

# Garbage\_Bin\_Level\_Precision\_and\_Collection

March 1, 2024

## 1 Importing required libraries

```
[1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from sklearn.metrics import mean_squared_error
```

## 2 Suppress warnings

```
[2]: import warnings
warnings.filterwarnings('ignore')
```

## 3 Load data

```
[3]: df=pd.read_csv("C:/Users/geeth/Downloads/trash data PS-2 (5).csv")
df
```

```
[3]:
```

	BIN ID	Date	TIME	WEEK NO	FILL LEVEL(IN LITRES)	\
0	BIN 1	10/1/2021	12:00:00 AM	1		5
1	BIN 1	10/1/2021	01:00:00 AM	1		29
2	BIN 1	10/1/2021	02:00:00 AM	1		53
3	BIN 1	10/1/2021	03:00:00 AM	1		77
4	BIN 1	10/1/2021	04:00:00 AM	1		101
...	...	...	...	...	...	...
11036	BIN 5	12/31/2021	07:00:00 PM	5		480
11037	BIN 5	12/31/2021	08:00:00 PM	5		504
11038	BIN 5	12/31/2021	09:00:00 PM	5		528
11039	BIN 5	12/31/2021	10:00:00 PM	5		552

11040 BIN 5 12/31/2021 11:00:00 PM 5 576

	TOTAL(LITRES)	FILL PERCENTAGE	LOCATION	LATITUDE	LONGITUDE \
0	660	1%	MANAPAKKAM	13.0213° N	80.1832° E
1	660	4%	MANAPAKKAM	13.0213° N	80.1832° E
2	660	8%	MANAPAKKAM	13.0213° N	80.1832° E
3	660	12%	MANAPAKKAM	13.0213° N	80.1832° E
4	660	15%	MANAPAKKAM	13.0213° N	80.1832° E
...	...	...	...	...	...
11036	660	73%	T-NAGAR	13.0418° N	80.2341° E
11037	660	76%	T-NAGAR	13.0418° N	80.2341° E
11038	660	80%	T-NAGAR	13.0418° N	80.2341° E
11039	660	84%	T-NAGAR	13.0418° N	80.2341° E
11040	660	87%	T-NAGAR	13.0418° N	80.2341° E

	TEMPERATURE( IN C)	BATTERY LEVEL	FILL LEVEL INDICATOR(Above 550)
0	24	100%	False
1	24.6	100%	False
2	24.6	100%	False
3	24.8	100%	False
4	25	100%	False
...	...	...	...
11036	37.8	87%	False
11037	37.5	87%	False
11038	37	87%	False
11039	36.5	87%	True
11040	32	87%	True

[11041 rows x 13 columns]

[4]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11041 entries, 0 to 11040
Data columns (total 13 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   BIN ID                                11041 non-null  object
1   Date                                  11041 non-null  object
2   TIME                                  11041 non-null  object
3   WEEK NO                               11041 non-null  int64
4   FILL LEVEL(IN LITRES)                 11041 non-null  int64
5   TOTAL(LITRES)                         11041 non-null  int64
6   FILL PERCENTAGE                       11041 non-null  object
7   LOCATION                              11041 non-null  object
8   LATITUDE                              11041 non-null  object
9   LONGITUDE                             11041 non-null  object
10  TEMPERATURE( IN C)                   11041 non-null  object
```

```

11 BATTERY LEVEL          11041 non-null object
12 FILL LEVEL INDICATOR(Above 550) 11041 non-null bool
dtypes: bool(1), int64(3), object(9)
memory usage: 1.0+ MB

```

```
[5]: df.isnull().sum()
```

```

[5]: BIN ID          0
Date                0
TIME                0
WEEK NO             0
FILL LEVEL(IN LITRES) 0
TOTAL(LITRES)       0
FILL PERCENTAGE     0
LOCATION              0
LATITUDE             0
LONGITUDE           0
TEMPERATURE( IN C)  0
BATTERY LEVEL       0
FILL LEVEL INDICATOR(Above 550) 0
dtype: int64

```

```
[6]: df.nunique()
```

```

[6]: BIN ID          5
Date                92
TIME                24
WEEK NO             5
FILL LEVEL(IN LITRES) 682
TOTAL(LITRES)       1
FILL PERCENTAGE     124
LOCATION              5
LATITUDE             5
LONGITUDE           5
TEMPERATURE( IN C)  51
BATTERY LEVEL       14
FILL LEVEL INDICATOR(Above 550) 2
dtype: int64

```

## 4 Data Exploration

### 4.1 Check columns

```

[7]: cat_cols=df.select_dtypes(include=['object']).columns

num_cols = df.select_dtypes (include=np.number).columns.tolist()

print("Categorical Variables:")

```

```
print(cat_cols)

print("Numerical Variables:")

print(num_cols)
```

Categorical Variables:

```
Index(['BIN ID', 'Date', 'TIME', 'FILL PERCENTAGE', 'LOCATION ', 'LATITUDE',
      'LONGITUDE', 'TEMPERATURE( IN C)', 'BATTERY LEVEL '],
      dtype='object')
```

Numerical Variables:

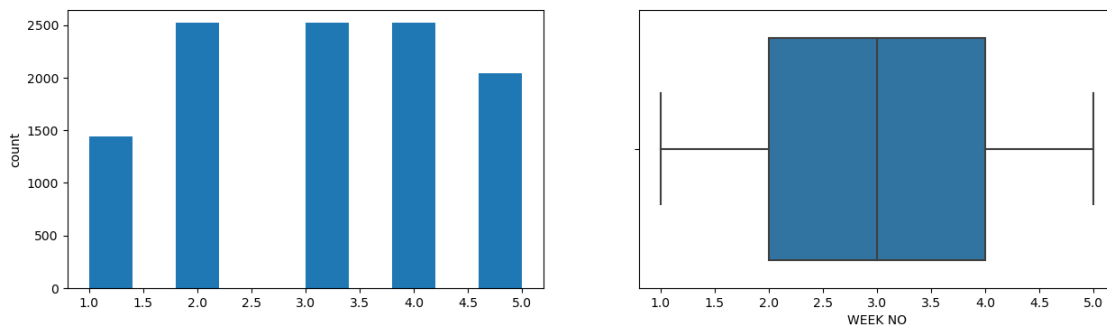
```
['WEEK NO', 'FILL LEVEL(IN LITRES)', 'TOTAL(LITRES)']
```

## 4.2 Explore numerical variables

