Air Quality Forecast: Machine Learning Model

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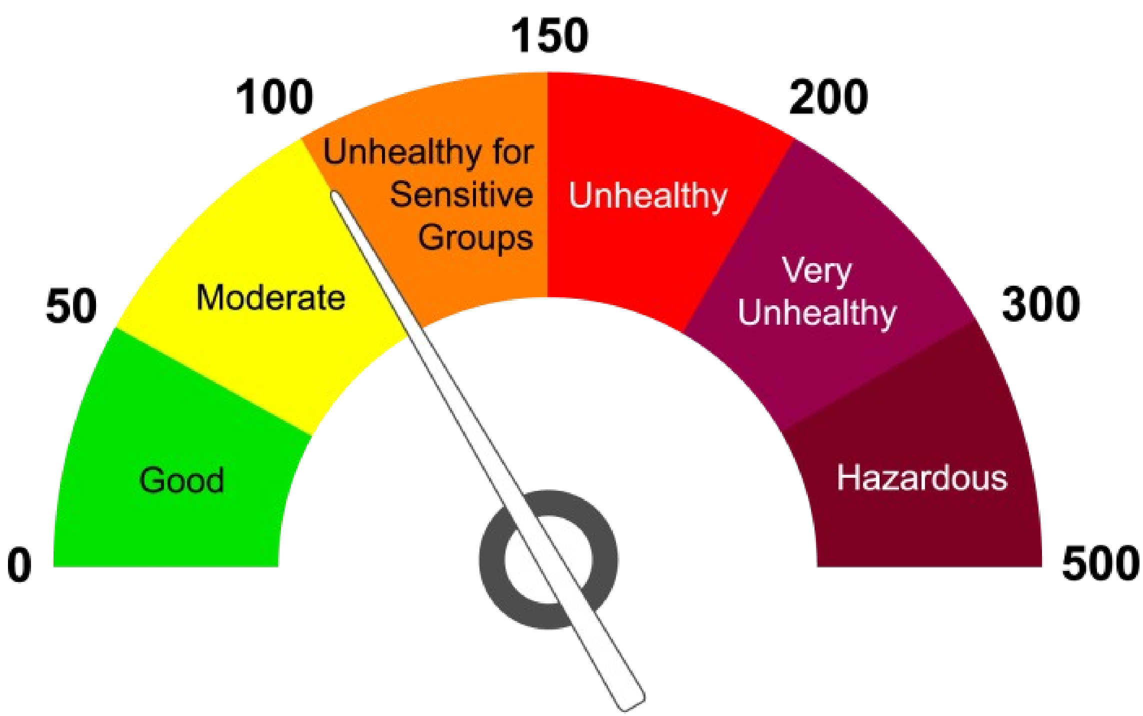
Description :

```
This project predicts the Air Quality Index (AQI) using pollutant data
like PM2.5, PM10, NOx, NH3, CO, SO2, O3, and volatile organic
compounds. By analyzing historical trends, the model forecasts AQI
values to assist in issuing health alerts, formulating policies, and
optimizing industrial and traffic management.
```




```
Our model predicts future AQI values based on the levels of various
pollutants that affect air quality. These predictions assist decision-
makers in issuing health alerts, formulating environmental policies,
optimizing traffic and industrial management, and helping the general
public plan their daily activities.
```

Key Challenges:

```
Missing data in pollutant and AQI values.
Seasonal variations impacting trends.
Data standardization for consistent unit representation.
```

Machine Learning Models Used:

```
We applied various models, including Linear Regression, K-Nearest
Neighbors (KNN),Decision Tree, and Random Forest, to determine which
provides the highest accuracy for AQI prediction.
```

Importing necessary libraries

```
import numpy as np              # Numerical computations and linear
algebra
import pandas as pd             # Data operations

# Visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns

import datetime
from warnings import filterwarnings
filterwarnings('ignore')

# Machine learning libraries
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.preprocessing import StandardScaler
```

Loading and Analyzing the Health Care Dataset

```
df = pd.read_csv(r'C:\Users\Ashish Mishra\OneDrive\Desktop\Code Unnati
Program\air quality data.csv')

df.head()    # shows first 5 records

        City        Date  PM2.5  PM10     NO    NO2    NOx  NH3     CO
SO2  \
0  Ahmedabad  2015-01-01    NaN   NaN   0.92  18.22  17.15  NaN   0.92
27.64
1  Ahmedabad  2015-01-02    NaN   NaN   0.97  15.69  16.46  NaN   0.97
24.55
2  Ahmedabad  2015-01-03    NaN   NaN  17.40  19.30  29.70  NaN  17.40
29.07
3  Ahmedabad  2015-01-04    NaN   NaN   1.70  18.48  17.97  NaN   1.70
18.59
4  Ahmedabad  2015-01-05    NaN   NaN  22.10  21.42  37.76  NaN  22.10
```

```
39.33

       O3  Benzene  Toluene  Xylene  AQI AQI_Bucket
0  133.36     0.00     0.02    0.00  NaN        NaN
1   34.06     3.68     5.50    3.77  NaN        NaN
2   30.70     6.80    16.40    2.25  NaN        NaN
3   36.08     4.43    10.14    1.00  NaN        NaN
4   39.31     7.01    18.89    2.78  NaN        NaN
```

```
df.tail()     # shows last 5 records
```

```
                City        Date  PM2.5   PM10    NO    NO2    NOx
NH3  \
29526  Visakhapatnam  2020-06-27  15.02  50.94  7.68  25.06  19.54
12.47
29527  Visakhapatnam  2020-06-28  24.38  74.09  3.42  26.06  16.53
11.99
29528  Visakhapatnam  2020-06-29  22.91  65.73  3.45  29.53  18.33
10.71
29529  Visakhapatnam  2020-06-30  16.64  49.97  4.05  29.26  18.80
10.03
29530  Visakhapatnam  2020-07-01  15.00  66.00  0.40  26.85  14.05
5.20

         CO    SO2     O3  Benzene  Toluene  Xylene   AQI
AQI_Bucket
29526  0.47   8.55  23.30     2.24    12.07    0.73  41.0
Good
29527  0.52  12.72  30.14     0.74     2.21    0.38  70.0
Satisfactory
29528  0.48   8.42  30.96     0.01     0.01    0.00  68.0
Satisfactory
29529  0.52   9.84  28.30     0.00     0.00    0.00  54.0
Satisfactory
29530  0.59   2.10  17.05      NaN      NaN     NaN  50.0
Good
```

```
df.shape      # shape (number of rows and columns) of the dataset
```

```
(29531, 16)
```

```
df.info()     # summary of the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29531 entries, 0 to 29530
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   City        29531 non-null  object
 1   Date        29531 non-null  object
 2   PM2.5       24933 non-null  float64
```

```
 3   PM10        18391 non-null  float64
 4   NO          25949 non-null  float64
 5   NO2         25946 non-null  float64
 6   NOx         25346 non-null  float64
 7   NH3         19203 non-null  float64
 8   CO          27472 non-null  float64
 9   SO2         25677 non-null  float64
 10  O3          25509 non-null  float64
 11  Benzene     23908 non-null  float64
 12  Toluene     21490 non-null  float64
 13  Xylene      11422 non-null  float64
 14  AQI         24850 non-null  float64
 15  AQI_Bucket  24850 non-null  object
dtypes: float64(13), object(3)
memory usage: 3.6+ MB
```

```
missing_values = df.isnull().sum()       # count of missing values for each column
print("Missing values in each column:")
print(missing_values)
```

```
Missing values in each column:
City              0
Date              0
PM2.5          4598
PM10          11140
NO             3582
NO2            3585
NOx            4185
NH3           10328
CO             2059
SO2            3854
O3             4022
Benzene        5623
Toluene        8041
Xylene        18109
AQI            4681
AQI_Bucket     4681
dtype: int64
```

```
df.duplicated().sum()         # duplicate rows in the dataset and count them
```

```
0
```

The 'AQI' column is essential for analysis and prediction. Missing AQI values would impact model accuracy and predictions. Removing rows with missing AQI values ensures the dataset remains clean and reliable for accurate analysis.

```
df1 = df.dropna(subset=['AQI'], inplace=True)
```

```python
df.isnull().sum().sort_values(ascending=False)
```

```
Xylene        15372
PM10           7086
NH3            6536
Toluene        5826
Benzene        3535
NOx            1857
O3              807
PM2.5           678
SO2             605
CO              445
NO2             391
NO              387
City              0
Date              0
AQI               0
AQI_Bucket        0
dtype: int64
```

```python
df.shape
```

```
(24850, 16)
```

```python
df.describe().T       # summary statistics of Dataset
```

```
           count        mean        std   min      25%      50%
75%  \
PM2.5    24172.0   67.476613  63.075398  0.04  29.0000   48.785
80.9250
PM10     17764.0  118.454435  89.487976  0.03  56.7775   96.180
150.1825
NO       24463.0   17.622421  22.421138  0.03   5.6600    9.910
20.0300
NO2      24459.0   28.978391  24.627054  0.01  11.9400   22.100
38.2400
NOx      22993.0   32.289012  30.712855  0.00  13.1100   23.680
40.1700
NH3      18314.0   23.848366  25.875981  0.01   8.9600   16.310
30.3600
CO       24405.0    2.345267   7.075208  0.00   0.5900    0.930
1.4800
SO2      24245.0   14.362933  17.428693  0.01   5.7300    9.220
15.1400
O3       24043.0   34.912885  21.724525  0.01  19.2500   31.250
46.0800
Benzene  21315.0    3.458668  16.036020  0.00   0.2300    1.290
3.3400
Toluene  19024.0    9.525714  20.881085  0.00   1.0275    3.575
10.1800
```

```
Xylene    9478.0    3.588683    6.754324   0.00   0.3900    1.420
4.1200
AQI      24850.0  166.463581  140.696585  13.00  81.0000  118.000
208.0000

             max
PM2.5     914.94
PM10      917.08
NO        390.68
NO2       362.21
NOx       378.24
NH3       352.89
CO        175.81
SO2       186.08
O3        257.73
Benzene   455.03
Toluene   454.85
Xylene    170.37
AQI      2049.00

# Calculate the percentage of missing values
null_values_percentage = (df.isnull().mean() *
100).round(2).sort_values(ascending=False)
print("Percentage of missing values per column:")
print(null_values_percentage)

Percentage of missing values per column:
Xylene        61.86
PM10          28.52
NH3           26.30
Toluene       23.44
Benzene       14.23
NOx            7.47
O3             3.25
PM2.5          2.73
SO2            2.43
CO             1.79
NO2            1.57
NO             1.56
City           0.00
Date           0.00
AQI            0.00
AQI_Bucket     0.00
dtype: float64
```

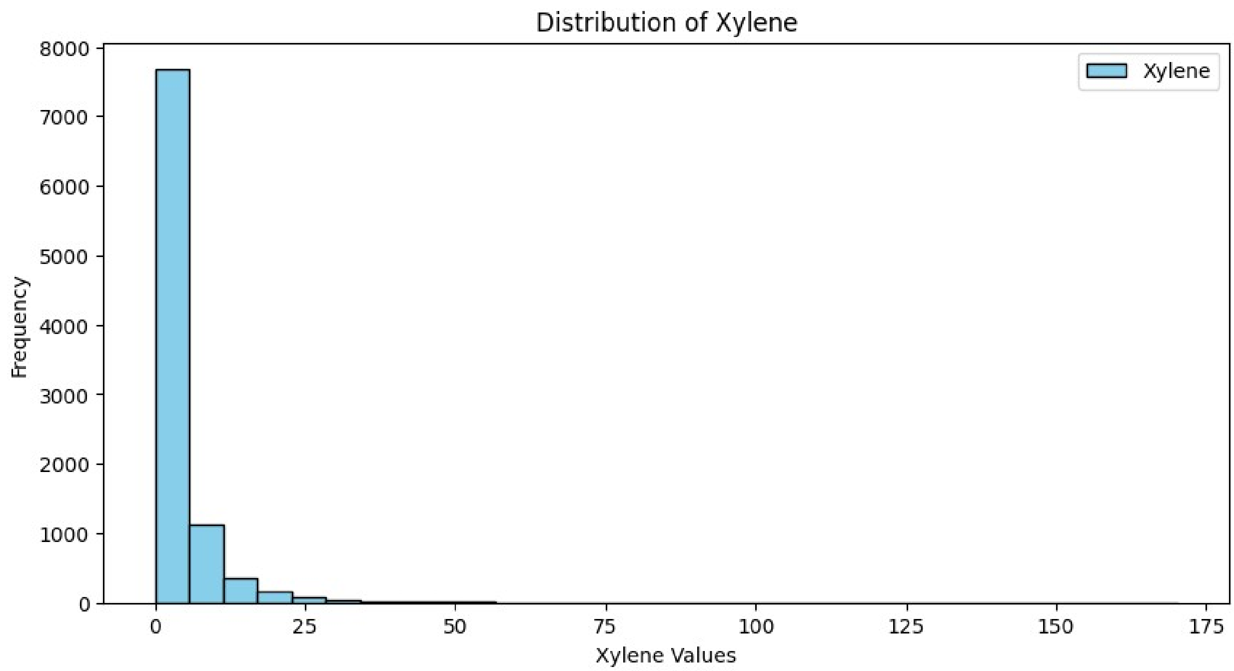
Missing Values Analysis and Handling

```
Xylene: Has the highest percentage of missing values (61.86%). The
feature is removed to simplify the analysis.
PM10 and NH3: Have significant missing data (around 28-26%).
```

