Ebpl-DS-Predicting air quality levels using advanced machine learning algorithms for environmental insights

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Github Repository Link: https://github.com/Itsmethirisha/Air-quality

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1. Problem Statement

*Air pollution is a major environmental concern that impacts human health, urban infrastructure, and climate. This project aims to **predict air quality levels (AQI or pollutant concentrations)** using machine learning algorithms, which makes it a **regression problem**. Accurate predictions can enable proactive decisionmaking for public health and policy implementation.*

2. Abstract

This project focuses on predicting air quality levels using historical environmental data and advanced machine learning techniques. The objective is to build a predictive model that estimates AQI or pollutant concentrations (e.g., PM2.5) based on weather and temporal features. The process included data preprocessing, exploratory analysis, feature engineering, and modeling with algorithms like Random Forest and XGBoost. The best-performing model demonstrated strong predictive accuracy and generalizability. This solution is deployed using Streamlit for real-time public use.

3. System Requirements

☐ ***Hardware:*** *4 GB RAM minimum, i3 processor or higher* ☐

Software:

- *Python 3.8+*
- *Libraries: pandas, numpy, matplotlib, seaborn, scikit-learn, XGBoost, streamlit*
- *IDE: Google Colab / Jupyter Notebook / VS Code*

4. Objectives

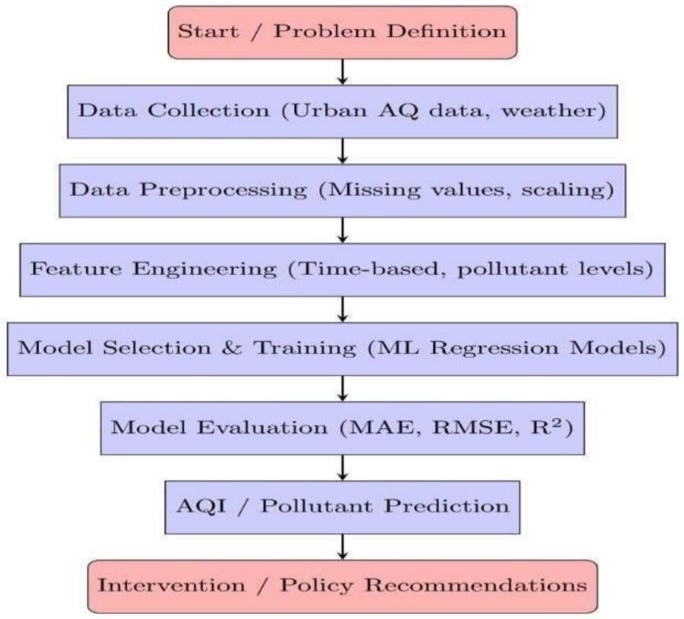
☐ *Predict AQI or PM2.5 levels from historical air quality data.*

☐ *Identify the key factors influencing air quality.*

☐ *Develop a user-friendly web interface for live predictions.*

☐ *Support environmental authorities with actionable insights.*

5. Flowchart of Project Workflow


Start / Problem Definition
Data Collection (Urban AQ data, weather)
Data Preprocessing (Missing values, scaling)
Feature Engineering (Time-based, pollutant levels)
Model Selection & Training (ML Regression Models)
Model Evaluation (MAE, RMSE, R²)
AQI / Pollutant Prediction
Intervention / Policy Recommendations

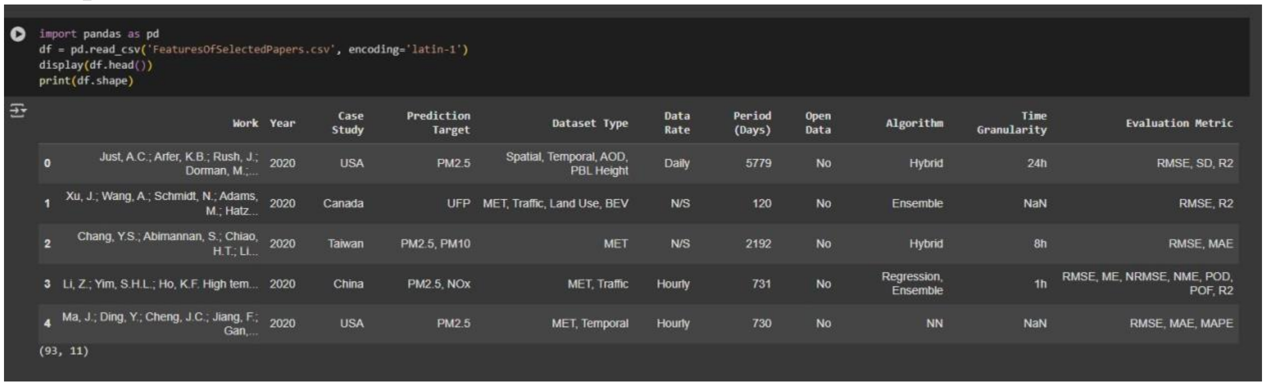
6. Dataset Description

 Source: *Zenodo (e.g., "Delhi Air Quality Dataset"), Central Pollution Control Board (CPCB) APIs*