```
[8]: for col in num_cols:
      print(col)
      print('Skew:', round(df[col].skew(), 2))
      plt.figure(figsize = (15, 4))
      plt.subplot(1, 2, 1)
      df[col].hist(grid=False)
      plt.ylabel('count')
      plt.subplot(1, 2, 2)
      sns.boxplot(x=df[col])
      plt.show()
```

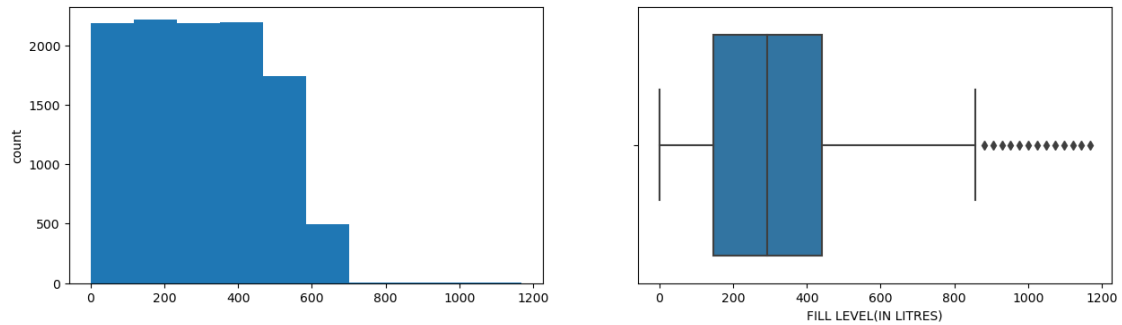
WEEK NO

Skew: -0.06

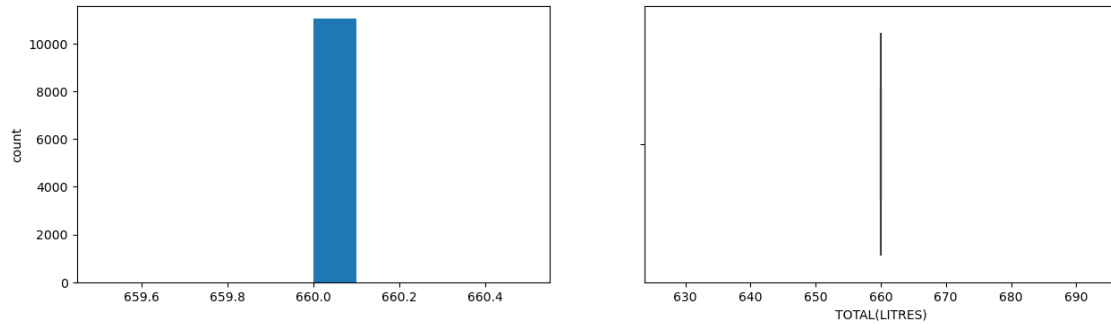


FILL LEVEL(IN LITRES)

Skew: 0.17



TOTAL(LITRES)  
Skew: 0



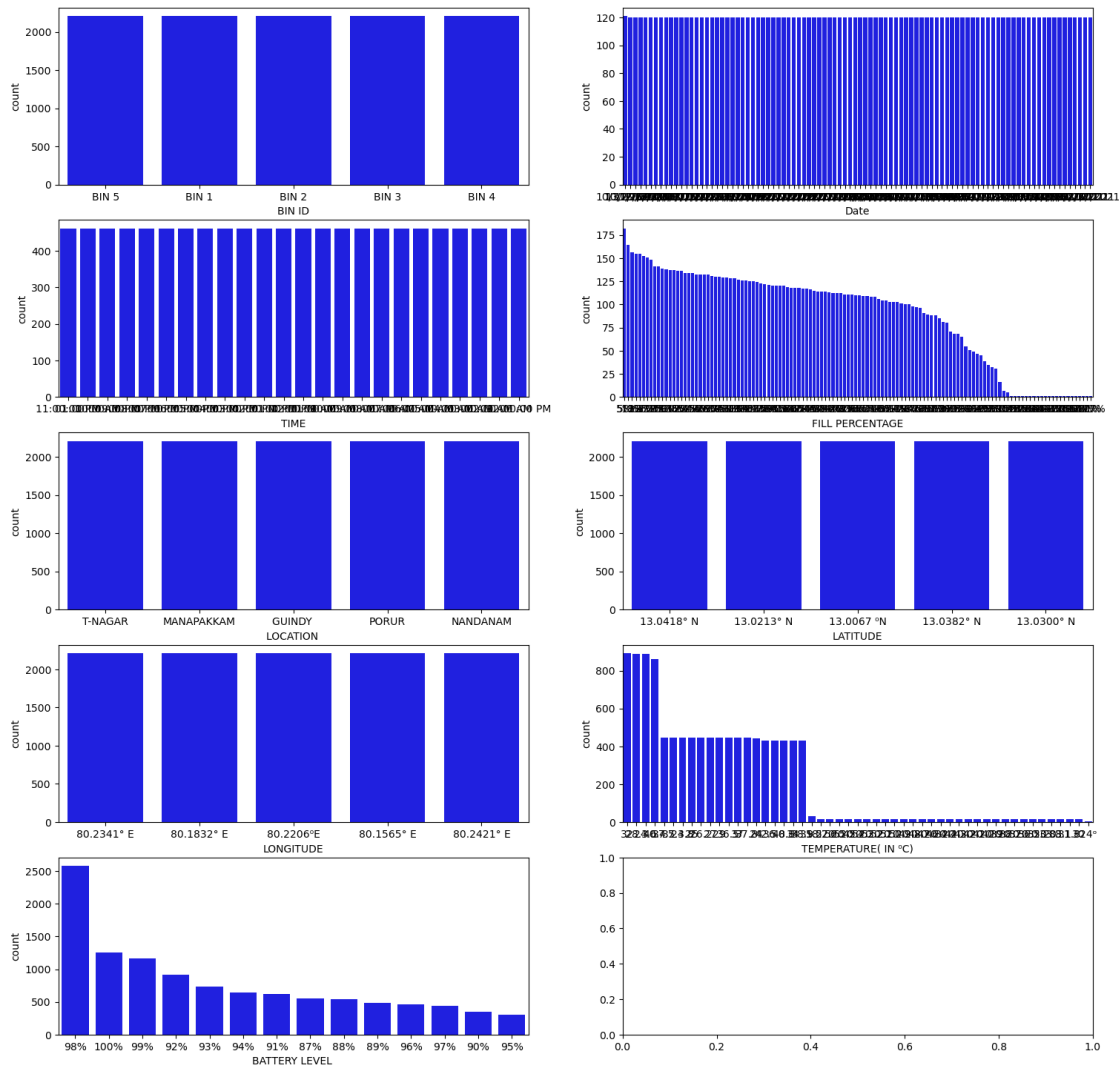
### 4.3 Explore categorical variables

```
[9]: fig, axes = plt.subplots (5, 2, figsize = (18, 18))

fig.suptitle('Bar plot for all categorical variables in the dataset',
    ↪ fontsize=24)
sns.countplot(ax = axes[0, 0], x = 'BIN ID', data = df, color = 'blue', order =
    ↪ df['BIN ID'].value_counts().index);
sns.countplot(ax = axes[0, 1], x = 'Date', data = df, color = 'blue', order =
    ↪ df['Date'].value_counts().index);
sns.countplot(ax = axes[1, 0], x = 'TIME', data = df, color = 'blue', order =
    ↪ df['TIME'].value_counts().index);
sns.countplot(ax = axes[1, 1], x = 'FILL PERCENTAGE', data = df, color =
    ↪ 'blue', order = df['FILL PERCENTAGE'].value_counts().index);
sns.countplot(ax = axes[2, 0], x = 'LOCATION ', data = df, color = 'blue',
    ↪ order = df['LOCATION '].value_counts().index);
sns.countplot(ax = axes[2, 1], x = 'LATITUDE', data = df, color = 'blue', order
    ↪ = df['LATITUDE'].value_counts().index);
```

```
sns.countplot(ax = axes[3, 0], x = 'LONGITUDE', data = df, color = 'blue',
               order = df['LONGITUDE'].value_counts().index);
sns.countplot(ax = axes[3, 1], x = 'TEMPERATURE( IN C)' , data = df, color =
               'blue', order = df['TEMPERATURE( IN C)'].value_counts().index);
sns.countplot(ax = axes[4, 0], x = 'BATTERY LEVEL ', data = df, color = 'blue',
               order = df['BATTERY LEVEL '].value_counts().index);
```

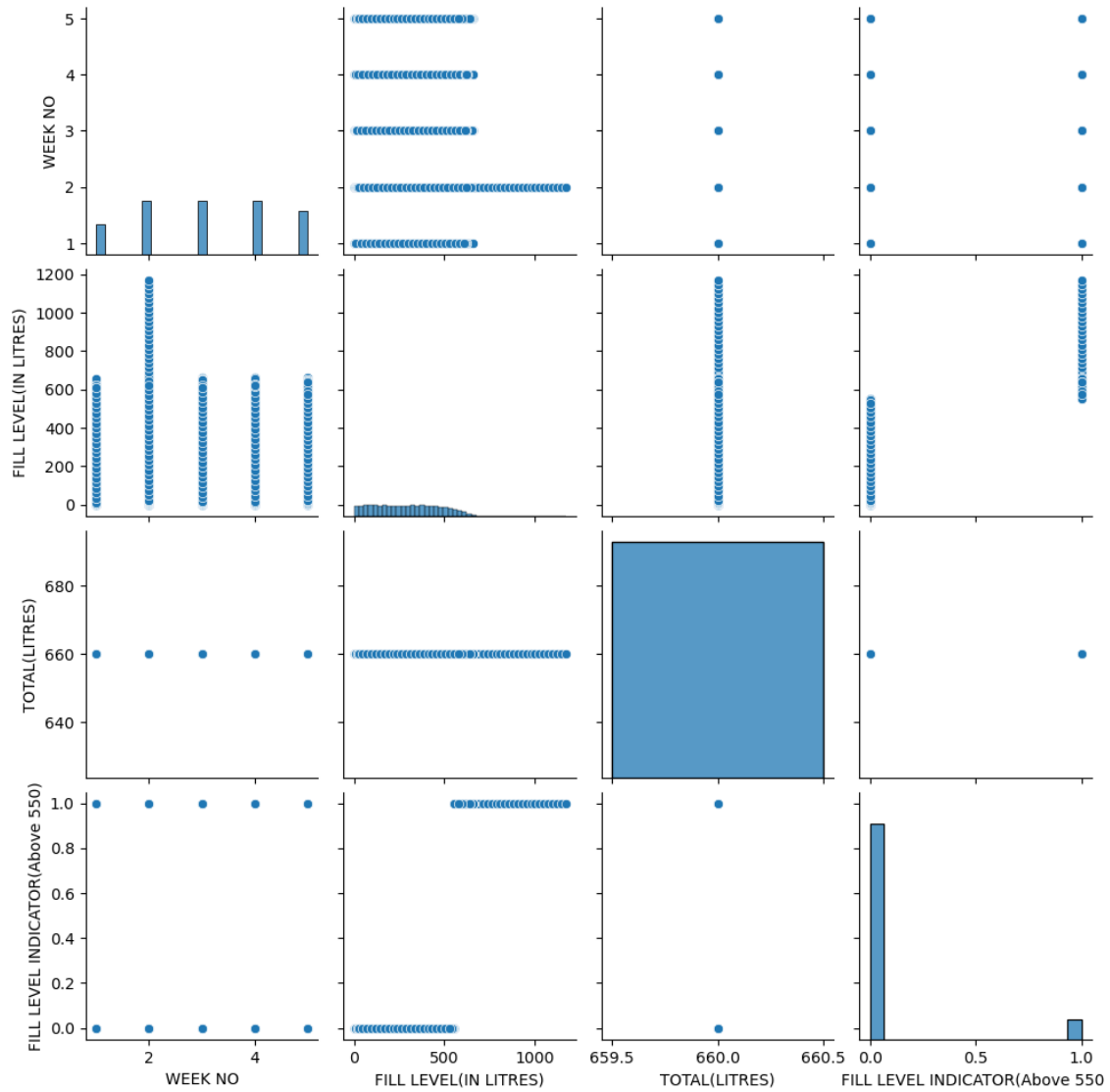
Bar plot for all categorical variables in the dataset



## 5 Pairplot