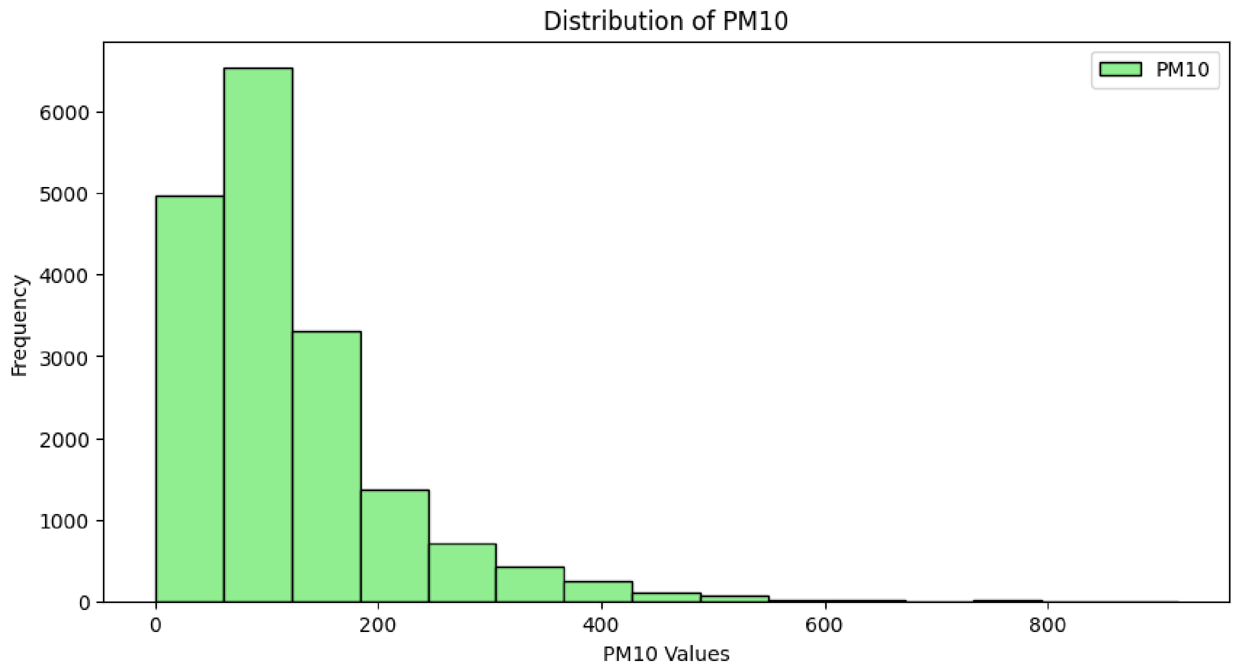
```
City, Date, AQI, AQI_Bucket: These columns have no missing values
(0%).
```

Data Exploration with Visualization: Univariate Analysis for Each Feature

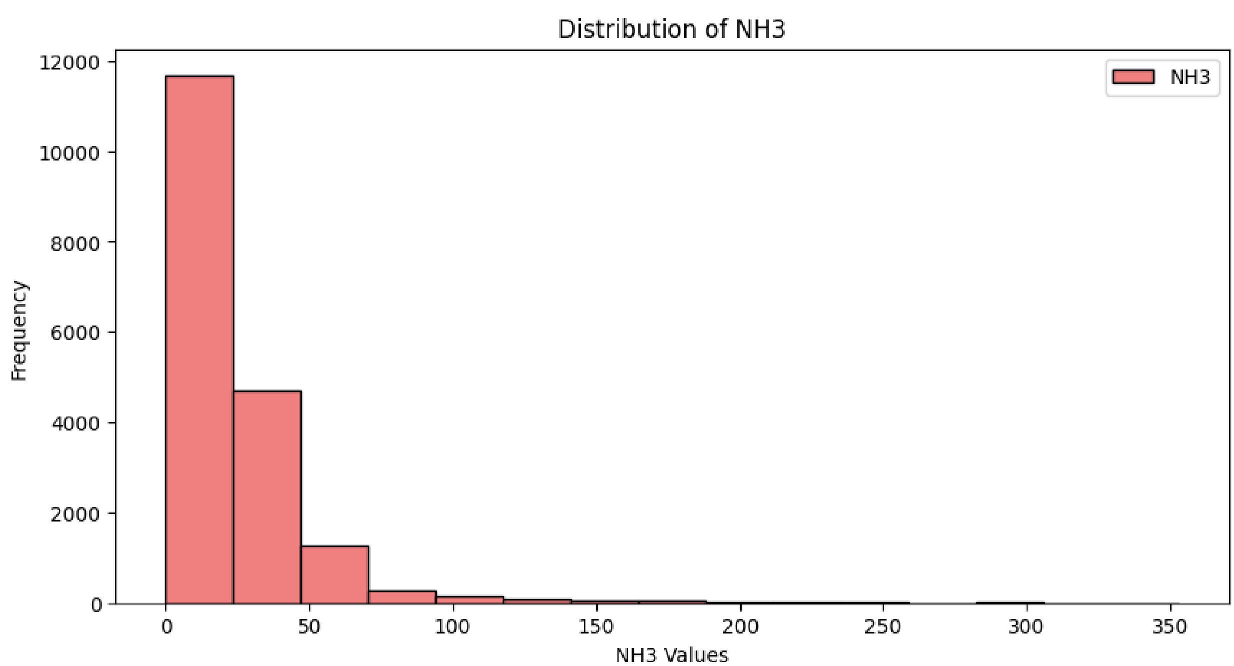
```
plt.figure(figsize=(10, 5))
plt.hist(df['Xylene'], bins= 30, color='skyblue', edgecolor='black')
plt.title('Distribution of Xylene')
plt.xlabel('Xylene Values')
plt.ylabel('Frequency')
plt.legend(['Xylene'])
plt.show()
```



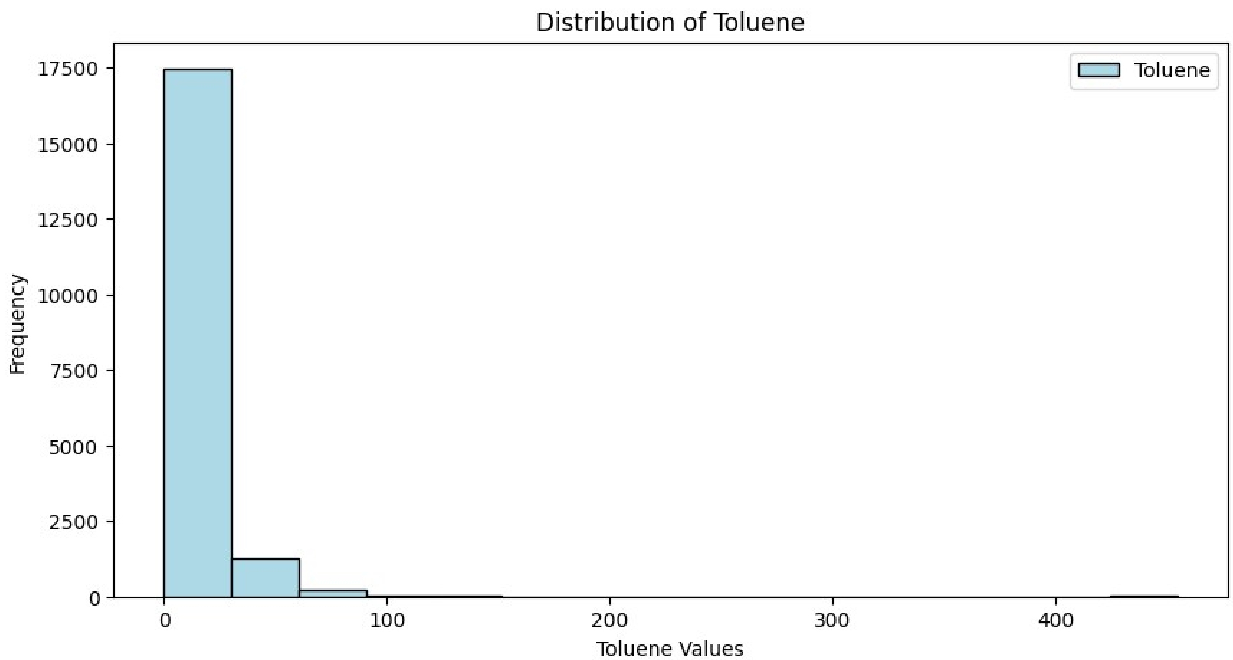

```

plt.figure(figsize=(10, 5))
plt.hist(df['PM10'], bins= 15, color='lightgreen', edgecolor='black')
plt.title('Distribution of PM10')
plt.xlabel('PM10 Values')
plt.ylabel('Frequency')

plt.legend(['PM10'])
plt.show()
```



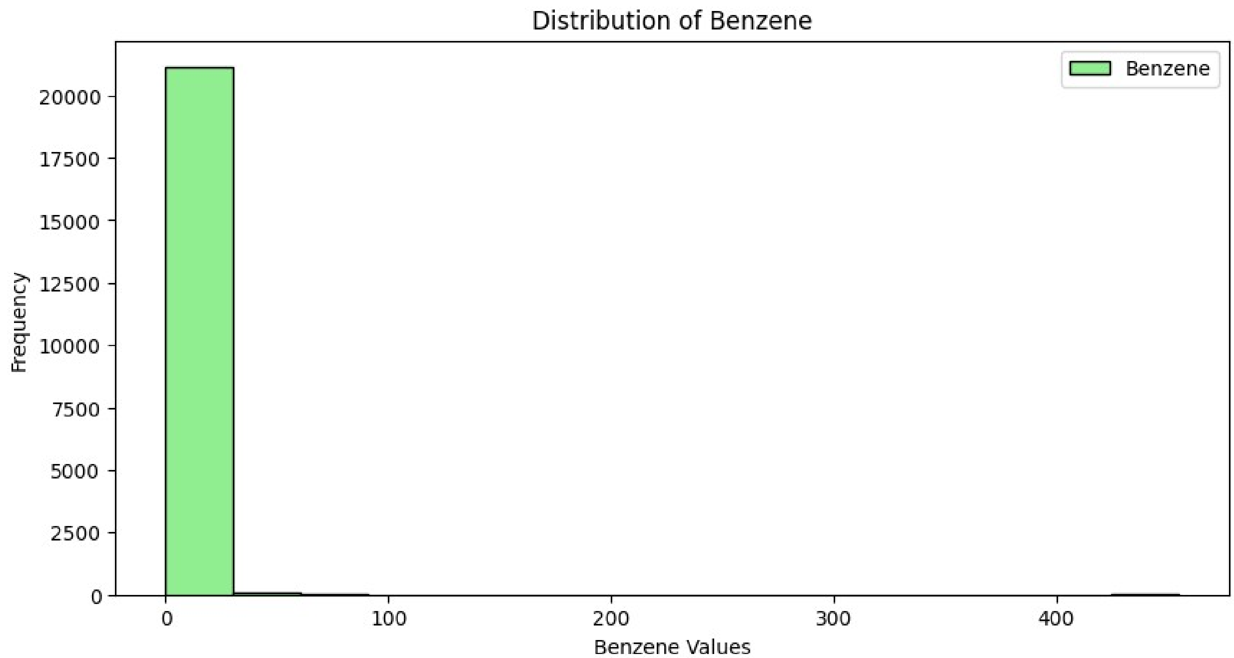

```
plt.figure(figsize=(10, 5))
plt.hist(df['NH3'], bins=15, color='lightcoral', edgecolor='black')
plt.title('Distribution of NH3')
plt.xlabel('NH3 Values')
plt.ylabel('Frequency')
plt.legend(['NH3'])
plt.show()
```