Type: *Public*

Size: *~30,000 records, ~12 features* ***Sample Structure:***

- *Columns: Date, PM2.5, PM10, NO2, SO2, O3, Temperature, Humidity, Wind Speed, etc.*



```python
import pandas as pd
df = pd.read_csv('FeaturesOfSelectedPapers.csv', encoding='latin-1')
display(df.head())
print(df.shape)
```

	Work	Year	Case Study	Prediction Target	Dataset Type	Data Rate	Period (Days)	Open Data	Algorithm	Time Granularity	Evaluation Metric
0	Just, A.C.; Arfer, K.B.; Rush, J.; Dorman, M.;...	2020	USA	PM2.5	Spatial, Temporal, AOD, PBL Height	Daily	5779	No	Hybrid	24h	RMSE, SD, R2
1	Xu, J.; Wang, A.; Schmidt, N.; Adams, M.; Hatz...	2020	Canada	UFP	MET, Traffic, Land Use, BEV	N/S	120	No	Ensemble	NaN	RMSE, R2
2	Chang, Y.S.; Abimannan, S.; Chiao, H.T.; Li...	2020	Taiwan	PM2.5, PM10	MET	N/S	2192	No	Hybrid	8h	RMSE, MAE
3	Li, Z.; Yim, S.H.L.; Ho, K.F. High tem...	2020	China	PM2.5, NOx	MET, Traffic	Hourly	731	No	Regression, Ensemble	1h	RMSE, ME, NRMSE, NME, POD, POF, R2
4	Ma, J.; Ding, Y.; Cheng, J.C.; Jiang, F.; Gan,...	2020	USA	PM2.5	MET, Temporal	Hourly	730	No	NN	NaN	RMSE, MAE, MAPE