```
[10]: plt.figure(figsize=(15,20))  
  
sns.pairplot(df)  
  
plt.show()
```

<Figure size 1500x2000 with 0 Axes>



## 6 Grouped bar plots

```
[11]: fig, axarr= plt.subplots(5, 2, figsize=(12, 18))

df.groupby('BIN ID')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[0][0], fontsize=12)
axarr[0][0].set_title("BIN ID Vs FILL LEVEL INDICATOR(Above 550)", fontsize=14)

df.groupby('Date')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[0][1], fontsize=12)
axarr[0][1].set_title("Date Vs FILL LEVEL INDICATOR(Above 550)", fontsize=14)

df.groupby('TIME')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[1][0], fontsize=12)
axarr[1][0].set_title("TIME Vs FILL LEVEL INDICATOR(Above 550)", fontsize=14)

df.groupby('FILL PERCENTAGE')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[1][1], fontsize=12)
axarr[1][1].set_title("FILL PERCENTAGE Vs FILL LEVEL INDICATOR(Above 550)",
    ↪fontsize=14)

df.groupby('LOCATION ')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).head(10).plot.bar(ax=axarr[2][0], fontsize=12)
axarr[2][0].set_title("LOCATION Vs FILL LEVEL INDICATOR(Above 550)",
    ↪fontsize=14)

df.groupby('LATITUDE')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[2][1], fontsize=12)
axarr[2][1].set_title("LATITUDE Vs FILL LEVEL INDICATOR(Above 550)",
    ↪fontsize=14)

df.groupby('LONGITUDE')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[3][0], fontsize=12)
axarr[3][0].set_title("LONGITUDE Vs FILL LEVEL INDICATOR(Above 550)",
    ↪fontsize=14)

df.groupby('TEMPERATURE( IN C)')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[3][1], fontsize=12)
axarr[3][1].set_title("TEMPERATURE( IN C) Vs FILL LEVEL INDICATOR(Above 550)",
    ↪fontsize=14)

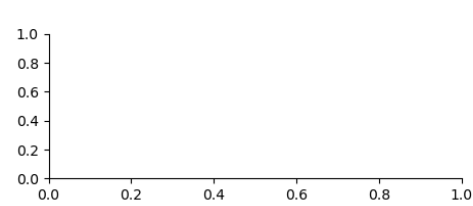
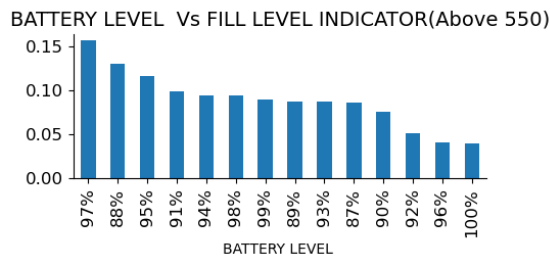
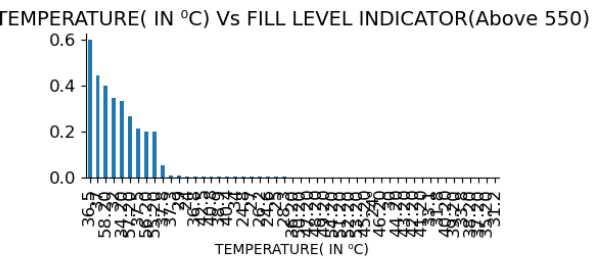
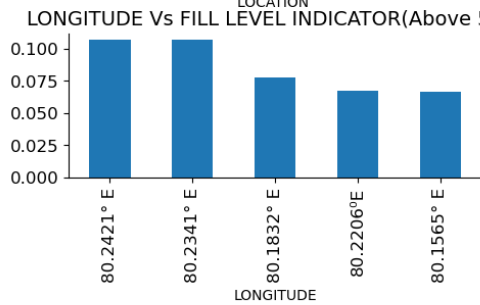
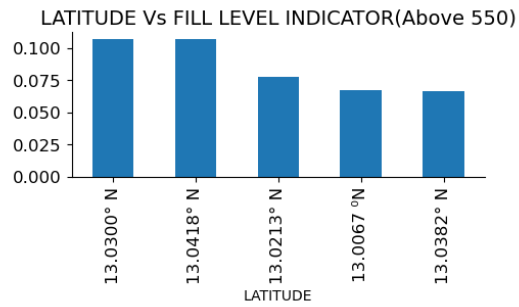
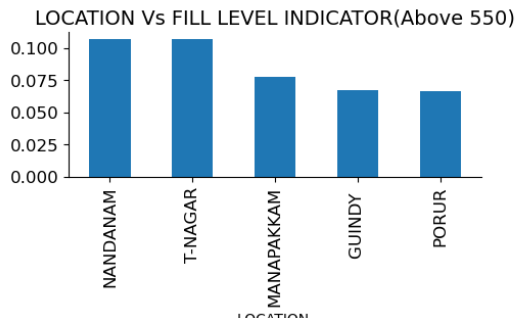
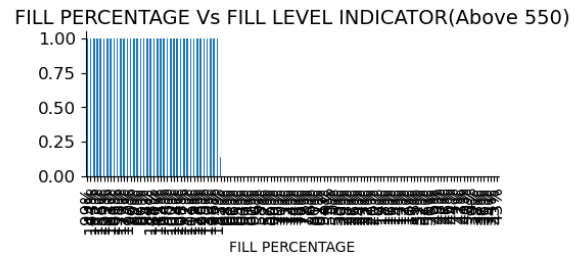
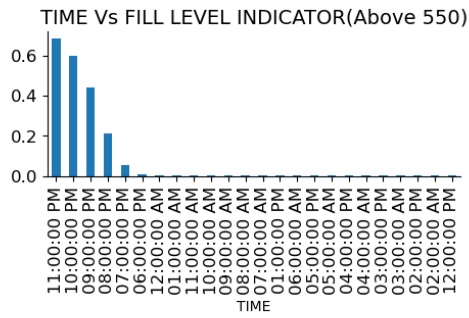
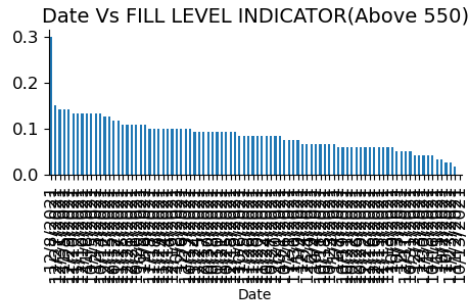
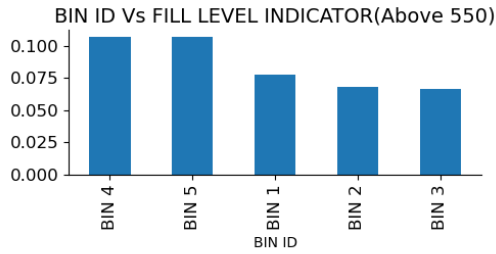
df.groupby('BATTERY LEVEL ')['FILL LEVEL INDICATOR(Above 550)'].mean().
    ↪sort_values(ascending=False).plot.bar(ax=axarr[4][0], fontsize=12)
axarr[4][0].set_title("BATTERY LEVEL Vs FILL LEVEL INDICATOR(Above 550)",
    ↪fontsize=14)
```



