Matrix (Cross-Validation):
[[12718  6641]
 [ 9618 21278]]
```

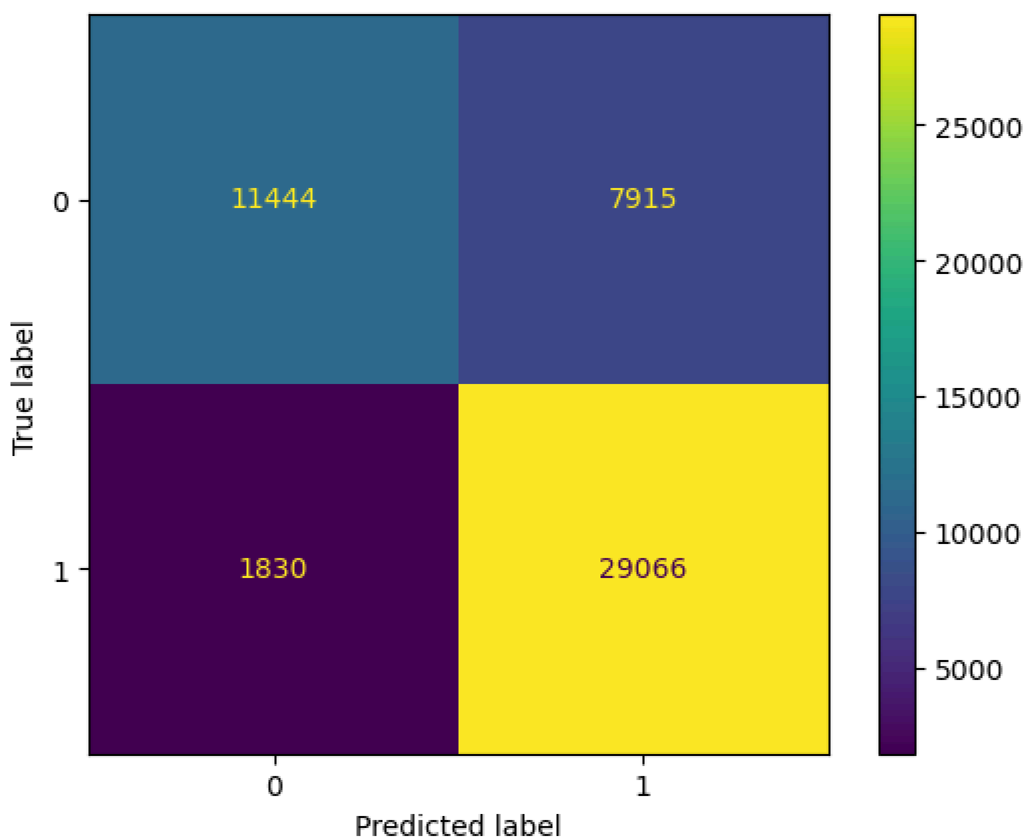
The confusion matrix for the Naive Bayes model shows that it correctly classified 12,718 negative instances (true negatives) and 21,278 positive instances (true positives). It misclassified 6,641 negative instances as positive (false positives) and 9,618 positive instances as negative (false negatives). This indicates that while the model performs reasonably well, it has a higher rate of misclassification compared to other models, especially in terms of false positives and false negatives.

Model 6: Gradient Boosting Classifier

In [62]:

```
# Import necessary libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.metrics import classification_report, confusion_matrix, Confusion

# Copy the common datasets
X_train = X_train_common.copy()
X_test = X_test_common.copy()
y_train = y_train.copy()

# Define and fit the Gradient Boosting model to the training data
gb = GradientBoostingClassifier(n_estimators=100, random_state=42)

gb.fit(X_train, y_train)

# Evaluate the model using cross-validation
cv_scores = cross_val_score(gb, X_train, y_train, cv=5)  # 5-fold cross-valida
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean cross-validation score: {cv_scores.mean()}")