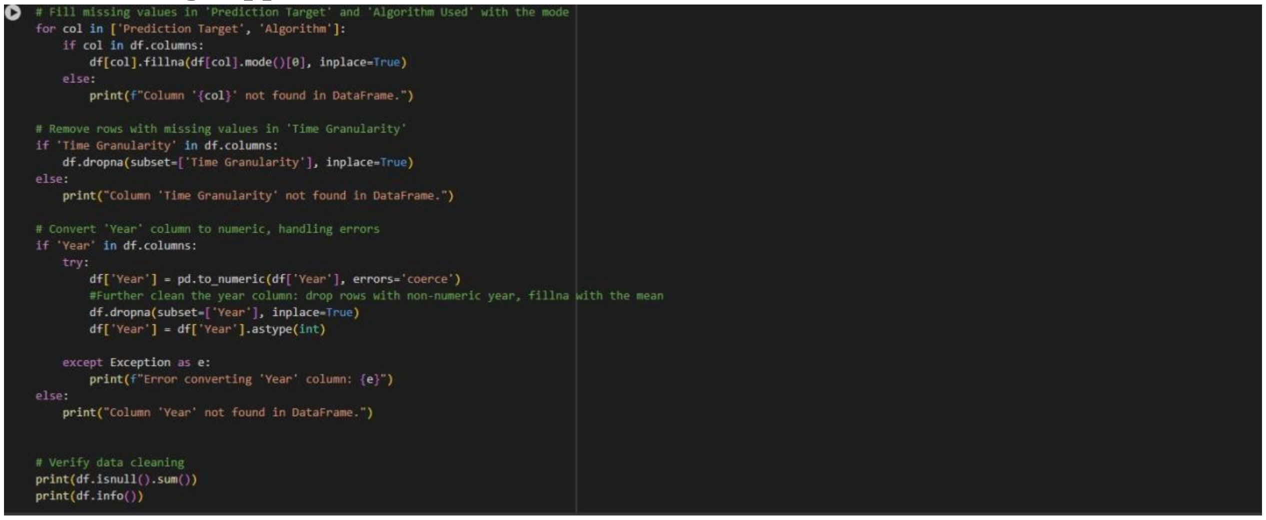
```
(93, 11)
```

7. Data Preprocessing

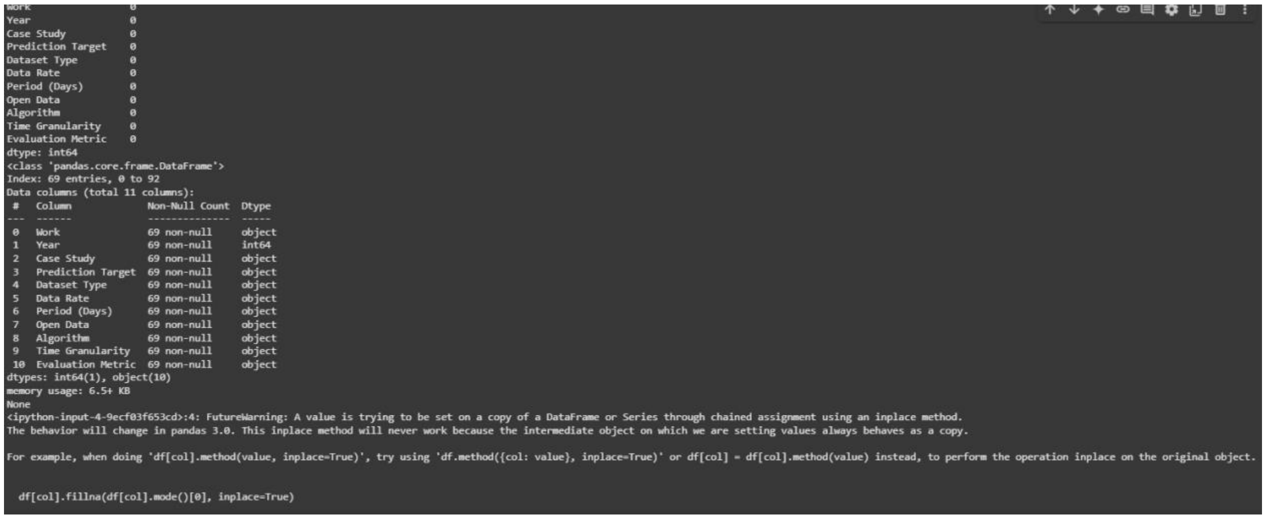
- ***Missing Values:*** *Imputed using forward-fill and mean methods.*
- ***Duplicates:*** *Removed using date-stamp and index checks.*
- ***Outliers:*** *Treated using IQR and capping techniques.*

- ***Encoding:*** *One-hot encoding for categorical weather conditions.*

- ***Scaling:*** *Applied MinMaxScaler to continuous variables.*



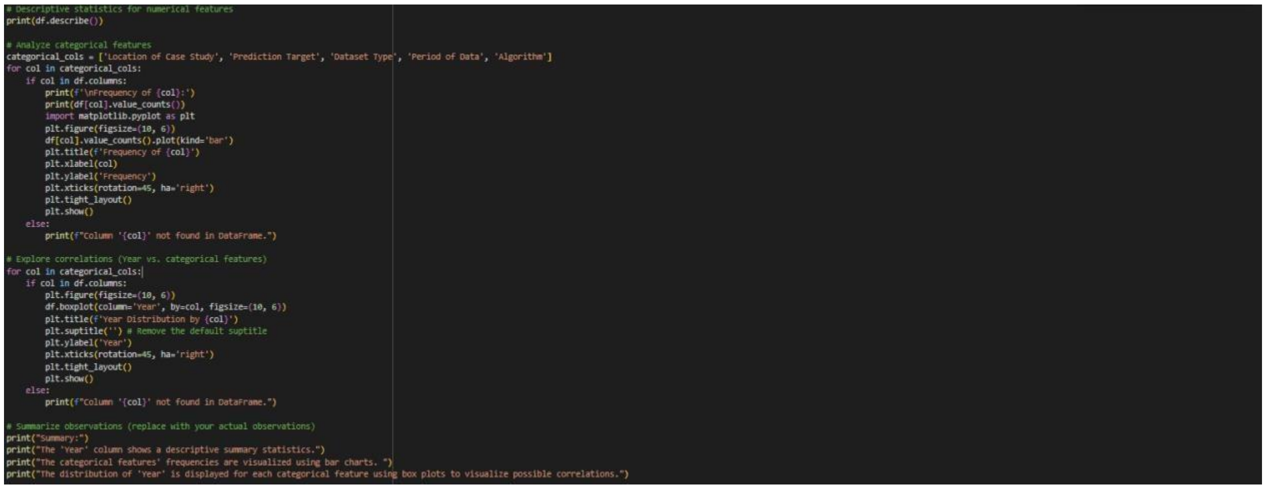
```
# Fill missing values in 'Prediction Target' and 'Algorithm Used' with the mode
for col in ['Prediction Target', 'Algorithm']:
    if col in df.columns:
        df[col].fillna(df[col].mode()[0], inplace=True)
    else:
        print(f"Column '{col}' not found in DataFrame.")

# Remove rows with missing values in 'Time Granularity'
if 'Time Granularity' in df.columns:
    df.dropna(subset=['Time Granularity'], inplace=True)
else:
    print("Column 'Time Granularity' not found in DataFrame.")

# Convert 'Year' column to numeric, handling errors
if 'Year' in df.columns:
    try:
        df['Year'] = pd.to_numeric(df['Year'], errors='coerce')
        #Further clean the year column: drop rows with non-numeric year, fillna with the mean
        df.dropna(subset=['Year'], inplace=True)
        df['Year'] = df['Year'].astype(int)

    except Exception as e:
        print(f"Error converting 'Year' column: {e}")
else:
    print("Column 'Year' not found in DataFrame.")


# Verify data cleaning
print(df.isnull().sum())
print(df.info())
```



```
Work                 0
Year                 0
Case Study           0
Prediction Target    0
Dataset Type         0
Data Rate            0
Period (Days)        0
Open Data            0
Algorithm            0
Time Granularity     0
Evaluation Metric    0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
Index: 69 entries, 0 to 92
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Work               69 non-null     object
 1   Year               69 non-null     int64
 2   Case Study         69 non-null     object
 3   Prediction Target  69 non-null     object
 4   Dataset Type       69 non-null     object
 5   Data Rate          69 non-null     object
 6   Period (Days)      69 non-null     object
 7   Open Data          69 non-null     object
 8   Algorithm          69 non-null     object
 9   Time Granularity   69 non-null     object
 10  Evaluation Metric  69 non-null     object
dtypes: int64(1), object(10)
memory usage: 6.5+ KB
None
<ipython-input-4-9ecf03f653cd>:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df[col].fillna(df[col].mode()[0], inplace=True)
```