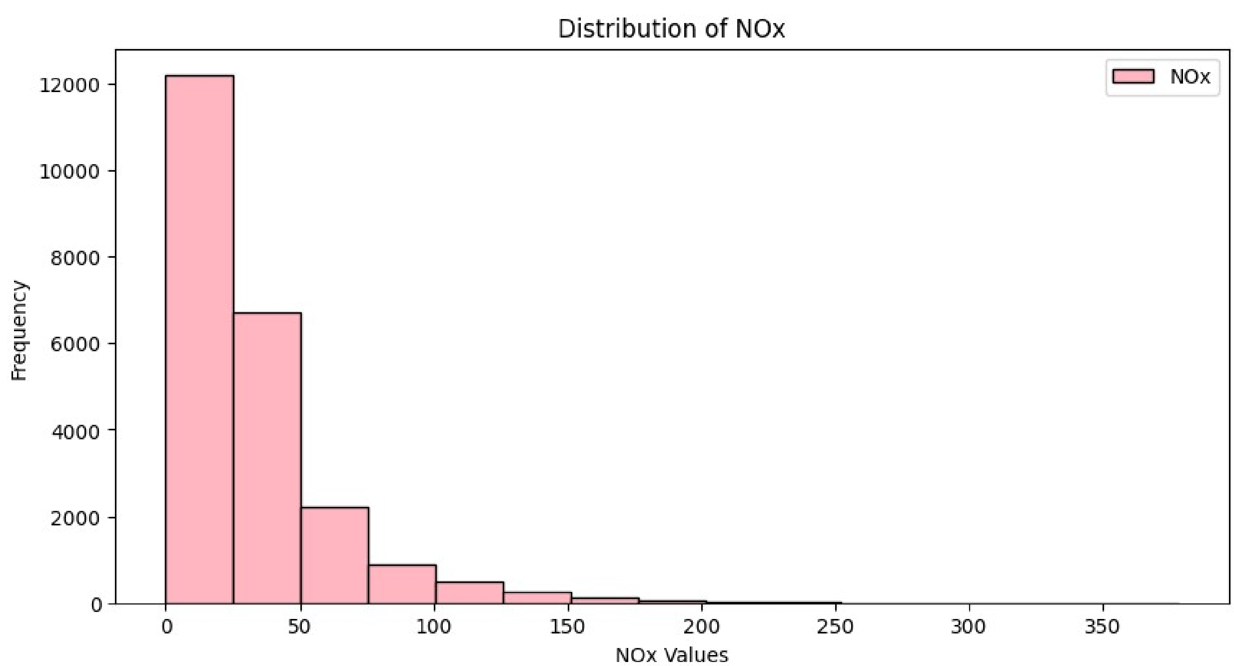
```
plt.figure(figsize=(10, 5))
plt.hist(df['Toluene'], bins=15, color='lightblue', edgecolor='black')
plt.title('Distribution of Toluene')
plt.xlabel('Toluene Values')
plt.ylabel('Frequency')
plt.legend(['Toluene'])
plt.show()
```



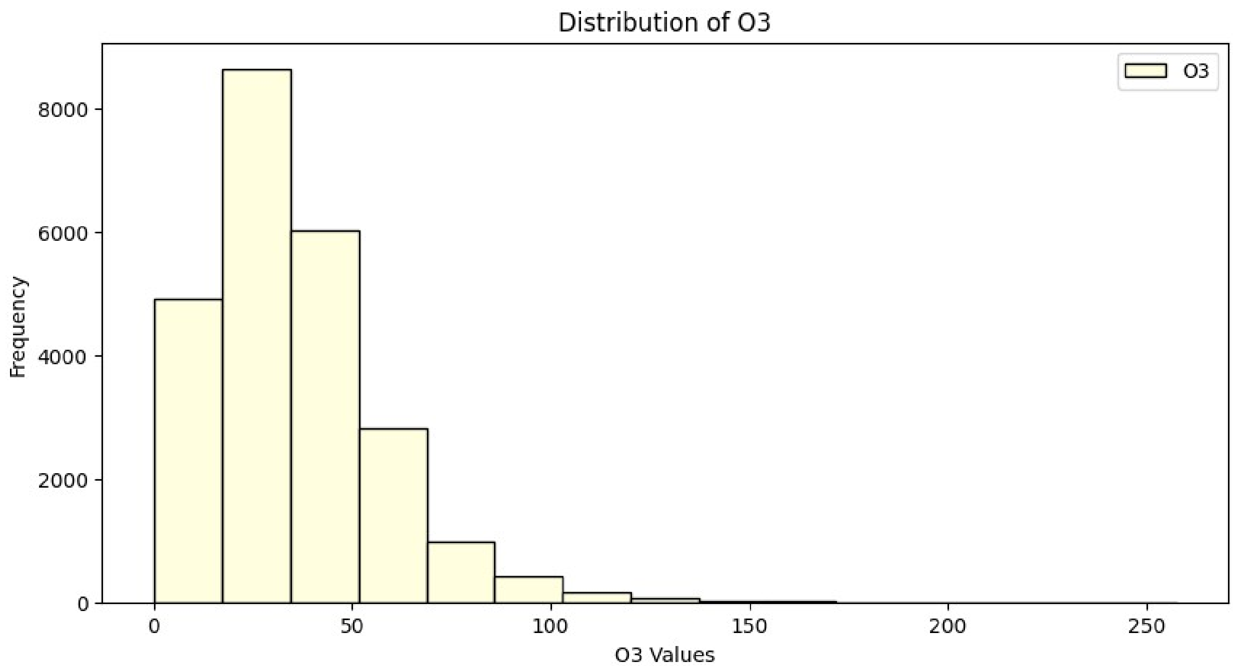

```
plt.figure(figsize=(10, 5))
plt.hist(df['Benzene'], bins=15, color='lightgreen',
edgecolor='black')
plt.title('Distribution of Benzene')
plt.xlabel('Benzene Values')
plt.ylabel('Frequency')
plt.legend(['Benzene'])
plt.show()
```



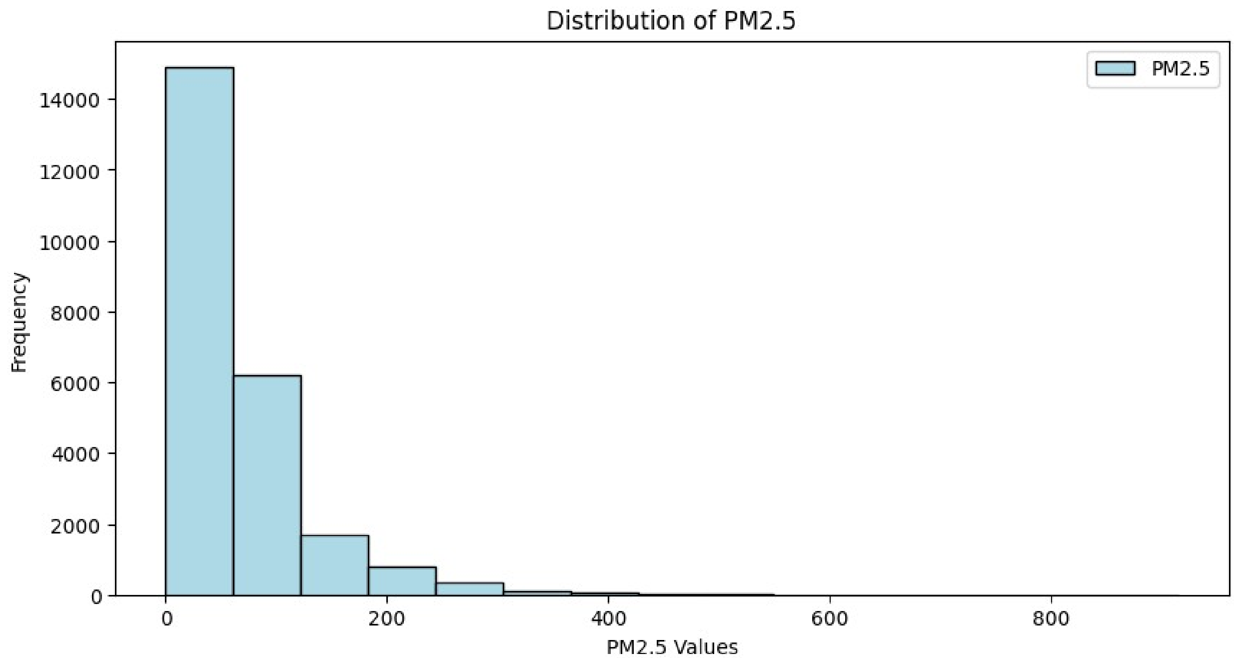

```
plt.figure(figsize=(10, 5))
plt.hist(df['NOx'], bins=15, color='lightpink', edgecolor='black')
plt.title('Distribution of NOx')
plt.xlabel('NOx Values')
plt.ylabel('Frequency')
plt.legend(['NOx'])
plt.show()
```



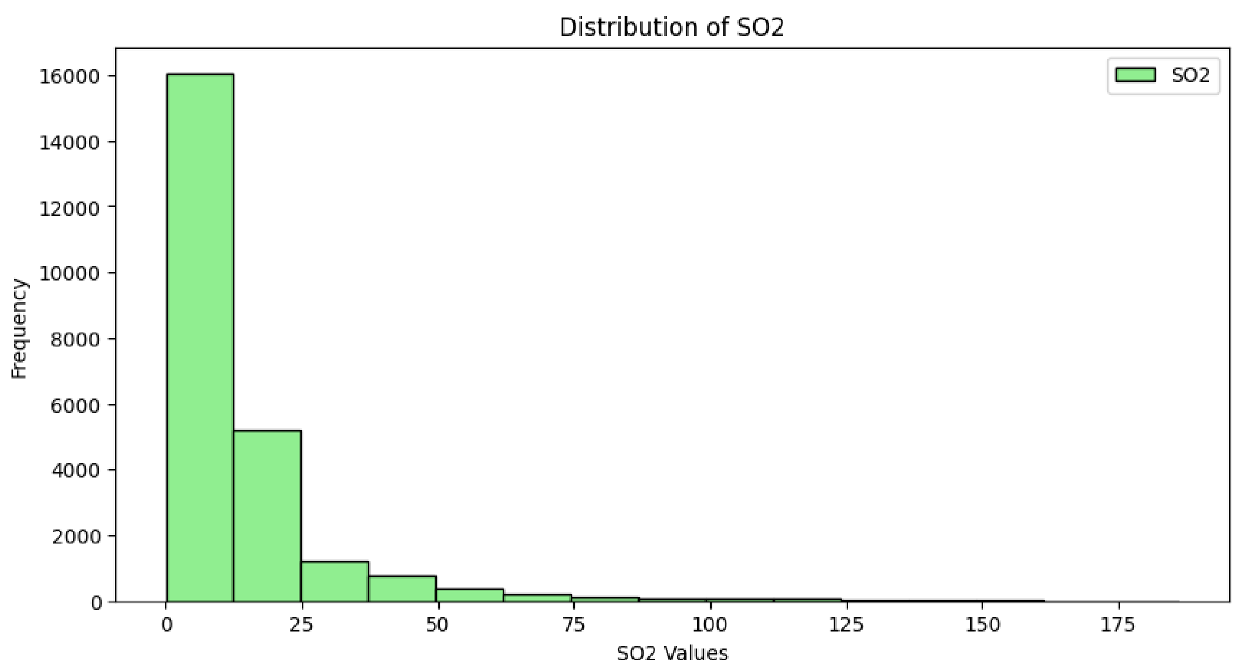
```python
plt.figure(figsize=(10, 5))
plt.hist(df['O3'], bins=15, color='lightyellow', edgecolor='black')
plt.title('Distribution of O3')
plt.xlabel('O3 Values')
plt.ylabel('Frequency')
plt.legend(['O3'])
plt.show()
```



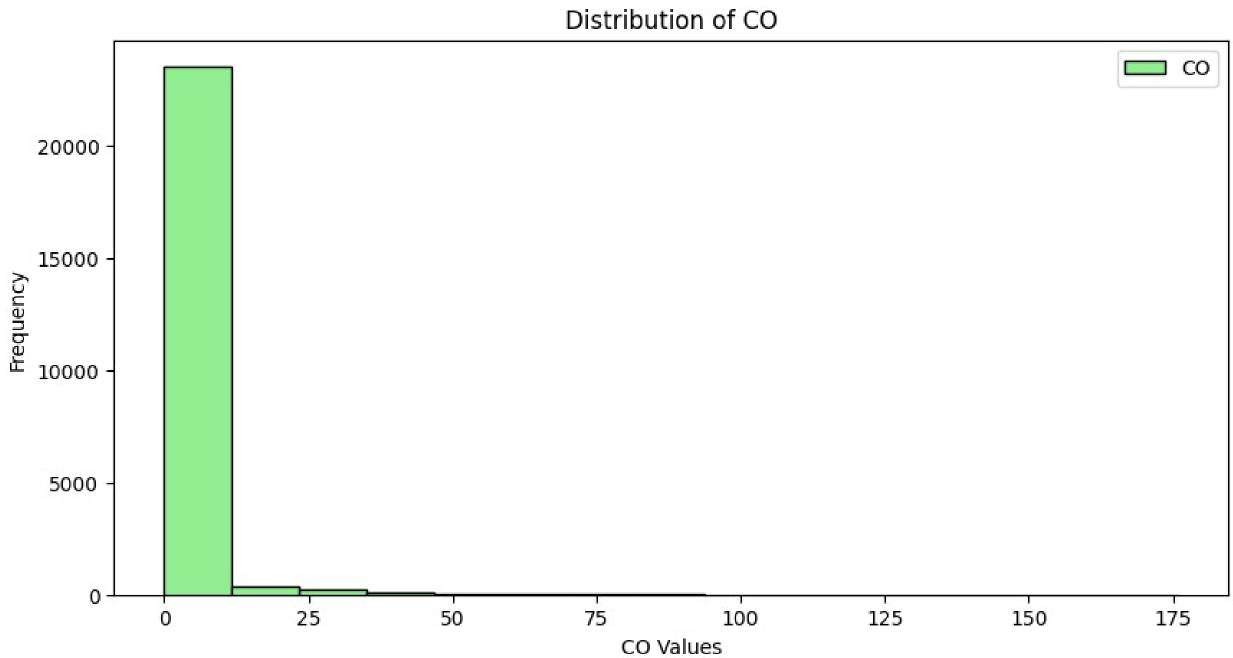

```python
plt.figure(figsize=(10, 5))
plt.hist(df['PM2.5'], bins=15, color='lightblue', edgecolor='black')
plt.title('Distribution of PM2.5')
plt.xlabel('PM2.5 Values')
plt.ylabel('Frequency')
plt.legend(['PM2.5'])
plt.show()
```