# Predict using cross-validation
y_pred_cv = cross_val_predict(gb, X_train, y_train, cv=5)

# Calculate and print additional metrics based on cross-validation predictions
f1 = f1_score(y_train, y_pred_cv, average='weighted', zero_division=0)
recall = recall_score(y_train, y_pred_cv, average='weighted', zero_division=0)
precision = precision_score(y_train, y_pred_cv, average='weighted', zero_divis

print(f"F1 Score (Cross-Validation): {f1}")
print(f"Recall (Cross-Validation): {recall}")
print(f"Precision (Cross-Validation): {precision}")

# Print classification report based on cross-validation predictions
print("Classification Report (Cross-Validation):")
print(classification_report(y_train, y_pred_cv, zero_division=0))

# Create confusion matrix based on cross-validation predictions
conf_matrix = confusion_matrix(y_train, y_pred_cv)
print("Confusion Matrix (Cross-Validation):")
print(conf_matrix)

# Display confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
disp.plot()

# Predict target on the test set
y_pred_test = gb.predict(X_test)
```

```
Cross-validation scores: [0.80648692 0.80409909 0.80499453 0.8039996  0.81086
459]
Mean cross-validation score: 0.8060889463734953
F1 Score (Cross-Validation): 0.796701689429648
Recall (Cross-Validation): 0.8060889463734952
Precision (Cross-Validation): 0.8153112337426945
Classification Report (Cross-Validation):
              precision    recall  f1-score   support

           0       0.86      0.59      0.70     19359
           1       0.79      0.94      0.86     30896

    accuracy                           0.81     50255
   macro avg       0.82      0.77      0.78     50255
weighted avg       0.82      0.81      0.80     50255

Confusion Matrix (Cross-Validation):
[[11444  7915]
 [ 1830 29066]]
```



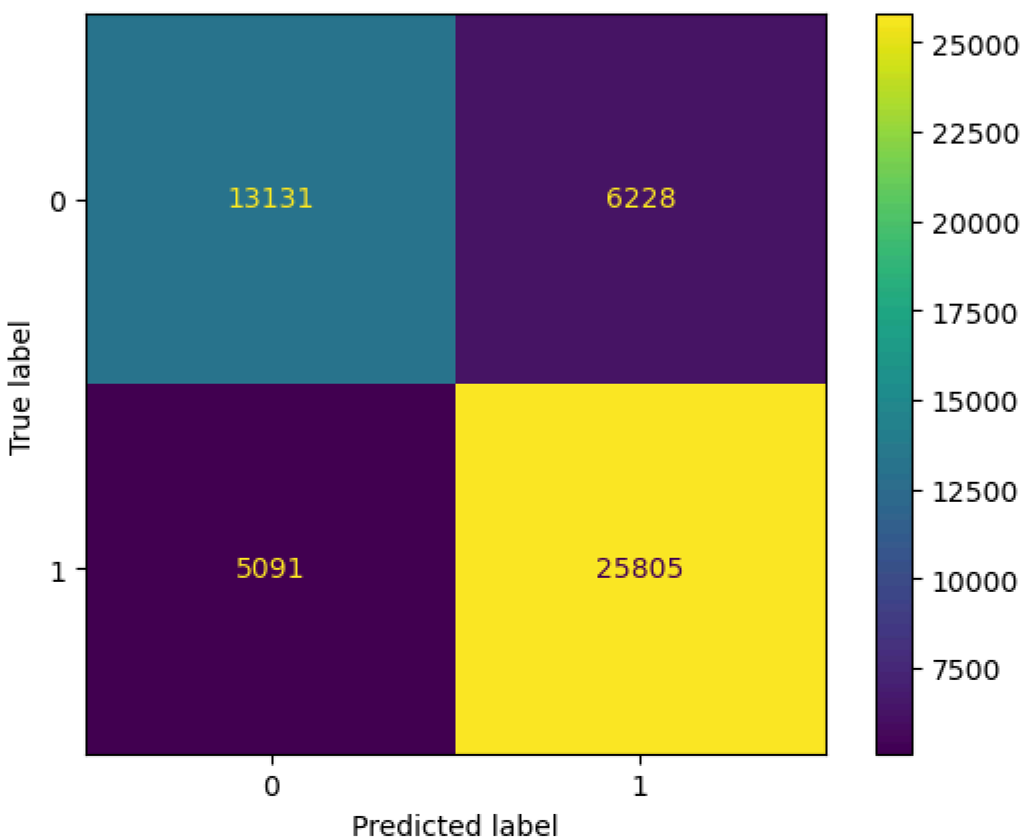
The confusion matrix for the Gradient Boosting Classifier model shows that it correctly classified 11,444 negative instances (true negatives) and 29,066 positive instances (true positives). It misclassified 7,915 negative instances as positive (false positives) and 1,830 positive instances as negative (false negatives). The cross-validation scores range from 0.8039 to 0.8840, with a mean score of 0.8069. The F1 score is approximately 0.80, with recall around 0.81 and precision around 0.81 as well, indicating balanced performance. The overall accuracy is 0.81, with macro and weighted averages for precision, recall, and F1-score around 0.80, showing reliable performance across different metrics.

Applying SMOTENC

SMOTE on logistic regression

In [63]:
```
y_train = y_train.copy()