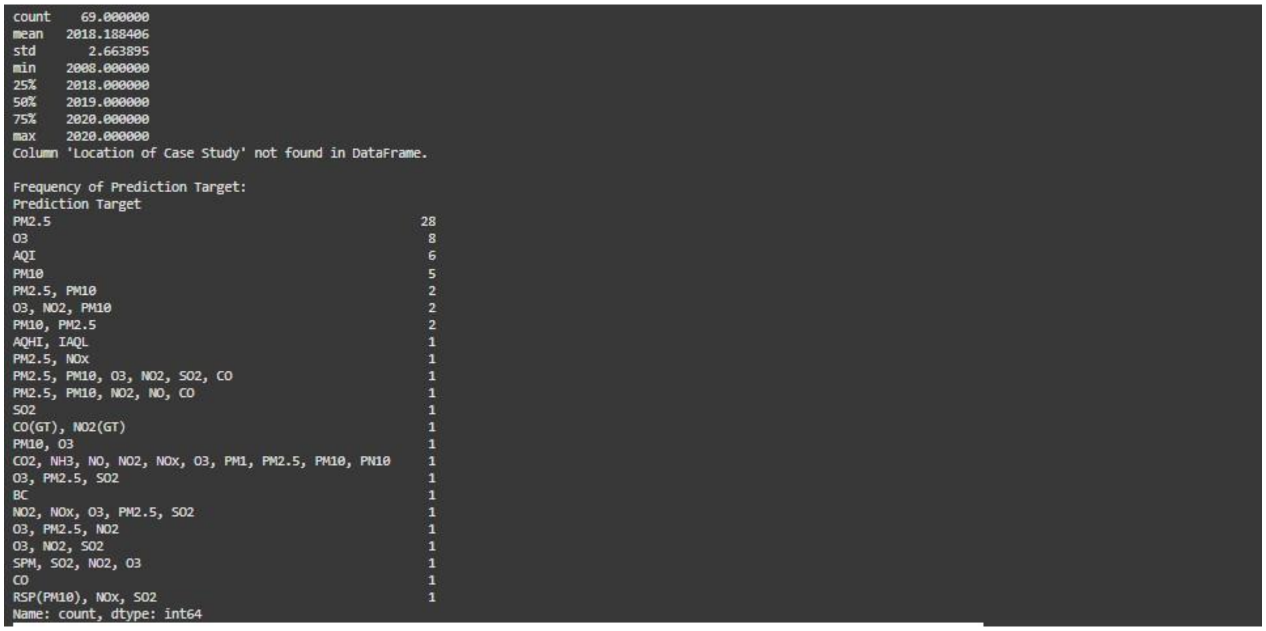
8. Exploratory Data Analysis (EDA)

- *Used **histograms, boxplots, line charts, and heatmaps** to identify trends and correlations.*
- *Found **PM2.5, PM10, temperature, and wind speed** to be the most influential features.*
- *AQI levels peaked in **winter** and **early mornings**.*