```
plt.subplots_adjust(hspace=1.2)

plt.subplots_adjust(wspace=.3)

sns.despine()
```



## 7 Encode categorical variables

```
[12]: # Define the columns to encode
columns = ['BIN ID', 'Date', 'TIME', 'LOCATION ', 'LATITUDE', 'LONGITUDE', 'FILL_
↵LEVEL INDICATOR(Above 550)', 'FILL PERCENTAGE', 'BATTERY LEVEL ', 'TEMPERATURE(
↵IN C)']

# Initialize the LabelEncoder
encoder = LabelEncoder()

# Encode each column separately
for column in columns:
    df[column] = encoder.fit_transform(df[column])

# Now df contains the encoded values for each column
df
```

```
[12]:
```

	BIN ID	Date	TIME	WEEK NO	FILL LEVEL(IN LITRES)	TOTAL(LITRES)	\
0	0	0	22	1	5	660	
1	0	0	0	1	29	660	
2	0	0	2	1	53	660	
3	0	0	4	1	77	660	
4	0	0	6	1	101	660	
...	...	...	...	...	...	...	
11036	4	85	13	5	480	660	
11037	4	85	15	5	504	660	
11038	4	85	17	5	528	660	
11039	4	85	19	5	552	660	
11040	4	85	21	5	576	660	

	FILL PERCENTAGE	LOCATION	LATITUDE	LONGITUDE	TEMPERATURE( IN C)	\
0	1	1	1	1		0
1	58	1	1	1		1
2	102	1	1	1		1
3	12	1	1	1		2
4	23	1	1	1		4
...	...	...	...	...	...	
11036	95	4	4	3		25
11037	98	4	4	3		24
11038	103	4	4	3		21
11039	107	4	4	3		19
11040	110	4	4	3		12

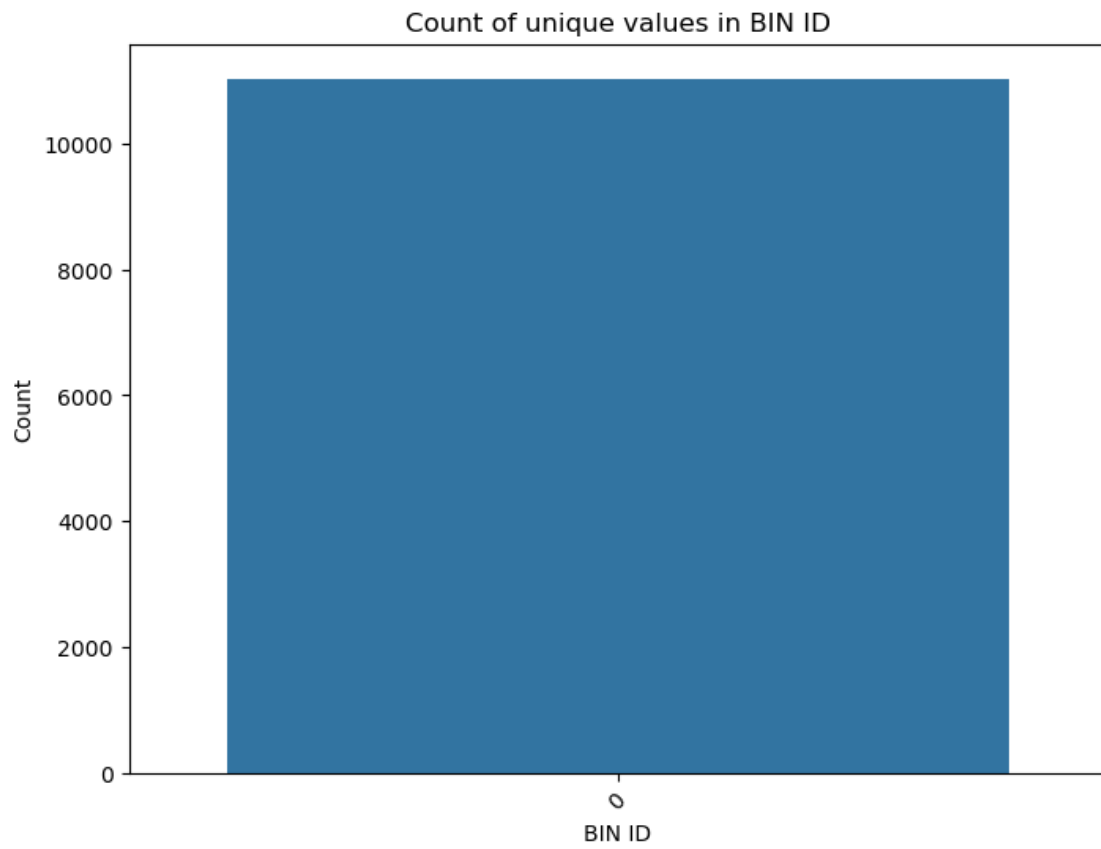
	BATTERY LEVEL	FILL LEVEL INDICATOR(Above 550)
0	0	0
1	0	0
2	0	0

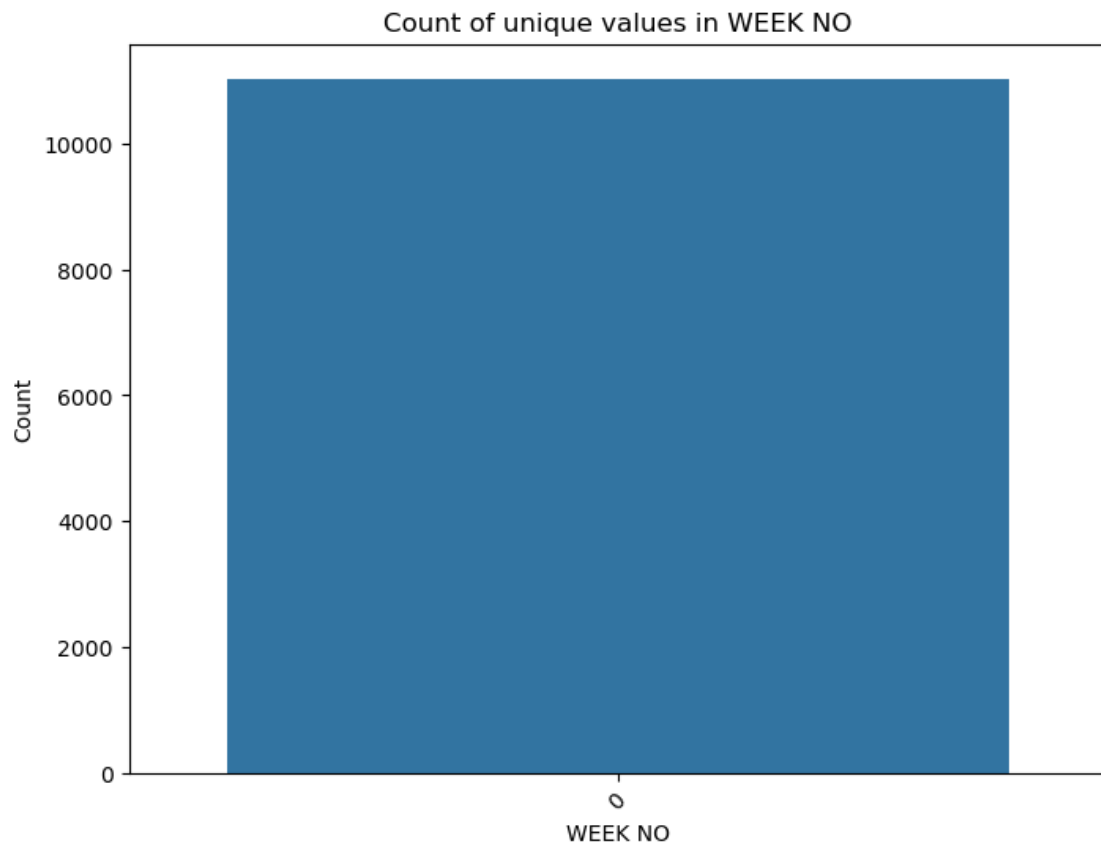
3	0	0
4	0	0
...	...	...
11036	1	0
11037	1	0
11038	1	0
11039	1	1
11040	1	1

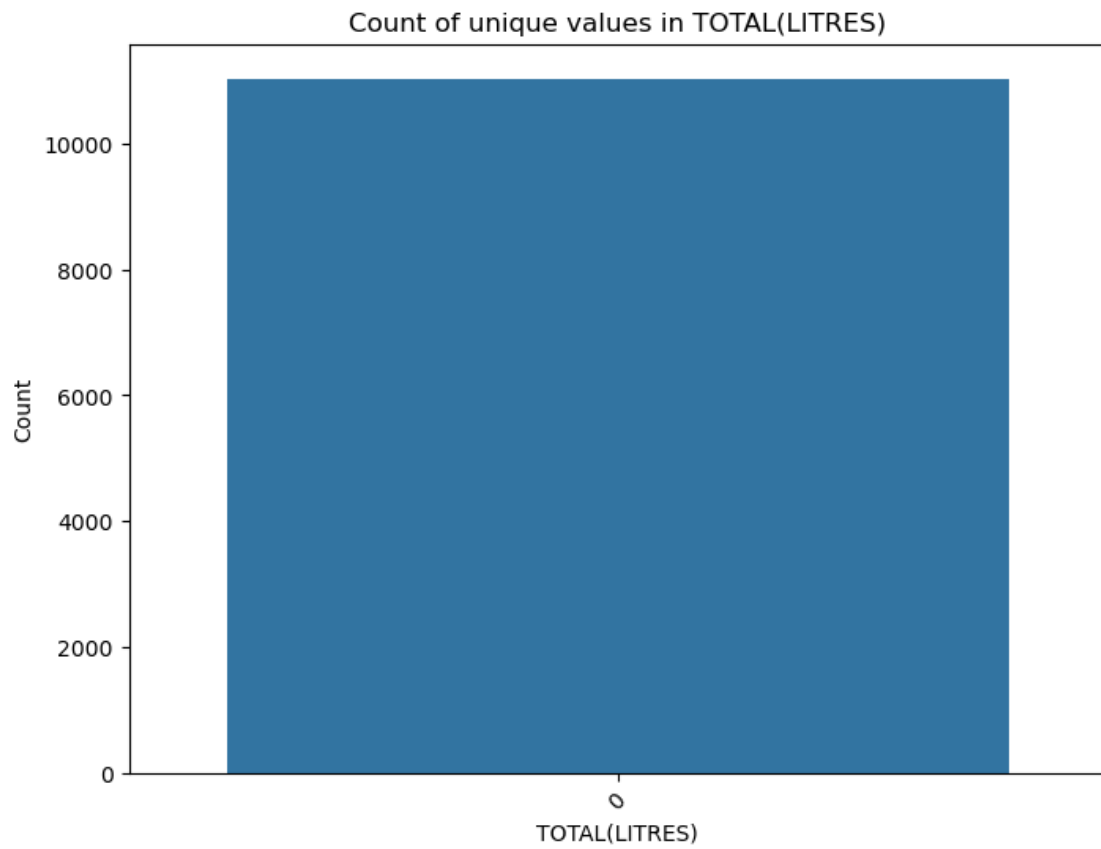
[11041 rows x 13 columns]

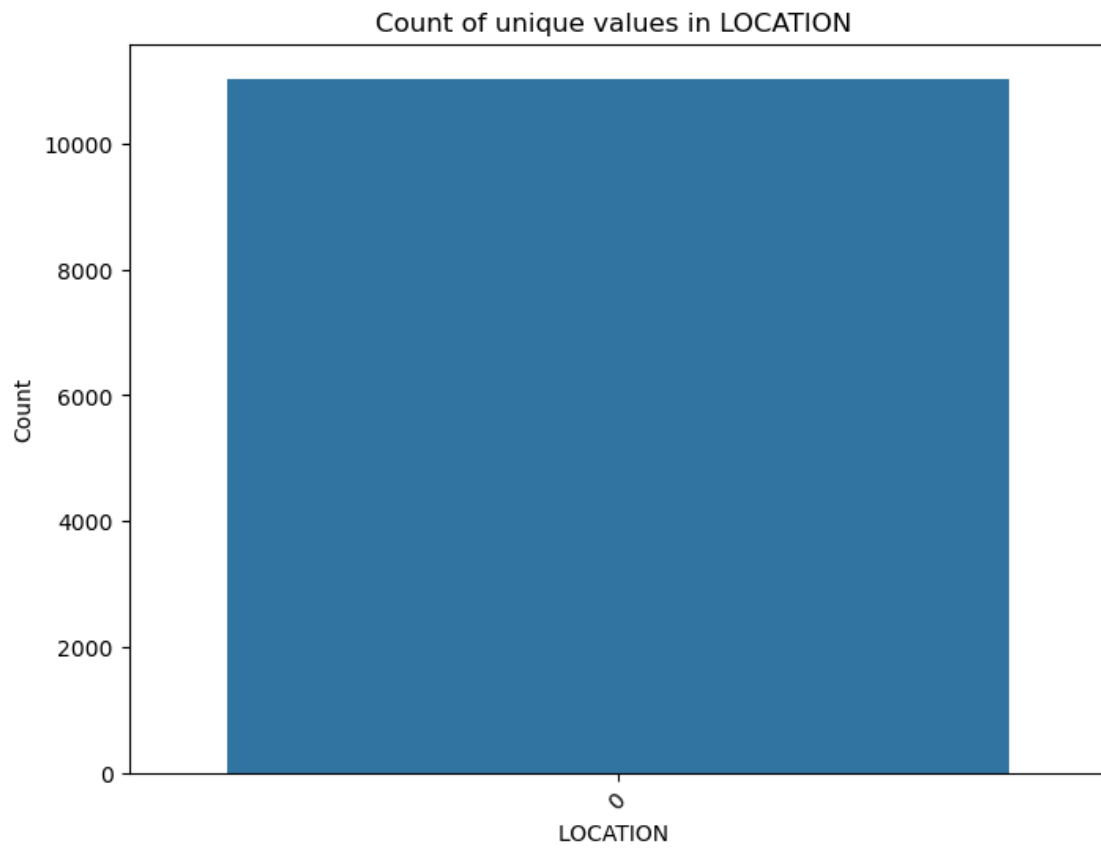
## 8 Count of unique values for categorical columns