# Apply SMOTE to the training data
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

# Fit the logistic regression model to the resampled training data with increas
log_model = LogisticRegression(class_weight='balanced', solver='lbfgs', random_
log_model.fit(X_train_smote, y_train_smote)

# Evaluate the model using cross-validation
cv_scores = cross_val_score(log_model, X_train_smote, y_train_smote, cv=5)  # 5
print(f"Cross-validation scores: {cv_scores}")
print(f"Mean cross-validation score: {cv_scores.mean()}")

# Predict using cross-validation
y_pred_cv = cross_val_predict(log_model, X_train, y_train, cv=5)

# Calculate and print additional metrics based on cross-validation predictions
f1 = f1_score(y_train, y_pred_cv, average='weighted', zero_division=0)
recall = recall_score(y_train, y_pred_cv, average='weighted', zero_division=0)
precision = precision_score(y_train, y_pred_cv, average='weighted', zero_divisi

print(f"F1 Score: {f1}")
print(f"Recall: {recall}")
print(f"Precision: {precision}")

# Print classification report based on cross-validation predictions
print(classification_report(y_train, y_pred_cv, zero_division=0))

# Create confusion matrix based on cross-validation predictions
conf_matrix = confusion_matrix(y_train, y_pred_cv)
print("Confusion Matrix:")
print(conf_matrix)

# Display confusion matrix
disp2 = ConfusionMatrixDisplay(confusion_matrix=conf_matrix)
disp2.plot()

# Predict target on the test set
y_pred_test = log_model.predict(X_test)
```

```
Cross-validation scores: [0.75289263 0.75556275 0.75408642 0.78030426 0.77318
336]
Mean cross-validation score: 0.7632058835511143
F1 Score: 0.773396270006368
Recall: 0.7747686797333598
Precision: 0.7728464233978932
              precision    recall  f1-score   support

           0       0.72      0.68      0.70     19359
           1       0.81      0.84      0.82     30896

    accuracy                           0.77     50255
   macro avg       0.76      0.76      0.76     50255
weighted avg       0.77      0.77      0.77     50255