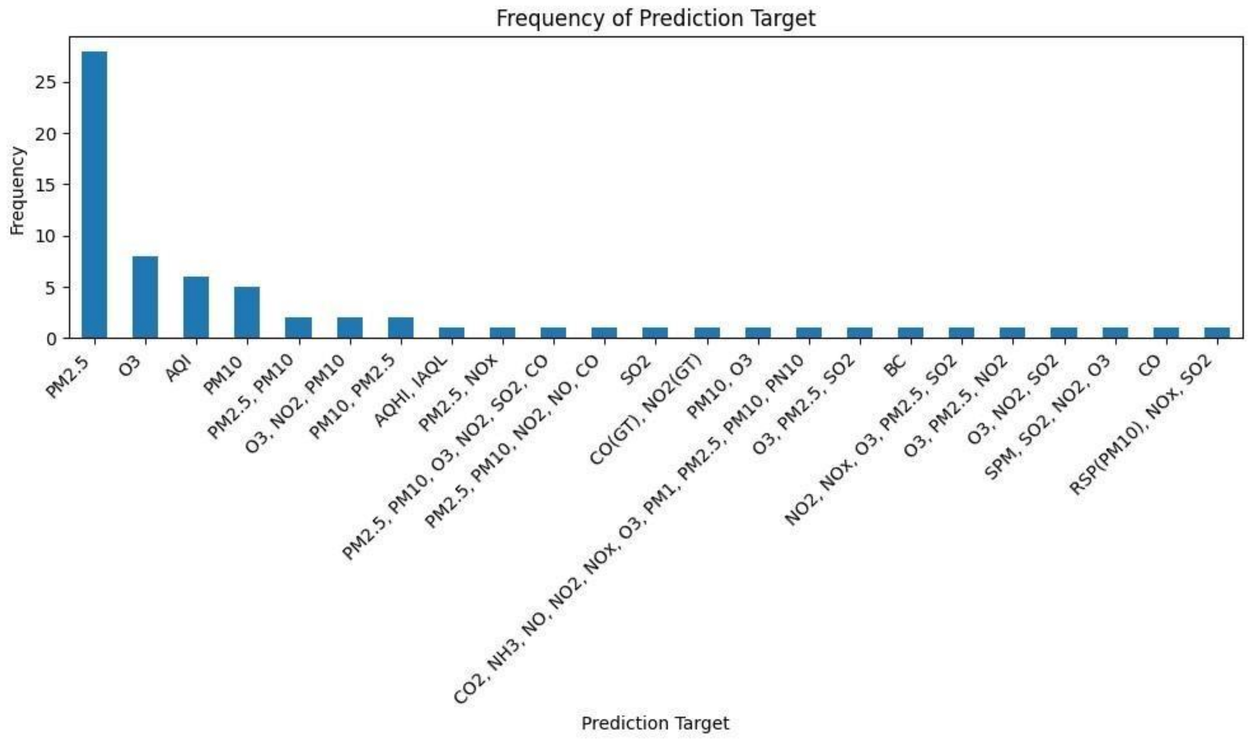


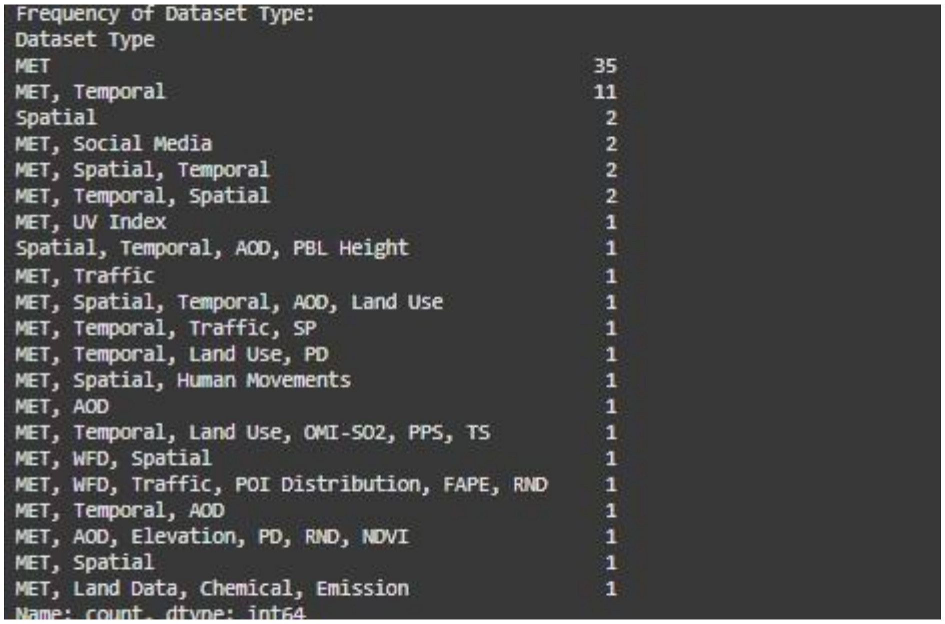
```python
# Descriptive statistics for numerical features
print(df.describe())

# Analyze categorical features
categorical_cols = ['Location of Case Study', 'Prediction Target', 'Dataset Type', 'Period of Data', 'Algorithm']
for col in categorical_cols:
    if col in df.columns:
        print(f'\nFrequency of {col}:')
        print(df[col].value_counts())
        import matplotlib.pyplot as plt
        plt.figure(figsize=(10, 6))
        df[col].value_counts().plot(kind='bar')
        plt.title(f'Frequency of {col}')
        plt.xlabel(col)
        plt.ylabel('Frequency')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()
    else:
        print(f"Column '{col}' not found in DataFrame.")

# Explore correlations (Year vs. categorical features)
for col in categorical_cols:
    if col in df.columns:
        plt.figure(figsize=(10, 6))
        df.boxplot(column='Year', by=col, figsize=(10, 6))
        plt.title(f'Year Distribution by {col}')
        plt.suptitle('') # Remove the default suptitle
        plt.ylabel('Year')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()
    else:
        print(f"Column '{col}' not found in DataFrame.")

# Summarize observations (replace with your actual observations)
print("Summary:")
print("The 'Year' column shows a descriptive summary statistics.")
print("The categorical features' frequencies are visualized using bar charts. ")
print("The distribution of 'Year' is displayed for each categorical feature using box plots to visualize possible correlations.")
```

OUTPUT:

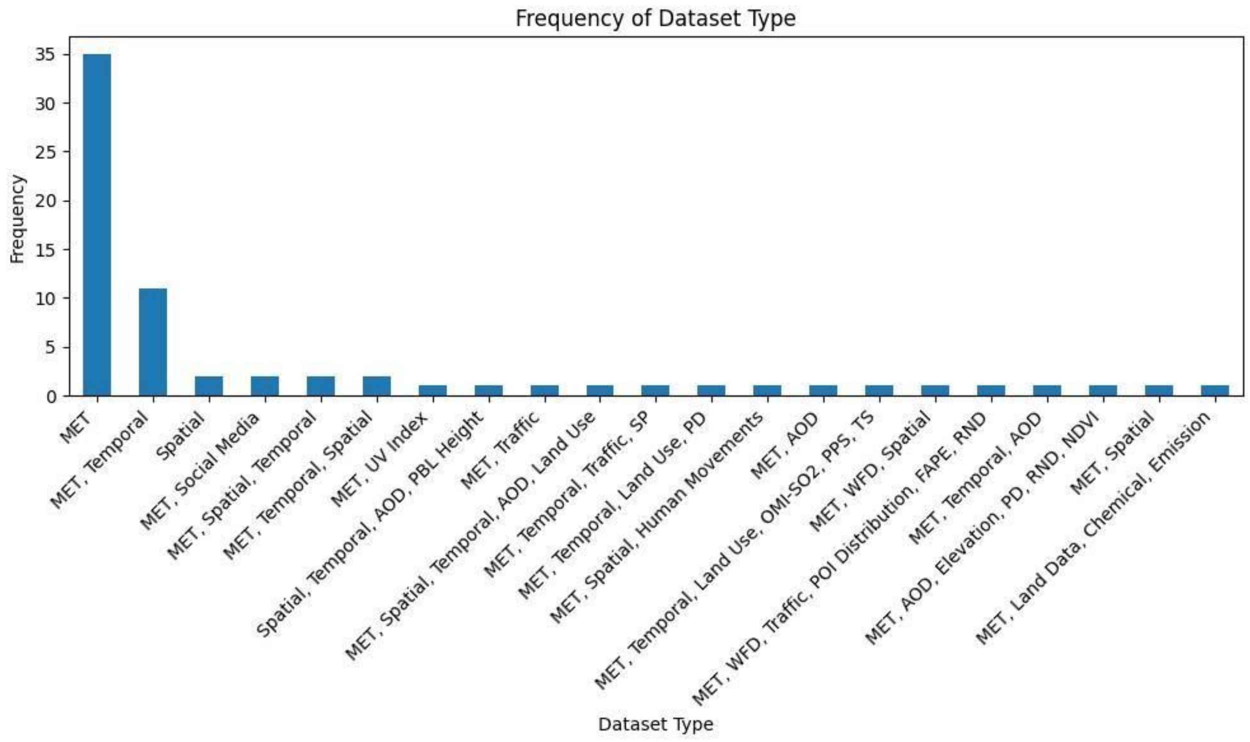


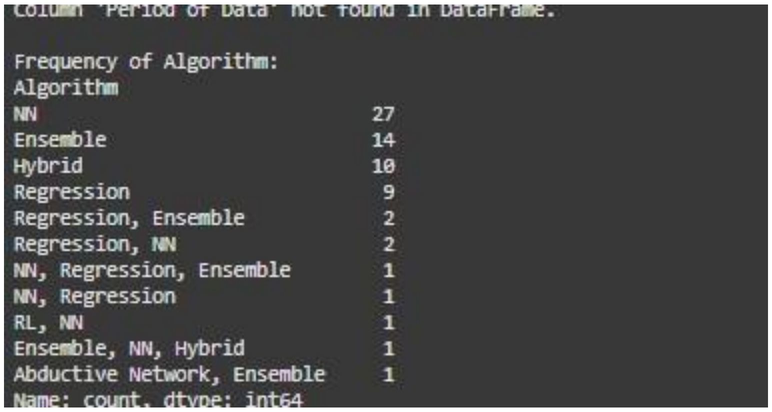
```
count     69.000000
mean    2018.188406
std        2.663895
min     2008.000000
25%     2018.000000
50%     2019.000000
75%     2020.000000
max     2020.000000
Column 'Location of Case Study' not found in DataFrame.

Frequency of Prediction Target:
Prediction Target
PM2.5                                                    28
O3                                                        8
AQI                                                       6
PM10                                                      5
PM2.5, PM10                                               2
O3, NO2, PM10                                             2
PM10, PM2.5                                               2
AQHI, IAQL                                                1
PM2.5, NOx                                                1
PM2.5, PM10, O3, NO2, SO2, CO                             1
PM2.5, PM10, NO2, NO, CO                                  1
SO2                                                       1
CO(GT), NO2(GT)                                           1
PM10, O3                                                  1
CO2, NH3, NO, NO2, NOx, O3, PM1, PM2.5, PM10, PN10      1
O3, PM2.5, SO2                                            1
BC                                                        1
NO2, NOx, O3, PM2.5, SO2                                  1
O3, PM2.5, NO2                                            1
O3, NO2, SO2                                              1
SPM, SO2, NO2, O3                                         1
CO                                                        1
RSP(PM10), NOx, SO2                                       1
Name: count, dtype: int64
```