```
[13]: categorical_columns = ['BIN ID', 'WEEK NO', 'TOTAL(LITRES)', 'LOCATION_
↳', 'LATITUDE', 'LONGITUDE', 'FILL LEVEL INDICATOR(Above 550)']
for column in categorical_columns:
    plt.figure(figsize=(8, 6))
    sns.countplot(df[column])
    plt.title(f'Count of unique values in {column}')
    plt.xlabel(column)
    plt.ylabel('Count')
    plt.xticks(rotation=45)
    plt.show()
```

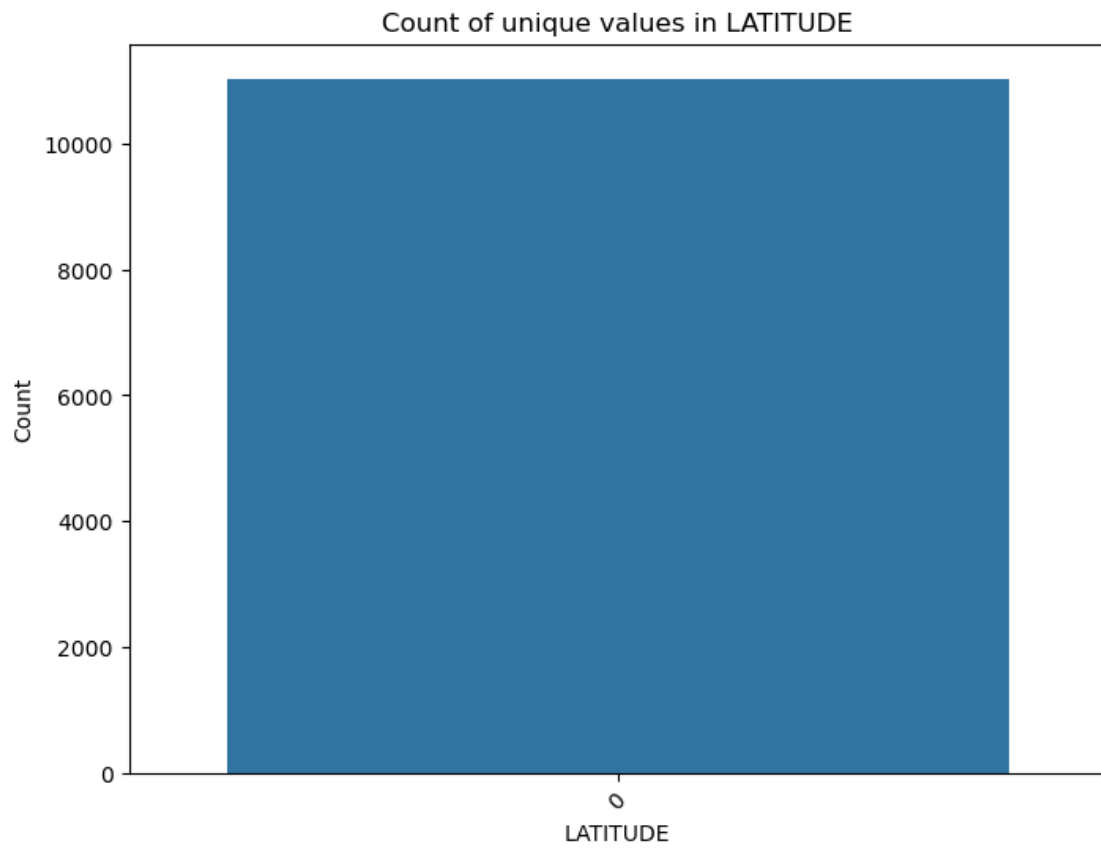


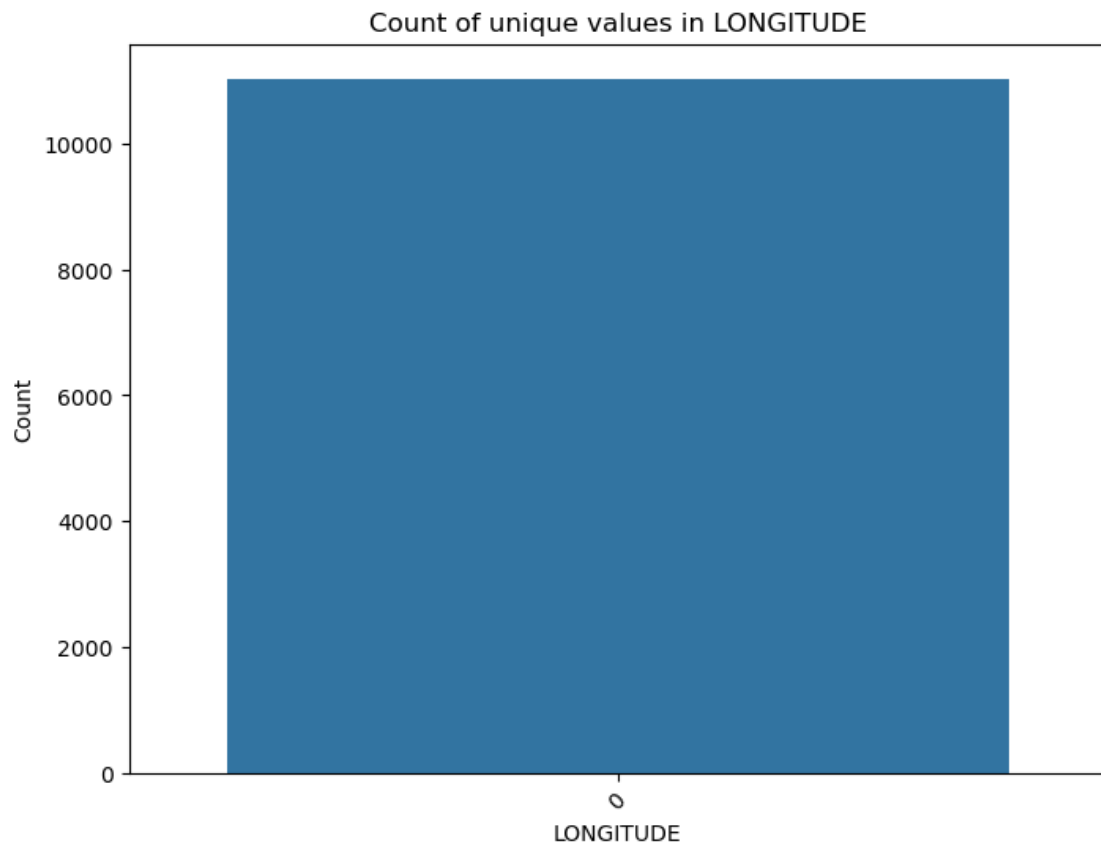


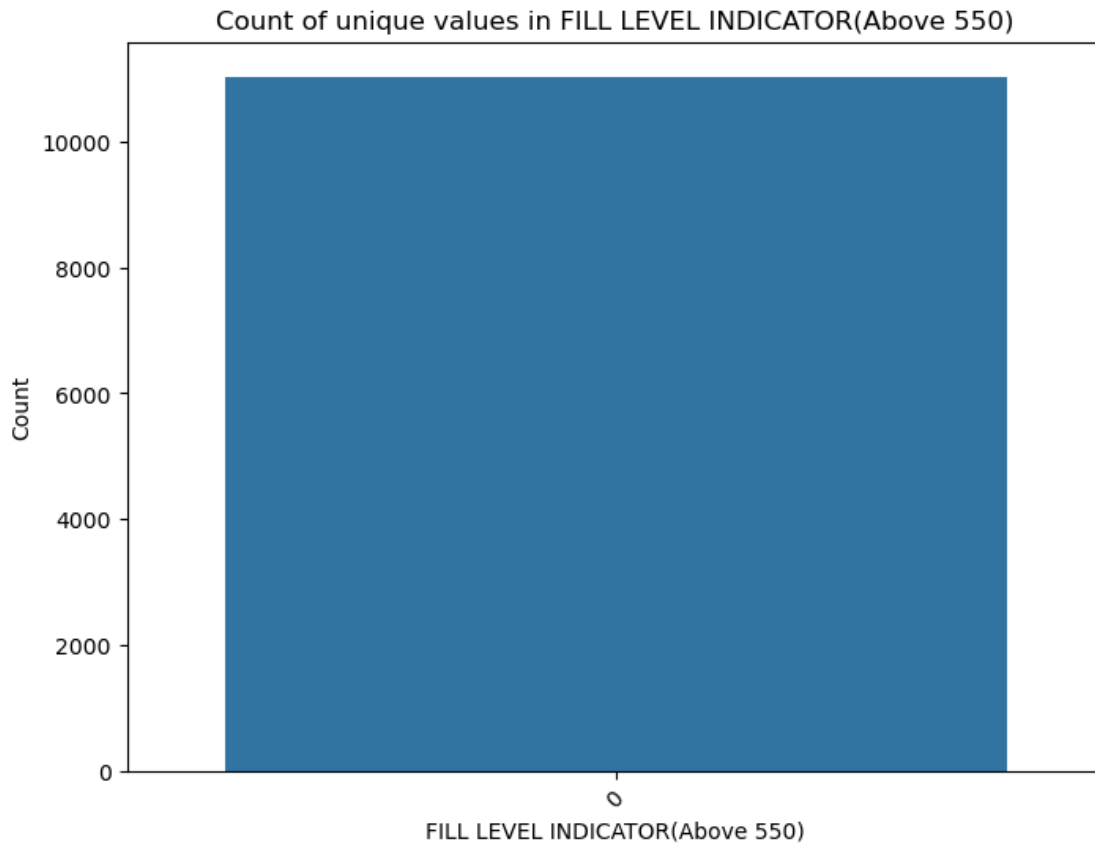