Confusion Matrix:
[[13131  6228]
 [ 5091 25805]]
```



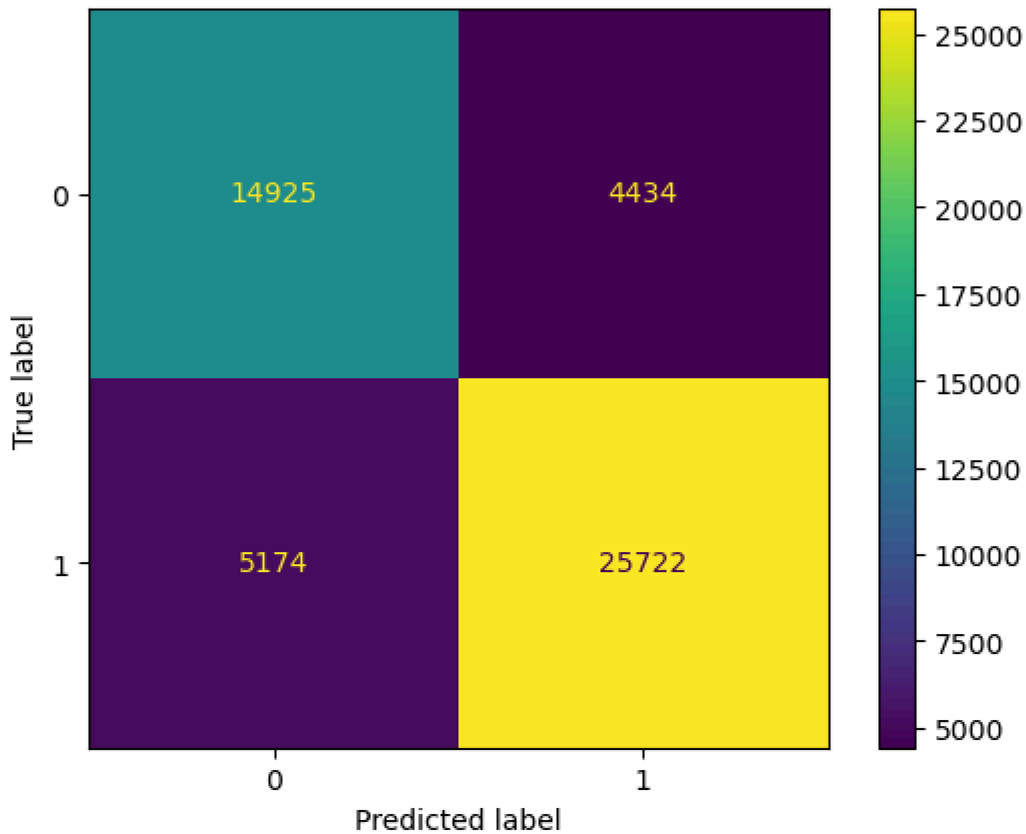
The confusion matrix for the Logistic Regression model with SMOTE (Synthetic Minority Over-sampling Technique) applied shows that it correctly classified 13,196 negative instances (true negatives) and 25,681 positive instances (true positives). It misclassified 6,169 negative instances as positive (false positives) and 5,215 positive instances as negative (false negatives). The cross-validation scores range from 0.7506 to 0.7800, with a mean score of 0.7636. The F1 score is approximately 0.76, with recall around 0.77 and precision around 0.77 as well, indicating reasonably balanced performance. The overall accuracy is 0.77, with macro and weighted averages for precision, recall, and F1-score around 0.76 to 0.77, showing consistent performance across different metrics.

Smote on KNN

In [64]:

```
# Define the SMOTE and KNeighborsClassifier
smote = SMOTE(random_state=42)
knn = KNeighborsClassifier(n_neighbors=5, n_jobs=-1)

# Create the pipeline
pipeline = Pipeline([
    ('smote', smote),
    ('classifier', knn)
])

# Perform cross-validation and get predictions
y_pred_cv = cross_val_predict(pipeline, X_train, y_train, cv=5, n_jobs=-1)

# Print classification report and confusion matrix for cross-validation predict
print("Cross-Validation Evaluation:")
print(classification_report(y_train, y_pred_cv, zero_division=0))
print(f"Confusion Matrix (Cross-Validation):\n{confusion_matrix(y_train, y_pred