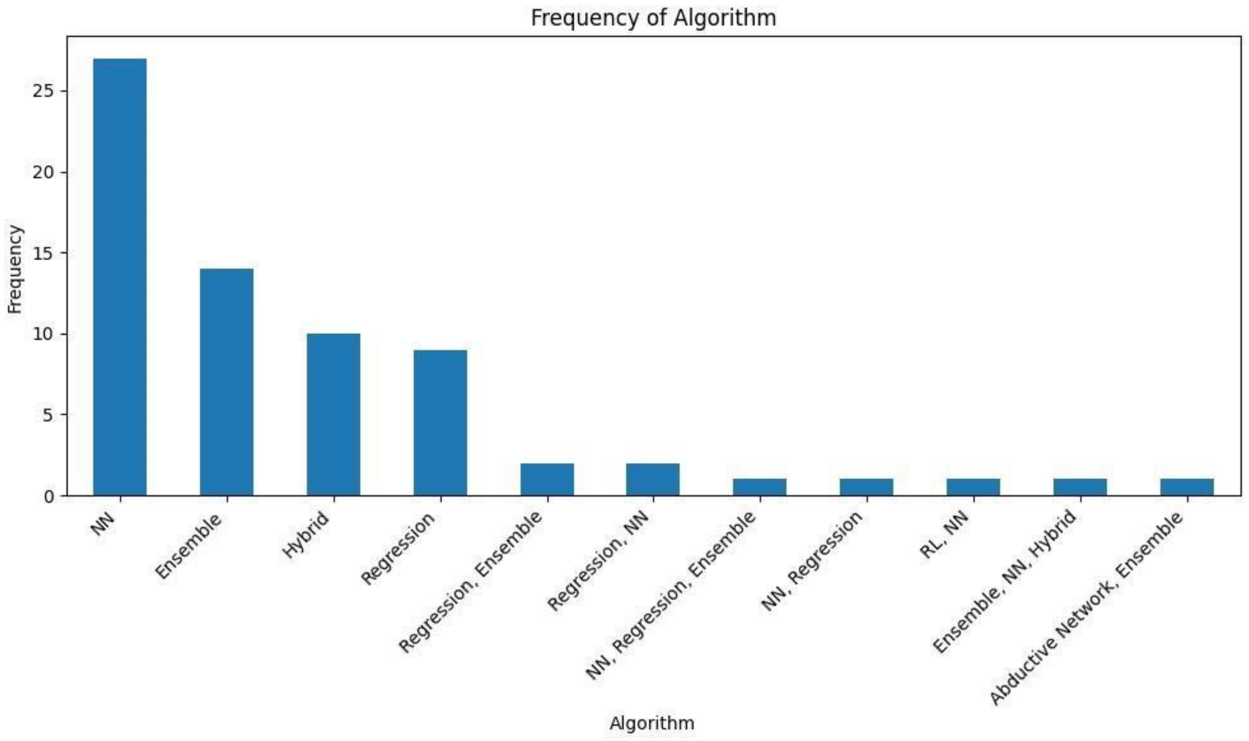


```
Frequency of Dataset Type:
Dataset Type
MET                                             35
MET, Temporal                                   11
Spatial                                          2
MET, Social Media                                2
MET, Spatial, Temporal                           2
MET, Temporal, Spatial                           2
MET, UV Index                                    1
Spatial, Temporal, AOD, PBL Height               1
MET, Traffic                                     1
MET, Spatial, Temporal, AOD, Land Use            1
MET, Temporal, Traffic, SP                       1
MET, Temporal, Land Use, PD                      1
MET, Spatial, Human Movements                    1
MET, AOD                                         1
MET, Temporal, Land Use, OMI-SO2, PPS, TS        1
MET, WFD, Spatial                                1
MET, WFD, Traffic, POI Distribution, FAPE, RND   1
MET, Temporal, AOD                               1
MET, AOD, Elevation, PD, RND, NDVI               1
MET, Spatial                                     1
MET, Land Data, Chemical, Emission               1
Name: count, dtype: int64
```