```
[14]: df.describe().T
```

```
[14]:
```

	count	mean	std	min	\
BIN ID	11041.0	2.000181	1.414342	0.0	
Date	11041.0	45.498053	26.557332	0.0	
TIME	11041.0	11.500860	6.922777	0.0	
WEEK NO	11041.0	3.109229	1.306071	1.0	
FILL LEVEL(IN LITRES)	11041.0	297.267458	176.612948	0.0	
TOTAL(LITRES)	11041.0	660.000000	0.000000	660.0	
FILL PERCENTAGE	11041.0	67.190653	29.388646	0.0	
LOCATION	11041.0	2.000181	1.414342	0.0	
LATITUDE	11041.0	2.000181	1.414342	0.0	
LONGITUDE	11041.0	2.000091	1.414246	0.0	
TEMPERATURE( IN C)	11041.0	15.733720	11.397134	0.0	
BATTERY LEVEL	11041.0	7.393533	4.537516	0.0	
FILL LEVEL INDICATOR(Above 550)	11041.0	0.085047	0.278964	0.0	

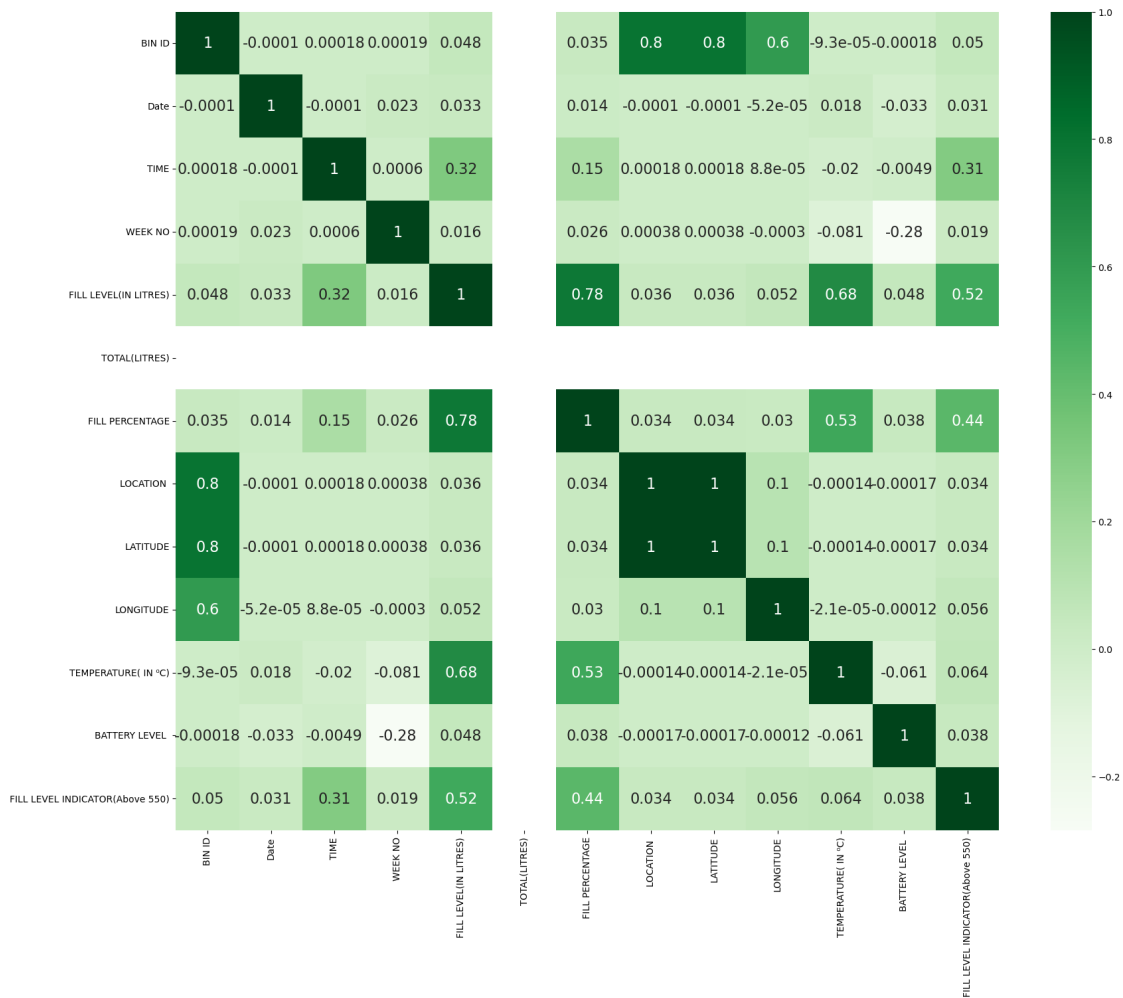
	25%	50%	75%	max
BIN ID	1.0	2.0	3.0	4.0
Date	23.0	45.0	68.0	91.0

TIME	6.0	12.0	18.0	23.0
WEEK NO	2.0	3.0	4.0	5.0
FILL LEVEL(IN LITRES)	147.0	293.0	440.0	1169.0
TOTAL(LITRES)	660.0	660.0	660.0	660.0
FILL PERCENTAGE	46.0	69.0	91.0	123.0
LOCATION	1.0	2.0	3.0	4.0
LATITUDE	1.0	2.0	3.0	4.0
LONGITUDE	1.0	2.0	3.0	4.0
TEMPERATURE( IN °C)	6.0	15.0	25.0	50.0
BATTERY LEVEL	3.0	8.0	12.0	13.0
FILL LEVEL INDICATOR(Above 550)	0.0	0.0	0.0	1.0

## 9 Heatmap of correlations

```
[15]: fig, ax = plt.subplots(figsize=(20,16))
sns.heatmap(df.corr(), annot=True, cmap='Greens', annot_kws={"fontsize":16})
```

[15]: <Axes: >



## 10 Modeling

### 10.1 Split data

```
[16]: x=df.drop(['BIN ID','Date','TIME','WEEK NO','TOTAL(LITRES)','BATTERY LEVEL',  
             ↵','FILL LEVEL INDICATOR(Above 550)'],axis=1)  
y=df['FILL LEVEL INDICATOR(Above 550)']  
x
```

```
[16]:
```

	FILL LEVEL(IN LITRES)	FILL PERCENTAGE	LOCATION	LATITUDE	LONGITUDE	\
0	5	1	1	1	1	
1	29	58	1	1	1	
2	53	102	1	1	1	
3	77	12	1	1	1	
4	101	23	1	1	1	
...	...	...	...	...	...	
11036	480	95	4	4	3	
11037	504	98	4	4	3	
11038	528	103	4	4	3	
11039	552	107	4	4	3	
11040	576	110	4	4	3	

	TEMPERATURE( IN C)
0	0
1	1
2	1
3	2
4	4
...	...
11036	25
11037	24
11038	21
11039	19
11040	12

```
[11041 rows x 6 columns]
```

```
[17]: from sklearn.model_selection import train_test_split  
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=0,test_size=0.2)
```

## 10.2 Logistic Regression

```
[18]: lr=LogisticRegression(max_iter=1000)
lr.fit(x_train,y_train)
pred_1=lr.predict(x_test)
acc_1=accuracy_score(y_test,pred_1)
mse_lr = mean_squared_error(y_test, pred_1)
print("Accuracy:", acc_1)
print("Mean Squared Error:", mse_lr)
```

Accuracy: 1.0

Mean Squared Error: 0.0

## 10.3 Random Forest

```
[19]: rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
pred_2=rfc.predict(x_test)
acc_2=accuracy_score(y_test,pred_2)
mse_rfc = mean_squared_error(y_test, pred_2)
print("Accuracy:", acc_2)
print("Mean Squared Error:", mse_rfc)
```

Accuracy: 1.0

Mean Squared Error: 0.0

## 10.4 KNN