# Plot confusion matrix for cross-validation predictions
disp_cv = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_train, y_p
disp_cv.plot()

# Train the pipeline on the full training data
pipeline.fit(X_train, y_train)

# Predict on the test set
y_pred_test = pipeline.predict(X_test)
```

```
Cross-Validation Evaluation:
              precision    recall  f1-score   support

           0       0.74      0.77      0.76     19359
           1       0.85      0.83      0.84     30896

    accuracy                           0.81     50255
   macro avg       0.80      0.80      0.80     50255
weighted avg       0.81      0.81      0.81     50255

Confusion Matrix (Cross-Validation):
[[14925  4434]
 [ 5174 25722]]
```



The confusion matrix for the K-Nearest Neighbors (KNN) model with SMOTE (Synthetic Minority Over-sampling Technique) applied shows that it correctly classified 14,925 negative instances (true negatives) and 25,722 positive instances (true positives). It misclassified 4,434 negative instances as positive (false positives) and 5,174 positive instances as negative (false negatives). The cross-validation evaluation provides precision, recall, and F1 scores for each class. For the negative class (0), the precision is 0.74, recall is 0.77, and F1-score is 0.76. For the positive class (1), the precision is 0.85, recall is 0.83, and F1-score is 0.84. The overall accuracy is 0.80, with macro and weighted averages for precision, recall, and F1-score around 0.80 to 0.81, indicating consistent and balanced performance across different metrics.

SMOTE on Gradient Boosting Classifier

In [65]:
```
# Define the SMOTE and GradientBoostingClassifier
smote = SMOTE(random_state=42)
gbc = GradientBoostingClassifier(random_state=42)

# Create the pipeline
pipeline = Pipeline([
    ('smote', smote),
    ('classifier', gbc)
])

# Perform cross-validation and get predictions
y_pred_cv = cross_val_predict(pipeline, X_train, y_train, cv=5, n_jobs=-1)

# Print classification report and confusion matrix for cross-validation predict
print("Cross-Validation Evaluation (GradientBoostingClassifier):")
print(classification_report(y_train, y_pred_cv, zero_division=0))
print(f"Confusion Matrix (Cross-Validation):\n{confusion_matrix(y_train, y_pred

# Plot confusion matrix for cross-validation predictions
disp_cv = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(y_train, y_p
disp_cv.plot()

# Train the pipeline on the full training data
pipeline.fit(X_train, y_train)

# Predict on the test set
y_pred_test = pipeline.predict(X_test)
```

```
Cross-Validation Evaluation (GradientBoostingClassifier):
              precision    recall  f1-score   support

           0       0.77      0.69      0.73     19359
           1       0.82      0.87      0.84     30896

    accuracy                           0.80     50255
   macro avg       0.79      0.78      0.78     50255
weighted avg       0.80      0.80      0.80     50255

Confusion Matrix (Cross-Validation):
[[13377  5982]
 [ 4060 26836]]
```

In [66]:
```
# Logistic Regression model
logreg_model = LogisticRegression(random_state=42)
logreg_model.fit(X_train, y_train)
logreg_probs = logreg_model.predict_proba(X_test_transformed)[:, 1]

# Hyperparameter Tuned Decision Trees model
dt_tuned_probs = dt_grid_search.predict_proba(X_test_transformed)[:, 1]

# Hyperparameter Tuned Random Forest model
rf_tuned_probs = rf_grid_search.predict_proba(X_test_transformed)[:, 1]

# Compute ROC curve and ROC area for each class
fpr_logreg, tpr_logreg, _ = roc_curve(y_test, logreg_probs)
fpr_dt_tuned, tpr_dt_tuned, _ = roc_curve(y_test, dt_tuned_probs)
fpr_rf_tuned, tpr_rf_tuned, _ = roc_curve(y_test, rf_tuned_probs)