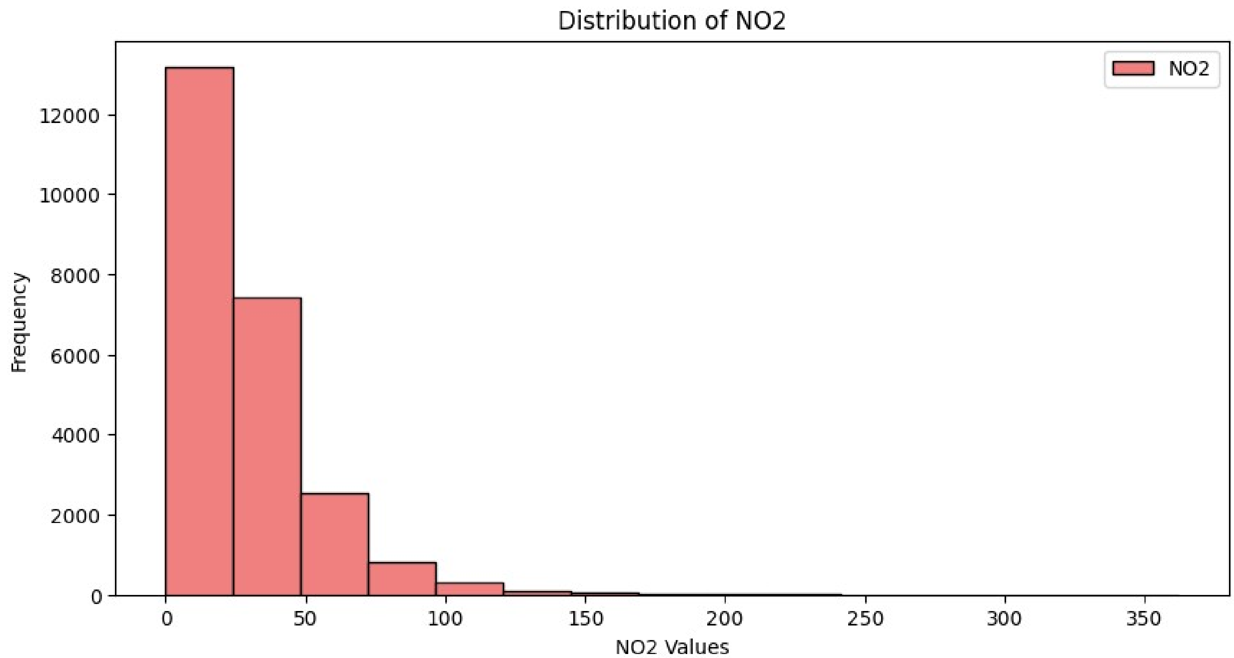

```
plt.figure(figsize=(10, 5))
plt.hist(df['SO2'], bins=15, color='lightgreen', edgecolor='black')
plt.title('Distribution of SO2')
plt.xlabel('SO2 Values')
plt.ylabel('Frequency')
plt.legend(['SO2'])
plt.show()
```



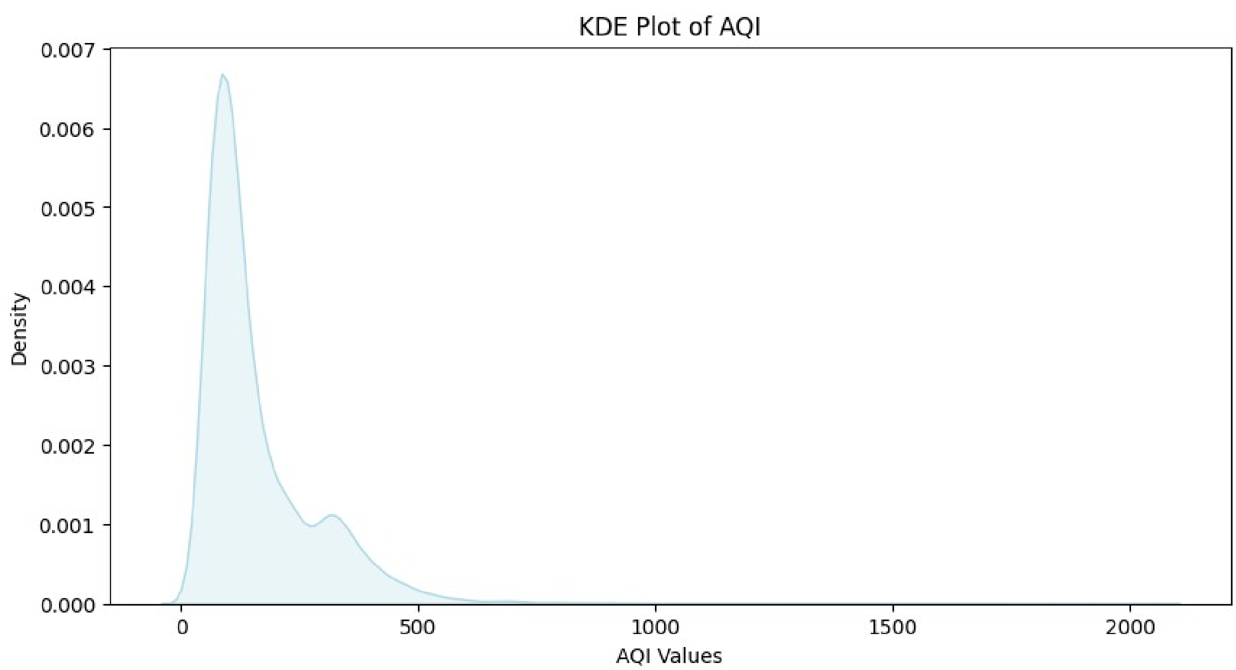
```
plt.figure(figsize=(10, 5))
plt.hist(df['CO'], bins=15, color='lightgreen', edgecolor='black')
plt.title('Distribution of CO')
plt.xlabel('CO Values')
plt.ylabel('Frequency')
plt.legend(['CO'])
plt.show()
```



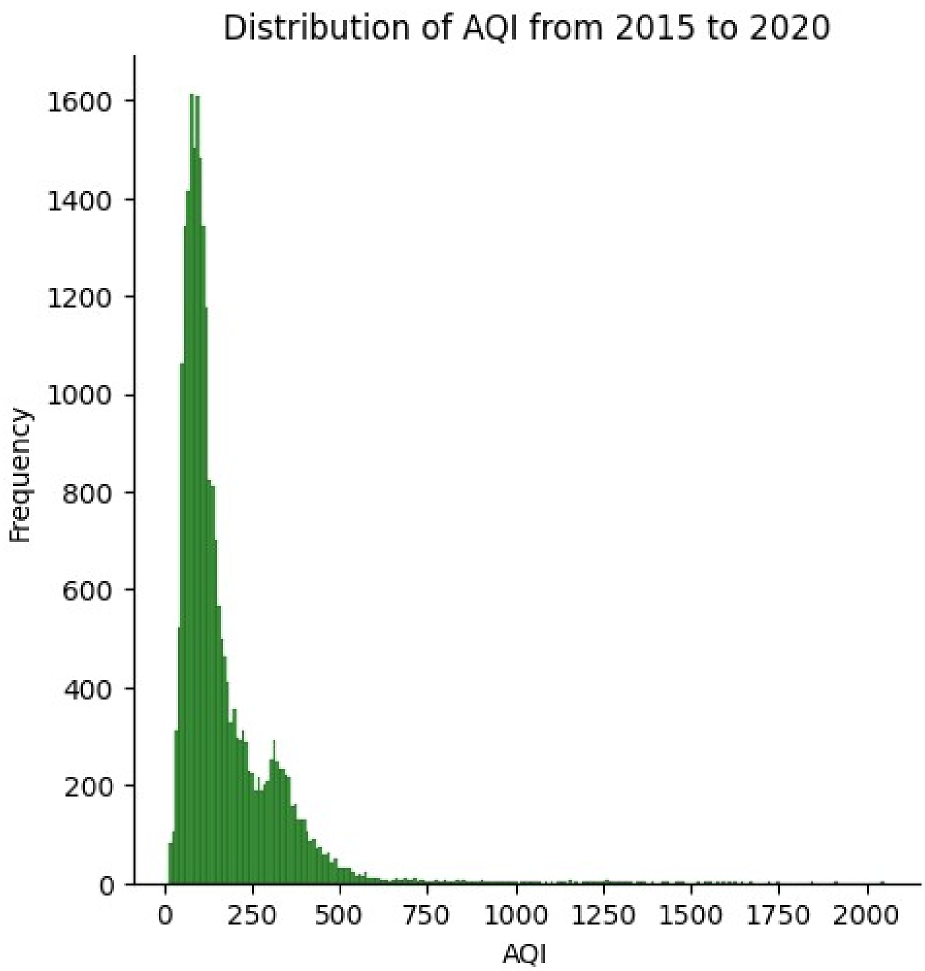

```
plt.figure(figsize=(10, 5))
plt.hist(df['NO2'], bins=15, color='lightcoral', edgecolor='black')
plt.title('Distribution of NO2')
plt.xlabel('NO2 Values')
plt.ylabel('Frequency')
plt.legend(['NO2'])
plt.show()
```




```python
plt.figure(figsize=(10, 5))
sns.kdeplot(df['AQI'].dropna(), shade=True, color='lightblue')
plt.title('KDE Plot of AQI')
plt.xlabel('AQI Values')
plt.ylabel('Density')
plt.show()
```



```
df['Date'] = pd.to_datetime(df['Date'])
# Filter data for the years 2015-2020
df_filtered = df[(df['Date'].dt.year >= 2015) & (df['Date'].dt.year <=
2020)]
sns.displot(df_filtered, x="AQI", color="green")
plt.title('Distribution of AQI from 2015 to 2020')
plt.xlabel('AQI')
plt.ylabel('Frequency')
plt.show()
```