```
[20]: best_k = None
best_acc_knn = 0
for i in range(1,21):
    knn=KNeighborsClassifier(n_neighbors=i)
    knn.fit(x_train,y_train)
    preds=knn.predict(x_test)
    acc_3=accuracy_score(y_test,preds)
    mse_knn = mean_squared_error(y_test,preds)
    if acc_3 > best_acc_knn:
        best_acc_knn = acc_3
        best_k = i
print("\nK-Nearest Neighbors (k =", i, "):")
print("Accuracy:", acc_3)
print("Mean Squared Error:", mse_knn)
```

K-Nearest Neighbors (k = 1 ):

Accuracy: 0.9990946129470348

Mean Squared Error: 0.0009053870529651426

K-Nearest Neighbors (k = 2 ):

Accuracy: 0.9995473064735174  
Mean Squared Error: 0.0004526935264825713

K-Nearest Neighbors (k = 3 ):  
Accuracy: 0.9995473064735174  
Mean Squared Error: 0.0004526935264825713

K-Nearest Neighbors (k = 4 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 5 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 6 ):  
Accuracy: 0.9990946129470348  
Mean Squared Error: 0.0009053870529651426

K-Nearest Neighbors (k = 7 ):  
Accuracy: 0.9986419194205522  
Mean Squared Error: 0.001358080579447714

K-Nearest Neighbors (k = 8 ):  
Accuracy: 0.9986419194205522  
Mean Squared Error: 0.001358080579447714

K-Nearest Neighbors (k = 9 ):  
Accuracy: 0.9990946129470348  
Mean Squared Error: 0.0009053870529651426

K-Nearest Neighbors (k = 10 ):  
Accuracy: 0.9995473064735174  
Mean Squared Error: 0.0004526935264825713

K-Nearest Neighbors (k = 11 ):  
Accuracy: 0.9986419194205522  
Mean Squared Error: 0.001358080579447714

K-Nearest Neighbors (k = 12 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 13 ):  
Accuracy: 0.9990946129470348  
Mean Squared Error: 0.0009053870529651426

K-Nearest Neighbors (k = 14 ):

Accuracy: 0.9990946129470348  
Mean Squared Error: 0.0009053870529651426

K-Nearest Neighbors (k = 15 ):  
Accuracy: 0.9990946129470348  
Mean Squared Error: 0.0009053870529651426

K-Nearest Neighbors (k = 16 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 17 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 18 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 19 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

K-Nearest Neighbors (k = 20 ):  
Accuracy: 1.0  
Mean Squared Error: 0.0

## 10.5 Custom Linear Regression

```
[21]: import numpy as np
      from sklearn.metrics import mean_squared_error

      class CustomLinearRegression:
          def __init__(self, learning_rate=0.01, num_iterations=1000):
              self.learning_rate = learning_rate
              self.num_iterations = num_iterations
              self.theta = None

          def fit(self, x, y):
              # Add bias term to input features
              ones = np.ones((x.shape[0], 1))
              x = np.concatenate((ones, x), axis=1)

              # Initialize parameters randomly
              np.random.seed(0)
              self.theta = np.random.rand(x.shape[1])
```



```

        # Gradient descent
        for _ in range(self.num_iterations):
            # Compute gradients
            gradients = np.dot(x.T, np.dot(x, self.theta) - y) / x.shape[0]

            # Update parameters
            self.theta -= self.learning_rate * gradients

    def predict(self, x):
        # Add bias term to input features
        ones = np.ones((x.shape[0], 1))
        x = np.concatenate((ones, x), axis=1)

        # Predict target variable
        return np.dot(x, self.theta)
    def score(self, X, y):
        # Calculate R^2 score or any other metric you want to use for scoring
        predictions = self.predict(X)
        return your_custom_scoring_function(y, predictions)
    def get_params(self, deep=True):
        return {'learning_rate': self.learning_rate, 'num_iterations': self.
↪ num_iterations}

# Example usage:
# Assuming x_train, y_train, x_test, y_test are your training and testing data
custom_lr = CustomLinearRegression(learning_rate=0.01, num_iterations=1000)
custom_lr.fit(x_train, y_train)
predictions = custom_lr.predict(x_test)

# Handle NaN values
predictions = np.nan_to_num(predictions)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y_test, predictions)
print("Mean Squared Error (MSE):", mse)

# Calculate Accuracy Score
threshold = 0.5 # Example threshold
predicted_classes = (predictions >= threshold).astype(int)
true_classes = (y_test >= threshold).astype(int)
accuracy = (predicted_classes == true_classes).mean()
print("Accuracy Score:", accuracy)

```

Mean Squared Error (MSE): 0.08782254413761884

Accuracy Score: 0.9121774558623812

## 11 Cross-validation

```
[22]: from sklearn.model_selection import cross_val_score
lr_cv_scores = cross_val_score(lr, x, y, cv=5)
print("Logistic Regression Cross-Validation Accuracy:", np.mean(lr_cv_scores))

rfc_cv_scores = cross_val_score(rfc, x, y, cv=5)
print("Random Forest Cross-Validation Accuracy:", np.mean(rfc_cv_scores))

knn_cv_scores = cross_val_score(knn, x, y, cv=5)
print(f"KNN Cross-Validation Accuracy with {best_k} neighbors:", np.
      ↪mean(knn_cv_scores))

# Cross-validation for Custom Linear Regression
custom_lr_cv_scores = cross_val_score(custom_lr, x, y, cv=5)
print("Custom Linear Regression Cross-Validation Accuracy:", np.
      ↪mean(custom_lr_cv_scores))
```

Logistic Regression Cross-Validation Accuracy: 1.0

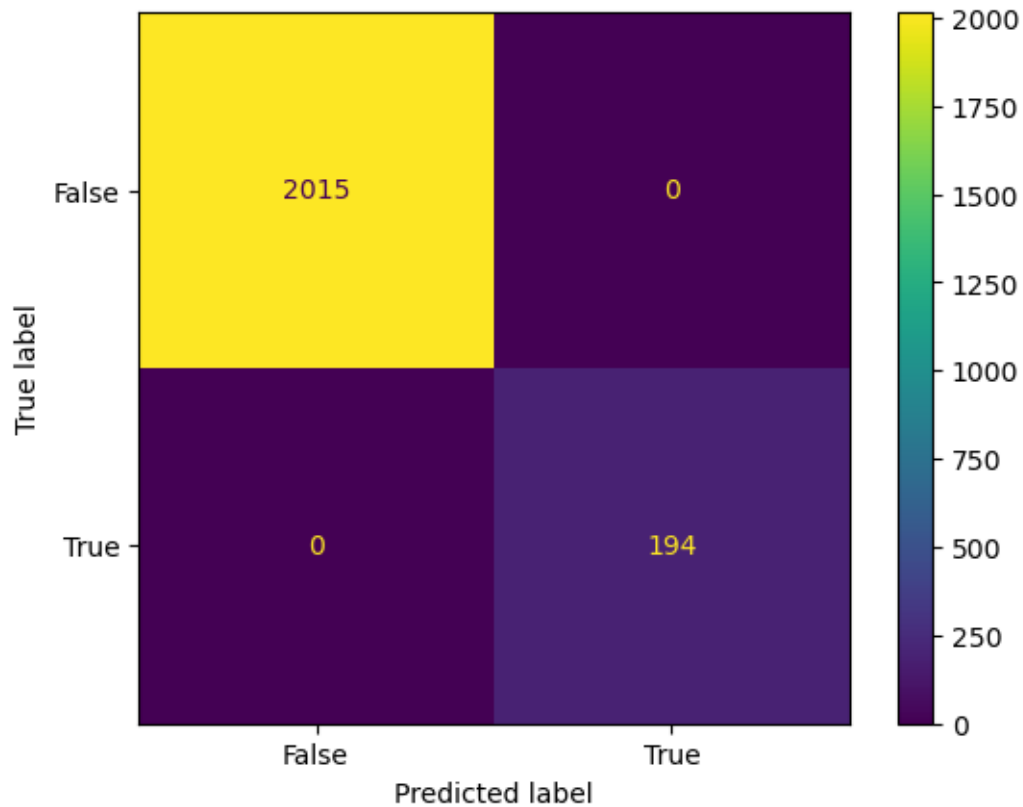
Random Forest Cross-Validation Accuracy: 1.0

KNN Cross-Validation Accuracy with 4 neighbors: 0.9999094612947035

Custom Linear Regression Cross-Validation Accuracy: nan

## 12 Metrics and Evaluation

```
[23]: from sklearn import metrics
confusion_matrix = metrics.confusion_matrix(y_test, preds)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix =
      ↪confusion_matrix, display_labels = [False, True])
cm_display.plot()
plt.show()
```



```
[24]: f1 = f1_score(y_test, preds)
      print("F1 score:", f1)
```

F1 score: 1.0

```
[25]: f1 = f1_score(y_test, preds)
      print("F1 score:", f1)
```

F1 score: 1.0

```
[26]: recall = recall_score(y_test, preds)
      print("Recall: {:.2f}".format(recall))
```

Recall: 1.00

```
[27]: new_bin_data = [[5, 58, 1, 1, 1, 25]]
      prediction = knn.predict(new_bin_data)
      if prediction[0] == 0:
          print("The bin didn't fill yet")
      else:
          print("The bin is full")
```

The bin didn't fill yet