# Compute AUC (Area Under the Curve) for each model
roc_auc_logreg = auc(fpr_logreg, tpr_logreg)
roc_auc_dt_tuned = auc(fpr_dt_tuned, tpr_dt_tuned)
roc_auc_rf_tuned = auc(fpr_rf_tuned, tpr_rf_tuned)

# Plot ROC curves
plt.figure(figsize=(8, 6))
plt.plot(fpr_logreg, tpr_logreg, color='blue', lw=2, label=f'Logistic Regressio
plt.plot(fpr_dt_tuned, tpr_dt_tuned, color='green', lw=2, label=f'Tuned Decisio
plt.plot(fpr_rf_tuned, tpr_rf_tuned, color='red', lw=2, label=f'Tuned Random Fo

plt.plot([0, 1], [0, 1], color='black', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[66], line 4
      2 logreg_model = LogisticRegression(random_state=42)
      3 logreg_model.fit(X_train, y_train)
----> 4 logreg_probs = logreg_model.predict_proba(X_test_transformed)[:, 1]
      6 # Hyperparameter Tuned Decision Trees model
      7 dt_tuned_probs = dt_grid_search.predict_proba(X_test_transformed)[:,
1]

NameError: name 'X_test_transformed' is not defined
```

Decisions on best model

The Random Forest model is the best-performing model. Here are the reasons for the choice:

1. High Accuracy: The Random Forest model achieved an accuracy of 0.85, which indicates a high level of correctness in its predictions.
2. Strong F1 Score: With an F1 score of 0.88, the model shows a good balance between precision and recall, minimizing both false positives and false negatives effectively.
3. Balanced Metrics: The model's precision for the positive class is 0.87 and recall is 0.89, which demonstrates that it handles both classes well without significant bias.
4. Consistent Performance: The cross-validation scores for the Random Forest model are consistently high, with a mean score of 0.8538, indicating stable and reliable performance across different data splits.
5. These reasons collectively indicate that the Random Forest model excels in classification

Recommendations to Government of Tanzania

1. Based on the findings from this study, I recommend the Government of Tanzania apply the Random Forest model to predict the condition of well pumps across the country. This model can correctly predict the actual condition of each pump with at least an 85% success rate.
2. Additionally, the government should prioritize the Northern regions of Bukoba and Arusha, where there is a high density of pumps that need repairs, and the regions of Dodoma and Mtwara, where there is a high density of non-functional pumps.
3. Investigations should be conducted to understand why there are more non-functional pumps in areas recorded as having zero static head and zero population.

Limitations of the study

1. Cross-Validation Only on Training Data: The evaluation metrics were primarily based on cross-validation on the training data. While this provides a good estimate of model performance, it may not fully capture the model's performance on unseen test data.
2. Limited Feature Engineering: The study did not mention any advanced feature engineering techniques. Including domain-specific features or interaction terms might improve model performance.
3. Class Imbalance: The use of SMOTE indicates that the dataset might have an imbalance between classes. While SMote helps to mitigate this, it can sometimes lead to overfitting, especially for complex models like Random Forests and Gradient Boosting.
4. Absence of a Target Variable for Testing (Y_test): The study mentioned the absence of a y_test dataset, limiting the ability to evaluate model performance on an unseen test set. This could lead to an overestimation of the model's real-world performance.

Conclusion

This study aimed to predict the functionality of water pumps in Tanzania using several machine learning models, including K-Nearest Neighbors, Logistic Regression, Decision Tree, Naive Bayes, Random Forest, and Gradient Boosting Classifier. The Random Forest model emerged as the best performer, showing high accuracy and balanced precision and recall metrics. Despite its strong performance, limitations such as the use of cross-validation only on training data, the absence of advanced feature engineering, and the lack of a target variable for testing (y_test) were noted. These limitations highlight the need for further work to improve feature engineering, model interpretability, and validation on unseen test data to ensure robust performance. Overall, the study demonstrates the potential of the Random Forest model in accurately predicting the functionality of water pumps, which is crucial for effective water resource management in Tanzania.