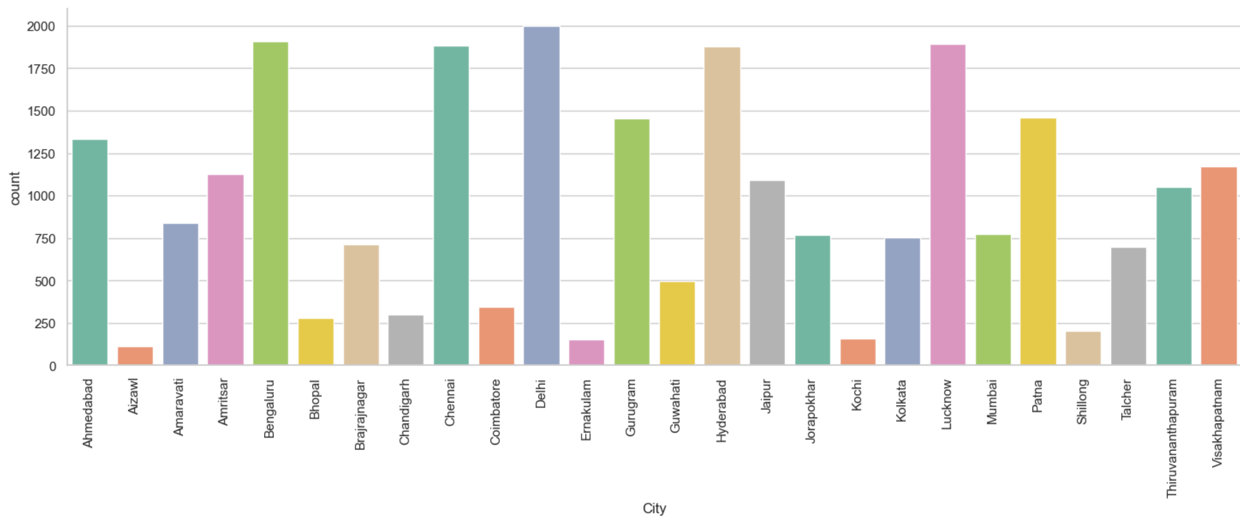


Bivariate analysis

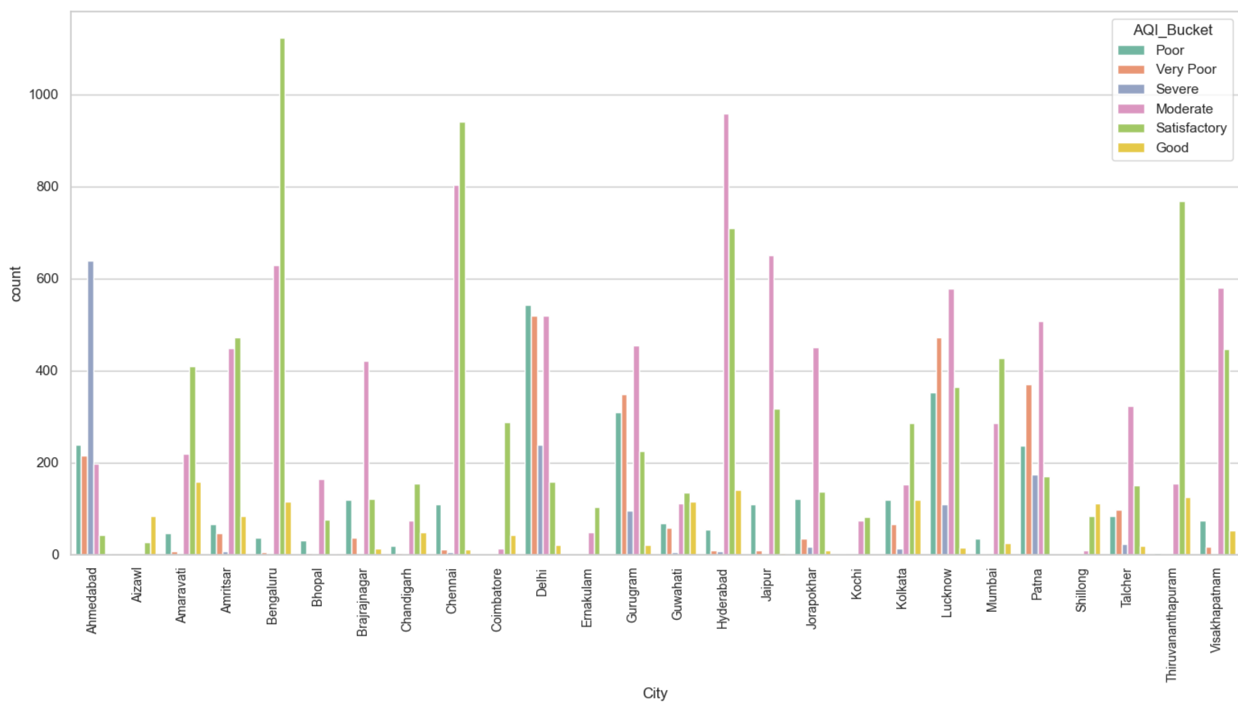
In the following plot, we observe the frequency of various city types across the entire dataset, which will be analyzed through Bivariate analysis.

```
sns.set(style="whitegrid")
sns.catplot(x="City", kind="count", data=df, height=5, aspect=3,
palette="Set2").set_xticklabels(rotation=90)
```

```
<seaborn.axisgrid.FacetGrid at 0x25d2982da60>
```



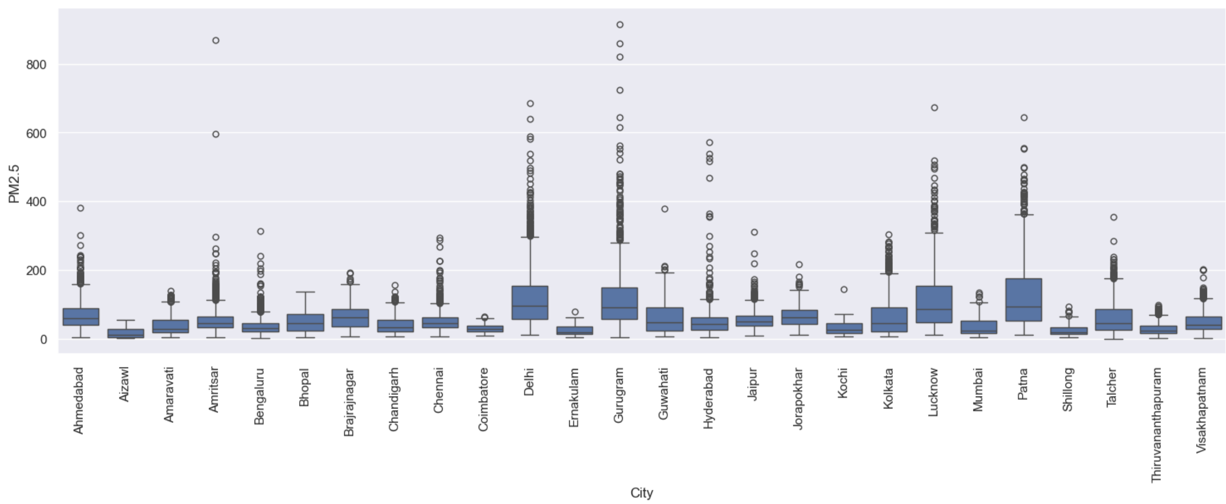

```
plt.figure(figsize=(14, 8))
sns.countplot(data=df, x="City", hue="AQI_Bucket", palette="Set2")
plt.xticks(rotation=90, fontsize=10)
plt.tight_layout()
plt.show()
```



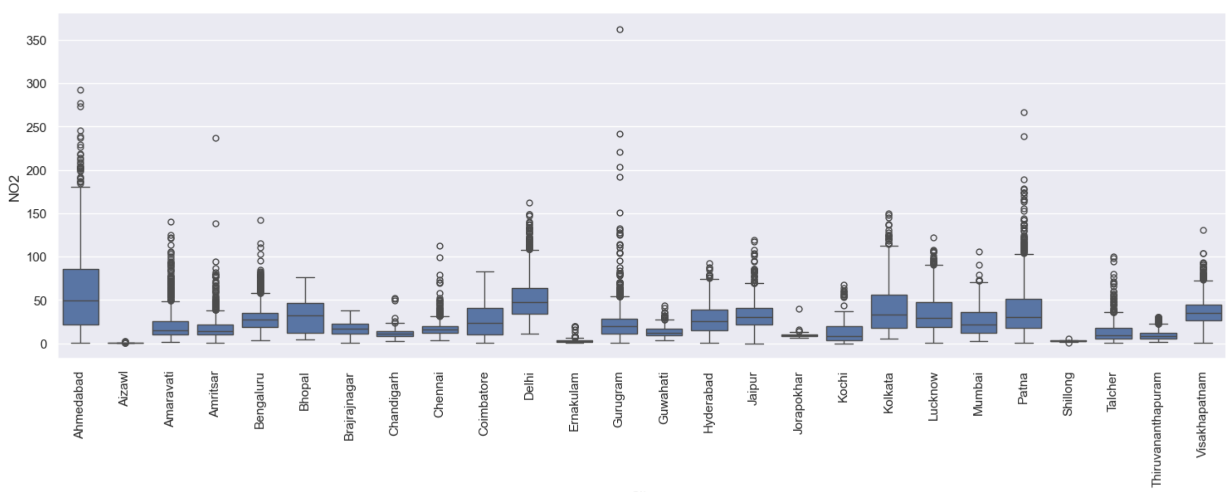
The bar plot above shows the distribution of different cities across various AQI categories, including 'Good,' 'Satisfactory,' 'Moderate,' 'Poor,' 'Very Poor,' and 'Severe.' Each city’s frequency is displayed within each AQI bucket, helping us understand how cities are spread across different air quality levels.

The following sequence of boxplots illustrates the distribution of numerical variables (non-null values) across different cities. These plots help visualize the spread, central tendency, and presence of any outliers in the data for each city.

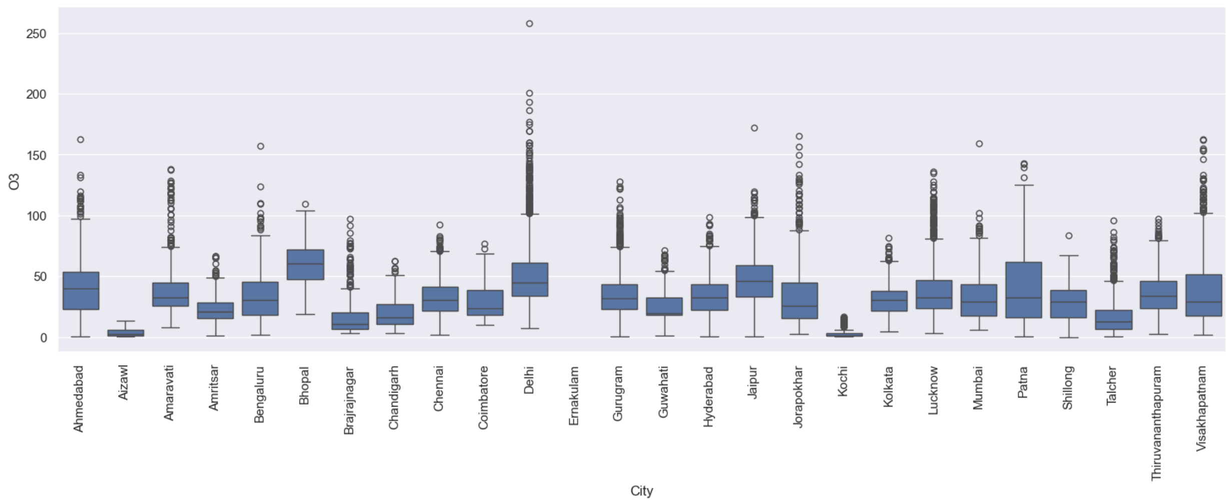
```
sns.set_style("darkgrid")
sns.catplot(x="City", y="PM2.5", kind="box", data=df, height=5,
aspect=3)
plt.xticks(rotation=90)
plt.show()
```



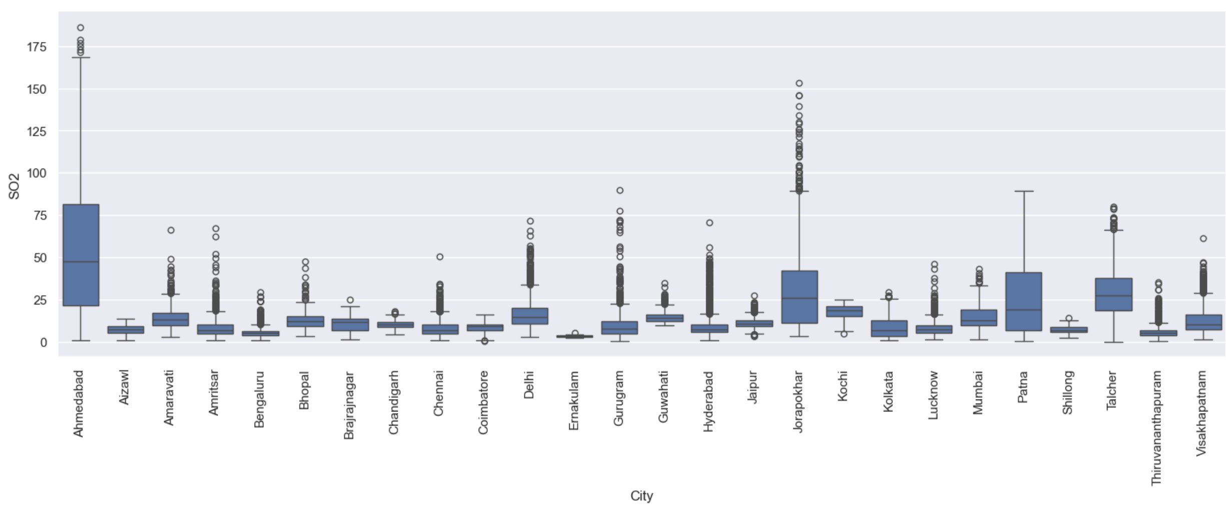

```
sns.set_style("darkgrid")
sns.catplot(x="City", y="NO2", kind="box", data=df, height=5,
aspect=3)
plt.xticks(rotation=90)
plt.show()
```



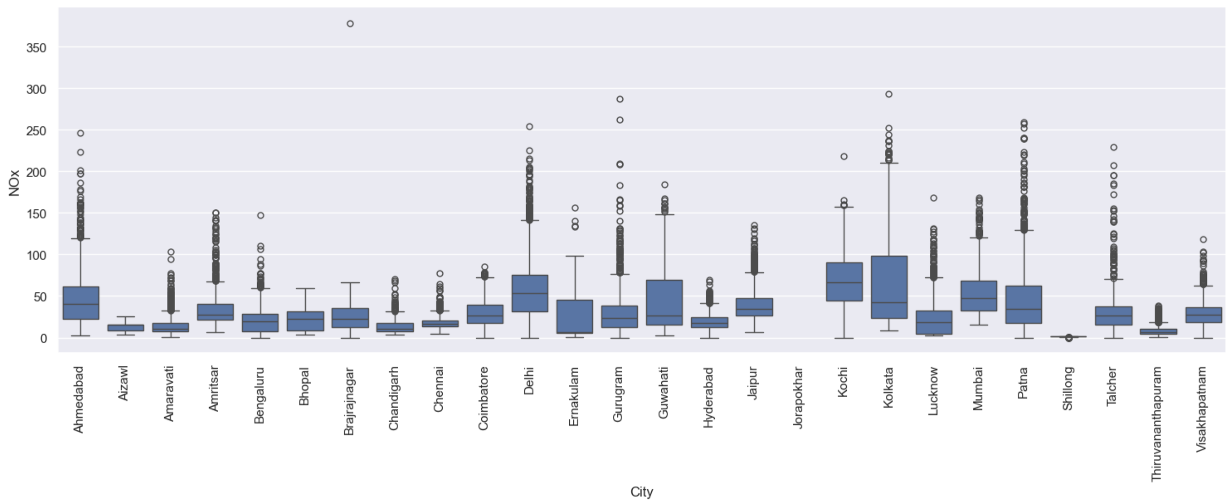
```
sns.set_style("darkgrid")
sns.catplot(x="City", y="O3", kind="box", data=df, height=5, aspect=3)
plt.xticks(rotation=90)
plt.show()
```



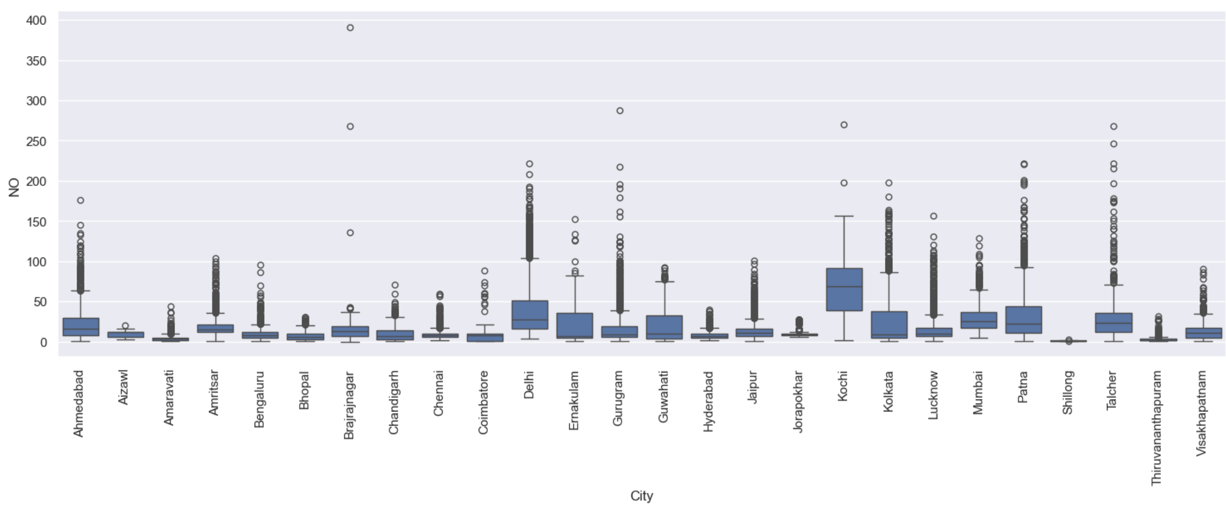

```
sns.set_style("darkgrid")
sns.catplot(x="City", y="SO2", kind="box", data=df, height=5,
aspect=3)
plt.xticks(rotation=90)
plt.show()
```



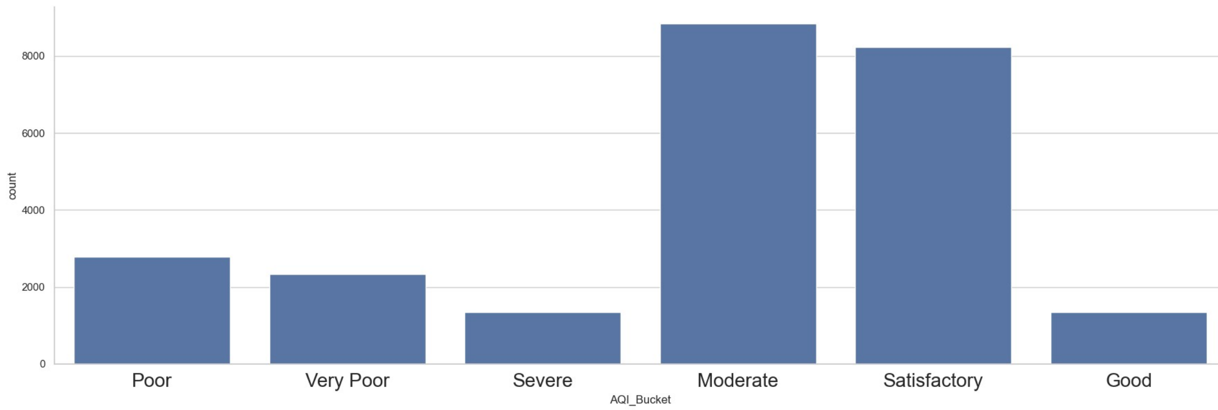

```
sns.set_style("darkgrid")
sns.catplot(x="City", y="NOx", kind="box", data=df, height=5,
aspect=3)
plt.xticks(rotation=90)
plt.show()
```




```
sns.set_style("darkgrid")
sns.catplot(x="City", y="NO", kind="box", data=df, height=5, aspect=3)
plt.xticks(rotation=90)
plt.show()
```




```
sns.set_style("whitegrid")
sns.catplot(x="AQI_Bucket", kind="count", data=df, height=6, aspect=3)
plt.xticks(fontsize=20)
plt.show()
```



The plot below illustrates the frequency distribution of different categories within the AQI_Bucket variable.

Identifying and Handling Missing Values

To identify and handle missing values, we first check for null or missing data in the dataset using functions like isnull() or isna(). Once missing values are detected, we can handle them by either dropping the rows/columns with missing data or imputing the missing values. Imputation methods can include replacing missing values with the mean, median, mode, or using more advanced techniques like interpolation. The choice of handling method depends on the nature of the data and the analysis requirements, ensuring that missing data does not affect the accuracy of the model or analysis.

```
missing_values =
df.isnull().sum().sort_values(ascending=False).to_frame('Missing
Count')
missing_values['% Missing Values'] = round((missing_values['Missing
Count'] / len(df)) * 100, 2)
print(missing_values)
```

```
            Missing Count  % Missing Values
Xylene              15372             61.86
PM10                 7086             28.52
NH3                  6536             26.30
Toluene              5826             23.44
Benzene              3535             14.23
NOx                  1857              7.47
O3                    807              3.25
PM2.5                 678              2.73
SO2                   605              2.43
CO                    445              1.79
NO2                   391              1.57
NO                    387              1.56
City                    0              0.00
Date                    0              0.00
AQI                     0              0.00
AQI_Bucket              0              0.00
```

In the dataset, we handled the missing values by replacing them with the mean of the respective features.

```
# Replacing missing values (NaN) in specific columns with the mean of those features
df['PM2.5'].fillna(df['PM2.5'].mean(), inplace=True)
df['PM10'].fillna(df['PM10'].mean(), inplace=True)
df['NO'].fillna(df['NO'].mean(), inplace=True)
df['NO2'].fillna(df['NO2'].mean(), inplace=True)
df['NOx'].fillna(df['NOx'].mean(), inplace=True)
df['NH3'].fillna(df['NH3'].mean(), inplace=True)
df['CO'].fillna(df['CO'].mean(), inplace=True)
df['SO2'].fillna(df['SO2'].mean(), inplace=True)
df['O3'].fillna(df['O3'].mean(), inplace=True)
df['Benzene'].fillna(df['Benzene'].mean(), inplace=True)
df['Toluene'].fillna(df['Toluene'].mean(), inplace=True)
df['Xylene'].fillna(df['Xylene'].mean(), inplace=True)

df.isnull().sum()

City          0
Date          0
PM2.5         0
PM10          0
NO            0
NO2           0
NOx           0
NH3           0
CO            0
SO2           0
O3            0
Benzene       0
Toluene       0
Xylene        0
AQI           0
AQI_Bucket    0
dtype: int64
```

We delete AQI_Bucket from the dataset because it is not a feature that affects air quality

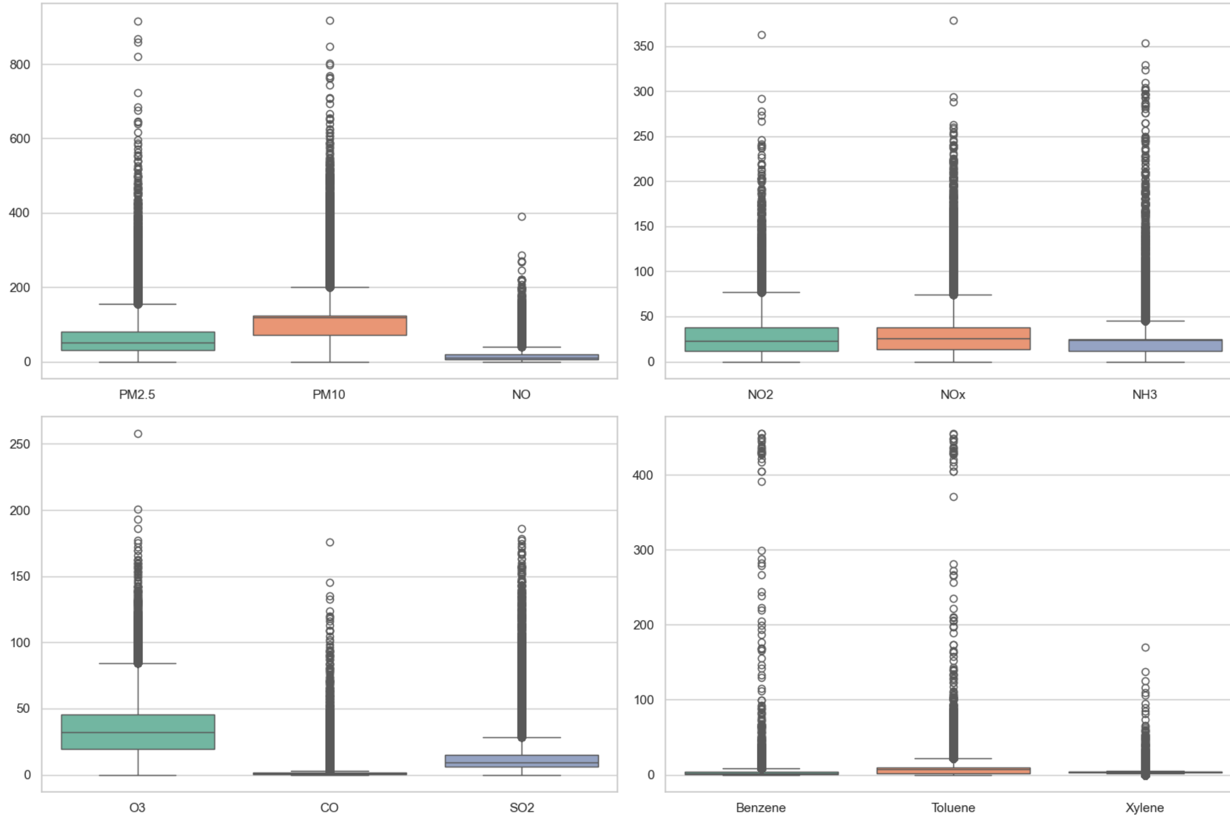
```
df = df.drop(["AQI_Bucket"], axis=1)
df.head()

         City        Date  PM2.5        PM10     NO    NO2    NOx
NH3  \
28  Ahmedabad 2015-01-29   83.13  118.454435   6.93  28.71  33.72
23.848366
29  Ahmedabad 2015-01-30   79.84  118.454435  13.85  28.68  41.08
23.848366
30  Ahmedabad 2015-01-31   94.52  118.454435  24.39  32.66  52.61
```

```
23.848366
31  Ahmedabad 2015-02-01  135.99  118.454435  43.48  42.08  84.57
23.848366
32  Ahmedabad 2015-02-02  178.33  118.454435  54.56  35.31  72.80
23.848366

       CO    SO2      O3  Benzene  Toluene  Xylene    AQI
28   6.93  49.52   59.76     0.02     0.00    3.14  209.0
29  13.85  48.49   97.07     0.04     0.00    4.81  328.0
30  24.39  67.39  111.33     0.24     0.01    7.67  514.0
31  43.48  75.23  102.70     0.40     0.04   25.87  782.0
32  54.56  55.04  107.38     0.46     0.06   35.61  914.0
```

Identifying and Handling Outliers

To detect and handle outliers, we can use statistical methods such as the IQR (Interquartile Range) or Z-score. Outliers can be identified by analyzing values that fall outside a specified range (e.g., below the first quartile or above the third quartile in the IQR method) or by calculating the Z-score for each data point. Once detected, outliers can be treated by either removing or replacing them with more reasonable values, such as the median or mean, depending on the context of the analysis. This process helps ensure that extreme values do not distort the results of your analysis or modeling.

```
sns.set(style="whitegrid")
palette = "Set2"
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
sns.boxplot(data=df[['PM2.5', 'PM10','NO']], ax=axes[0, 0],
palette=palette)
sns.boxplot(data=df[['NO2','NOx', 'NH3']], ax=axes[0, 1],
palette=palette)
sns.boxplot(data=df[['O3', 'CO', 'SO2']], ax=axes[1, 0],
palette=palette)
sns.boxplot(data=df[['Benzene', 'Toluene', 'Xylene']], ax=axes[1, 1],
palette=palette)
plt.tight_layout()
plt.show()
```



We identified a significant presence of outliers in our independent variables, which could lead to inaccurate modeling results. To maintain the integrity of the analysis, we used the statistical method of Interquartile Range (IQR) to address and modify these outliers.

```python
def replace_outliers_with_quartiles(df):
    for column in df.select_dtypes(include=['number']).columns:  # Loop through all numeric columns in the DataFrame
        Q1 = df[column].quantile(0.25)  # Calculate the first quartile (Q1)
        Q3 = df[column].quantile(0.75)  # Calculate the third quartile (Q3)
        IQR = Q3 - Q1  # Compute the Interquartile Range (IQR)

        lower_bound = Q1 - 1.5 * IQR  # Calculate the lower bound for outliers
        upper_bound = Q3 + 1.5 * IQR  # Calculate the upper bound for outliers

        # For each column, we identify outliers and replace them with Q1 or Q3.
        # We use the clip function to replace values that are outside the lower or upper bounds.
        # If the value is below the lower bound, it is replaced with Q1.
        # If the value is above the upper bound, it is replaced with
```

```
Q3.
        # Any value within the bounds remains unchanged.
        df[column] = df[column].clip(lower=lower_bound,
upper=upper_bound)

    return df

df = replace_outliers_with_quartiles(df)

df.describe().T

           count                           mean
min  \
Date       24850  2018-07-24 18:51:25.714285568  2015-01-01 00:00:00

PM2.5    24850.0                      61.237324                 0.04

PM10     24850.0                     108.929094                 0.03

NO       24850.0                      14.543704                 0.03

NO2      24850.0                      27.674746                 0.01

NOx      24850.0                      29.408656                  0.0

NH3      24850.0                      21.224648                 0.01

CO       24850.0                       1.163066                  0.0

SO2      24850.0                      11.697545                 0.01

O3       24850.0                      34.337646                 0.01

Benzene  24850.0                       2.368094                  0.0

Toluene  24850.0                       7.386748                  0.0

Xylene   24850.0                       3.165064             1.241975

AQI      24850.0                     157.342455                 13.0


                         25%                  50%                  75%
\
Date     2017-08-16 00:00:00  2018-11-05 00:00:00  2019-10-11 00:00:00

PM2.5                  29.56               50.165              79.5075

PM10                   71.78           118.454435             122.9575

NO                      5.72               10.075                19.71
```

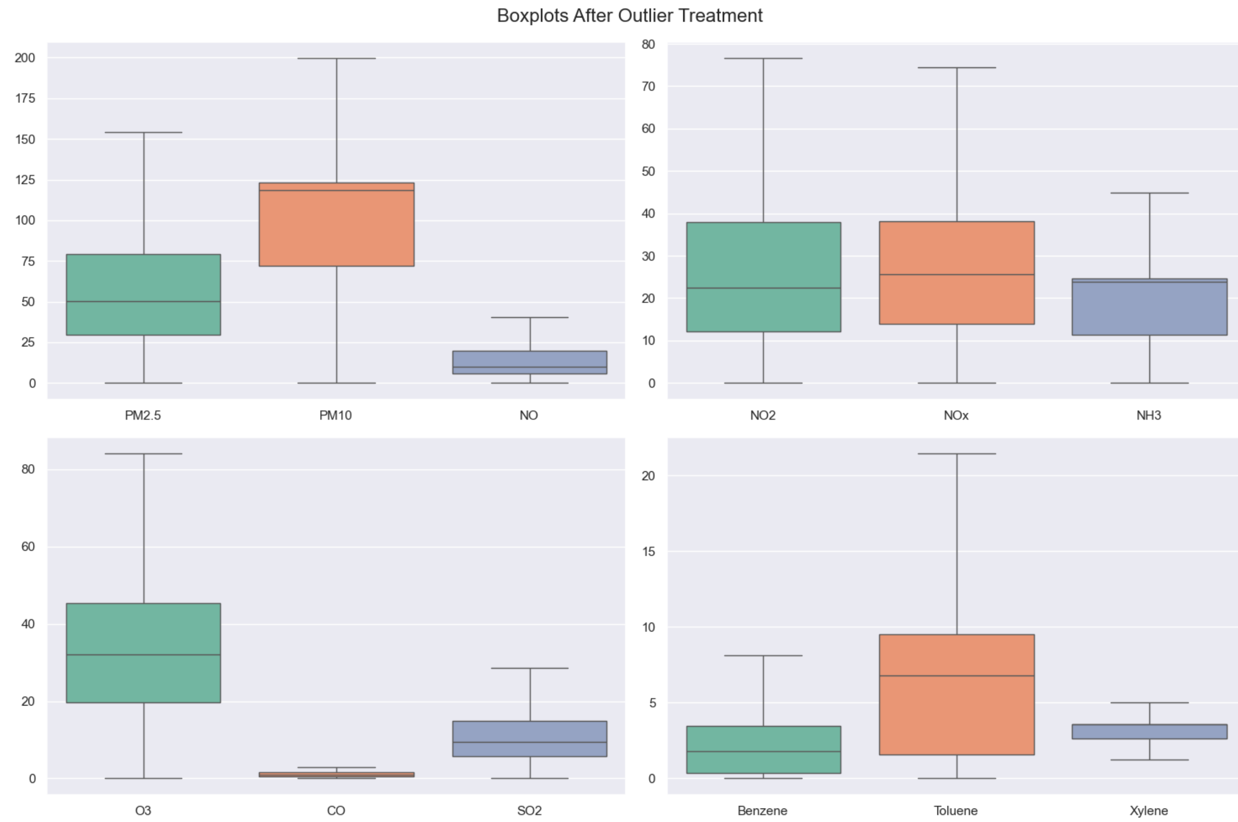
NO2	12.09	22.535	37.91
NOx	14.03	25.72	38.17
NH3	11.28	23.848366	24.71
CO	0.59	0.95	1.53
SO2	5.79	9.43	14.89
O3	19.64	32.06	45.3975
Benzene	0.34	1.81	3.458668
Toluene	1.58	6.79	9.525714
Xylene	2.65	3.588683	3.588683
AQI	81.0	118.0	208.0

	max	std
Date	2020-07-01 00:00:00	NaN
PM2.5	154.42875	41.541637
PM10	199.72375	48.775218
NO	40.695	12.028462
NO2	76.64	19.647444
NOx	74.38	20.512972
NH3	44.855	11.9539
CO	2.94	0.810274
SO2	28.54	7.838027
O3	84.03375	19.432894
Benzene	8.13667	2.294312
Toluene	21.444285	6.500939
Xylene	4.996708	1.099647
AQI	398.5	103.870019

To verify the effectiveness of the outlier handling procedure, we visualize the data distribution using boxplots after the outlier treatment. This will help us assess whether the outliers have been successfully addressed and if the data now shows a more appropriate distribution.

```
sns.set(style="darkgrid")
palette = "Set2"
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
sns.boxplot(data=df[['PM2.5', 'PM10','NO']], ax=axes[0, 0], 
palette=palette)
sns.boxplot(data=df[['NO2','NOx', 'NH3']], ax=axes[0, 1], 
palette=palette)
sns.boxplot(data=df[['O3', 'CO', 'SO2']], ax=axes[1, 0], 
palette=palette)
```

```
sns.boxplot(data=df[['Benzene', 'Toluene', 'Xylene']], ax=axes[1, 1],
palette=palette)
plt.suptitle("Boxplots After Outlier Treatment", fontsize=16)
plt.tight_layout()
plt.show()
```



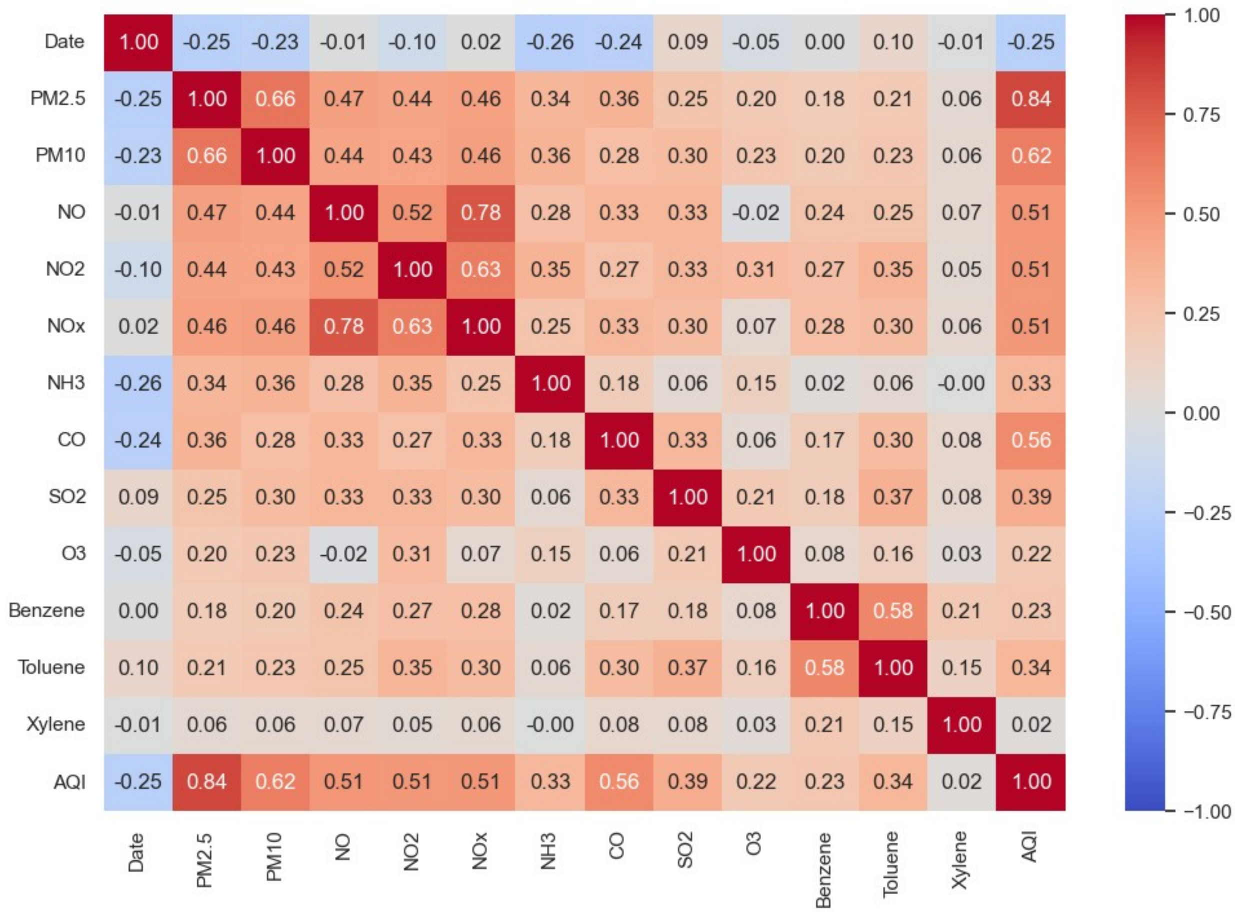
Multivariate analysis

```
df1 = df.drop('City', axis=1)

print(df1.corr())
```

```
                Date     PM2.5      PM10        NO       NO2       NOx
NH3  \
Date        1.000000 -0.246975 -0.225968 -0.008186 -0.097395  0.015514 -
0.255377
PM2.5      -0.246975  1.000000  0.658907  0.466931  0.444951  0.457536
0.341314
PM10       -0.225968  0.658907  1.000000  0.439079  0.432332  0.462553
0.358055
NO         -0.008186  0.466931  0.439079  1.000000  0.524358  0.782621
0.275222
NO2        -0.097395  0.444951  0.432332  0.524358  1.000000  0.631616
0.354895
NOx         0.015514  0.457536  0.462553  0.782621  0.631616  1.000000
```

```
0.251998
NH3     -0.255377  0.341314  0.358055  0.275222  0.354895  0.251998
1.000000
CO      -0.237567  0.358963  0.284255  0.329421  0.271991  0.325470
0.178888
SO2      0.088550  0.249982  0.300110  0.328602  0.326773  0.298302
0.061631
O3      -0.045778  0.204037  0.228623 -0.019042  0.311046  0.068127
0.148634
Benzene  0.000488  0.183083  0.202437  0.242873  0.274563  0.281723
0.022384
Toluene  0.098885  0.209409  0.230976  0.249974  0.350317  0.302230
0.059965
Xylene  -0.006502  0.061154  0.062823  0.068005  0.048370  0.062650 -
0.001363
AQI     -0.249575  0.836451  0.623235  0.508377  0.507633  0.506864
0.325857

               CO       SO2        O3   Benzene   Toluene    Xylene
AQI
Date    -0.237567  0.088550 -0.045778  0.000488  0.098885 -0.006502 -
0.249575
PM2.5    0.358963  0.249982  0.204037  0.183083  0.209409  0.061154
0.836451
PM10     0.284255  0.300110  0.228623  0.202437  0.230976  0.062823
0.623235
NO       0.329421  0.328602 -0.019042  0.242873  0.249974  0.068005
0.508377
NO2      0.271991  0.326773  0.311046  0.274563  0.350317  0.048370
0.507633
NOx      0.325470  0.298302  0.068127  0.281723  0.302230  0.062650
0.506864
NH3      0.178888  0.061631  0.148634  0.022384  0.059965 -0.001363
0.325857
CO       1.000000  0.326543  0.056085  0.173898  0.302643  0.081742
0.564829
SO2      0.326543  1.000000  0.210792  0.176102  0.372176  0.077308
0.393353
O3       0.056085  0.210792  1.000000  0.083860  0.158995  0.034045
0.216976
Benzene  0.173898  0.176102  0.083860  1.000000  0.583790  0.211419
0.230491
Toluene  0.302643  0.372176  0.158995  0.583790  1.000000  0.145310
0.335388
Xylene   0.081742  0.077308  0.034045  0.211419  0.145310  1.000000
0.019666
AQI      0.564829  0.393353  0.216976  0.230491  0.335388  0.019666
1.000000
```

```
plt.figure(figsize=(12, 8))
sns.heatmap(df1.corr(), annot=True, fmt='.2f', cmap='coolwarm', vmin=-
1, vmax=1)
plt.show()
```



The most important variables affecting the AQI value appear to be PM2.5, PM10, CO and NOx.We will make predictions based on data above 0.25

Data Preprocessing: Handling Missing Values, Encoding, and Splitting

The dataset consists of both numerical and categorical columns. First, we identify these columns separately. For the missing values in numerical columns, we fill them using a scaling technique. Categorical features are transformed using One-Hot Encoding to convert them into a format suitable for machine learning models. Next, we split the data into training, testing, and validation sets. Finally, we define the input features and target variable for each dataset.

```
df.head()

           City        Date      PM2.5        PM10       NO     NO2     NOx  \
28   Ahmedabad 2015-01-29   83.13000  118.454435    6.930   28.71   33.72
```

```
29  Ahmedabad 2015-01-30   79.84000  118.454435  13.850  28.68  41.08

30  Ahmedabad 2015-01-31   94.52000  118.454435  24.390  32.66  52.61

31  Ahmedabad 2015-02-01  135.99000  118.454435  40.695  42.08  74.38

32  Ahmedabad 2015-02-02  154.42875  118.454435  40.695  35.31  72.80


          NH3    CO    SO2        O3  Benzene  Toluene    Xylene
AQI
28  23.848366  2.94  28.54  59.76000     0.02     0.00  3.140000
209.0
29  23.848366  2.94  28.54  84.03375     0.04     0.00  4.810000
328.0
30  23.848366  2.94  28.54  84.03375     0.24     0.01  4.996708
398.5
31  23.848366  2.94  28.54  84.03375     0.40     0.04  4.996708
398.5
32  23.848366  2.94  28.54  84.03375     0.46     0.06  4.996708
398.5
```

```
# Dropping unnecessary columns
df.drop(['Date'], axis=1, inplace=True)        # We remove the 'Date'
column as it's not needed for our analysis.
df.drop(['City'], axis=1, inplace=True)        # We remove the 'City'
column because we are focusing on other parameters, not location.

from sklearn.preprocessing import StandardScaler
# Using StandardScaler to scale the features so that they have a mean
of 0 and standard deviation of 1.
# We use StandardScaler to make sure all the features are on the same
scale.
# This helps some machine learning models work better by making sure
no feature is too big or too small compared to others.
df1 = StandardScaler().fit_transform(df)

df1
```

```
array([[ 0.52701621,  0.19529452, -0.63298676, ..., -1.13628147,
        -0.02279349,  0.49733874],
       [ 0.44781697,  0.19529452, -0.05767303, ..., -1.13628147,
         1.49590673,  1.64302443],
       [ 0.80120448,  0.19529452,  0.81859962, ..., -1.1347432 ,
         1.66569939,  2.32177099],
       ...,
       [-0.92264288, -0.88569494, -0.92230638, ..., -1.1347432 ,
        -1.74885987, -0.86015438],
       [-1.07357883, -1.20881635, -0.87242369, ..., -1.13628147,
        -1.74885987, -0.99494094],
```

```
       [-1.11305808, -0.88015923, -1.17587674, ...,  0.32903067,
         0.38523967, -1.03345138]])
```

```python
df = pd.DataFrame(df1,columns = df.columns)

df.head()
```

```
      PM2.5      PM10        NO       NO2       NOx       NH3
CO  \
0  0.527016  0.195295 -0.632987  0.052693  0.210181  0.219491
2.193046
1  0.447817  0.195295 -0.057673  0.051166  0.568985  0.219491
2.193046
2  0.801204  0.195295  0.818600  0.253741  1.131080  0.219491
2.193046
3  1.799500  0.195295  2.174162  0.733202  2.192381  0.219491
2.193046
4  2.243371  0.195295  2.174162  0.388621  2.115355  0.219491
2.193046

        SO2        O3   Benzene   Toluene    Xylene       AQI
0  2.148856  1.308239 -1.023462 -1.136281 -0.022793  0.497339
1  2.148856  2.557370 -1.014744 -1.136281  1.495907  1.643024
2  2.148856  2.557370 -0.927571 -1.134743  1.665699  2.321771
3  2.148856  2.557370 -0.857832 -1.130128  1.665699  2.321771
4  2.148856  2.557370 -0.831679 -1.127052  1.665699  2.321771
```

Data Modeling

```python
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import r2_score
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor

# Data Preparation for Modeling: Selecting Features(x) and Target
Variable(y)
x=df[["PM2.5","PM10","NO","NO2","NOx","NH3","CO","SO2","O3","Benzene",
"Toluene","Xylene"]]
y=df["AQI"]

x.head()
```

```
      PM2.5      PM10        NO       NO2       NOx       NH3
CO  \
0  0.527016  0.195295 -0.632987  0.052693  0.210181  0.219491
2.193046
1  0.447817  0.195295 -0.057673  0.051166  0.568985  0.219491
2.193046
2  0.801204  0.195295  0.818600  0.253741  1.131080  0.219491
```

```
2.193046
3  1.799500  0.195295  2.174162  0.733202  2.192381  0.219491
2.193046
4  2.243371  0.195295  2.174162  0.388621  2.115355  0.219491
2.193046

        SO2        O3   Benzene   Toluene    Xylene
0  2.148856  1.308239 -1.023462 -1.136281 -0.022793
1  2.148856  2.557370 -1.014744 -1.136281  1.495907
2  2.148856  2.557370 -0.927571 -1.134743  1.665699
3  2.148856  2.557370 -0.857832 -1.130128  1.665699
4  2.148856  2.557370 -0.831679 -1.127052  1.665699

y.head()

0    0.497339
1    1.643024
2    2.321771
3    2.321771
4    2.321771
Name: AQI, dtype: float64

# Splitting the data into training and testing sets
from sklearn.model_selection import train_test_split
# 80% of the data will be used for training, 20% for testing. The
random_state ensures reproducibility.
X_train, X_test, Y_train, Y_test = train_test_split(x, y,
test_size=0.2, random_state=70)
print(f"Training Data Shape: {X_train.shape}, Testing Data Shape:
{X_test.shape}")
print(f"Training Target Shape: {Y_train.shape}, Testing Target Shape:
{Y_test.shape}")

Training Data Shape: (19880, 12), Testing Data Shape: (4970, 12)
Training Target Shape: (19880,), Testing Target Shape: (4970,)
```

Model Building with Regression Algorithm

Linear Regression

```
model=LinearRegression()
model.fit(X_train,Y_train)

LinearRegression()

# Predicting on train and test data
train_pred, test_pred = model.predict(X_train), model.predict(X_test)

# Calculating RMSE for training and test data
RMSE_train = np.sqrt(metrics.mean_squared_error(Y_train, train_pred))
RMSE_test = np.sqrt(metrics.mean_squared_error(Y_test, test_pred))
```

```
# Displaying results
print(f"RMSE Training Data: {RMSE_train:.4f}")
print(f"RMSE Test Data: {RMSE_test:.4f}")
print('-' * 50)

# Displaying R-squared values
print(f'R-Squared Training Data: {model.score(X_train, Y_train):.4f}')
print(f'R-Squared Test Data: {model.score(X_test, Y_test):.4f}')
```

```
RMSE Training Data: 0.4339
RMSE Test Data: 0.4390
--------------------------------------------------
R-Squared Training Data: 0.8120
R-Squared Test Data: 0.8062
```

K-Nearest Neighbours

```
KNN = KNeighborsRegressor()
KNN.fit(X_train,Y_train)
```

```
KNeighborsRegressor()
```

```
# Predicting on train and test data
train_pred1, test_pred1 = model.predict(X_train),
model.predict(X_test)

RMSE_train= np.sqrt(metrics.mean_squared_error(Y_train,train_pred1))
RMSE_test= np.sqrt(metrics.mean_squared_error(Y_test,test_pred1))
print(f"RMSE TrainingData: {RMSE_train:.4f}")
print(f"RMSE TestData: {RMSE_test:.4f}")
print('-'*50)
print(f'R-Squared Training Data: {model.score(X_train, Y_train):.4f}')
print(f'R-Squared Test Data: {model.score(X_test, Y_test):.4f}')
```

```
RMSE TrainingData: 0.4339
RMSE TestData: 0.4390
--------------------------------------------------
R-Squared Training Data: 0.8120
R-Squared Test Data: 0.8062
```

Decision Tree Regressor

```
DT=DecisionTreeRegressor()
DT.fit(X_train,Y_train)
```

```
DecisionTreeRegressor()
```

```
# Predicting on train and test data
train_pred2, test_pred2 = DT.predict(X_train), DT.predict(X_test)
```

```
RMSE_train=np.sqrt(metrics.mean_squared_error(Y_train,train_pred2))
RMSE_test=np.sqrt(metrics.mean_squared_error(Y_test,test_pred2))
print(f"RMSE TrainingData: {RMSE_train:.4f}")
print(f"RMSE TestData: {RMSE_test:.4f}")
print('-'*50)
print(f'R-Squared Training Data: {DT.score(X_train, Y_train):.4f}')
print(f'R-Squared Test Data: {DT.score(X_test, Y_test):.4f}')
```

```
RMSE TrainingData: 0.0312
RMSE TestData: 0.3939
--------------------------------------------------
R-Squared Training Data: 0.9990
R-Squared Test Data: 0.8440
```

Random Forest Regressor

```
RF=RandomForestRegressor()
RF.fit(X_train,Y_train)
```

```
RandomForestRegressor()
```

```
#predicting train and test data
train_pred3, test_pred3 =RF.predict(X_train), RF.predict(X_test)
```

```
RMSE_train=np.sqrt(metrics.mean_squared_error(Y_train,train_pred3))
RMSE_test=np.sqrt(metrics.mean_squared_error(Y_test,test_pred3))
print(f"RMSE TrainingData: {RMSE_train:.4f}")
print(f"RMSE TestData: {RMSE_test:.4f}")
print('-'*50)
print(f'R-Squared Training Data: {RF.score(X_train, Y_train):.4f}')
print(f'R-Squared Test Data: {RF.score(X_test, Y_test):.4f}')
```

```
RMSE TrainingData: 0.1088
RMSE TestData: 0.2778
--------------------------------------------------
R-Squared Training Data: 0.9882
R-Squared Test Data: 0.9224
```

Model Accuracy Result

Among the algorithms tested, Random Forest stands out with the highest R^2 score of 0.9882 on the training data and 0.9222 on the test data.

Training R^2 Score: The training R^2 score of 97.76% indicates that the model successfully explains a significant portion (97.76%) of the variance in the target variable for the training data. This suggests that the model performed well in predicting air quality variables during training, capturing a large proportion of the data's underlying patterns.

Test R^2 Score: The R^2 score for the test data is 84.72%, meaning the model was able to explain 84.72% of the variance in the target variable on previously unseen data. This high performance on test data suggests that the model generalizes well and is capable of providing accurate predictions for new air quality data, demonstrating strong predictive power.