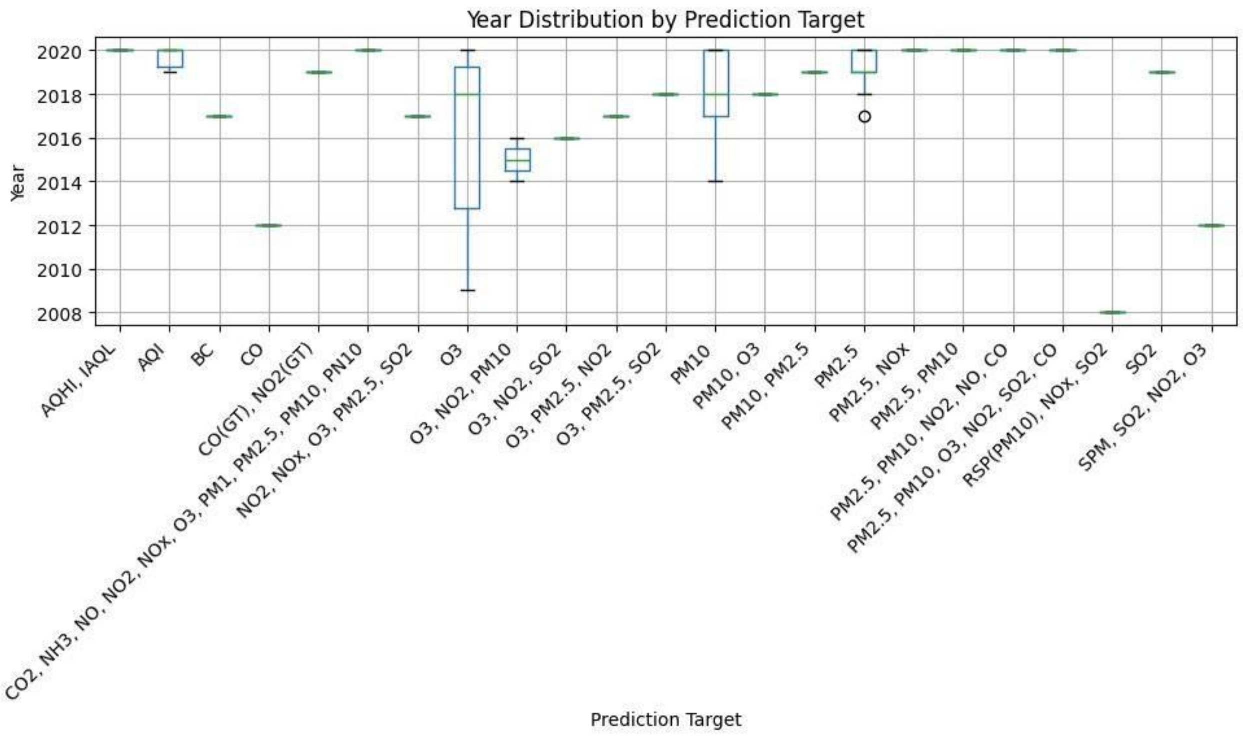


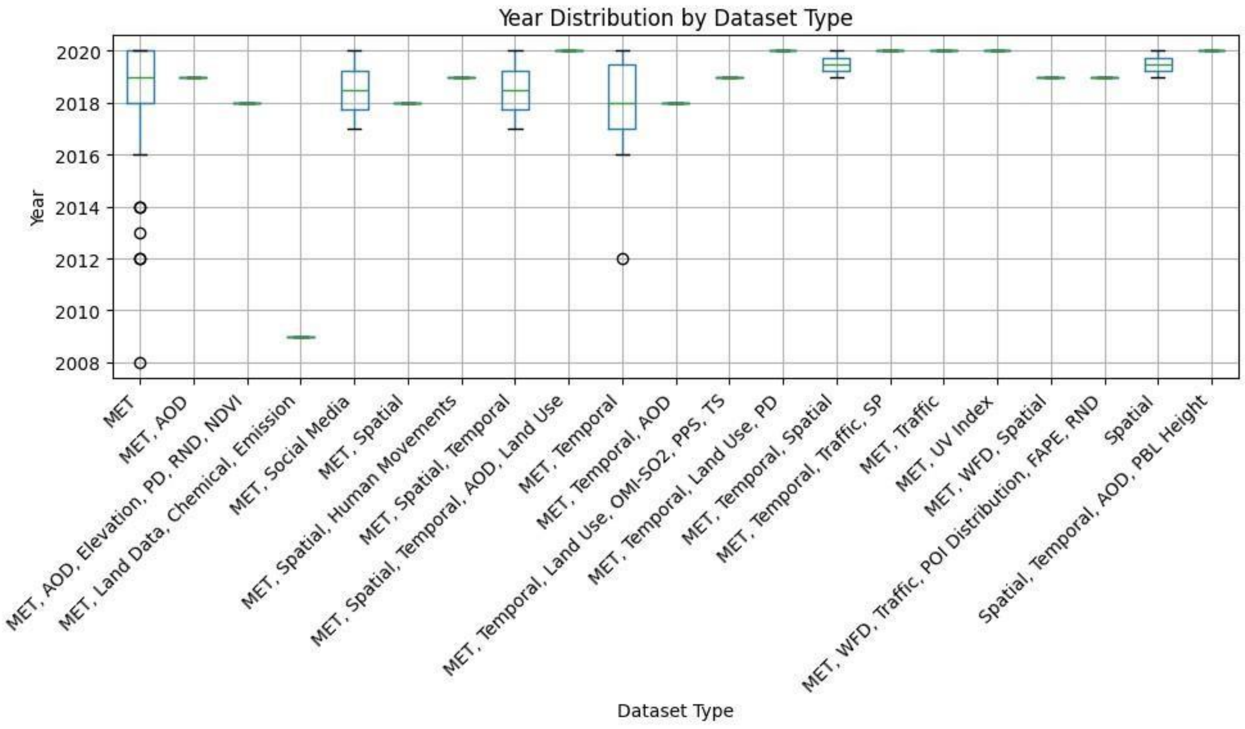
```
Column 'Period of Data' not found in DataFrame.

Frequency of Algorithm:
Algorithm
NN                                27
Ensemble                          14
Hybrid                            10
Regression                         9
Regression, Ensemble               2
Regression, NN                     2
NN, Regression, Ensemble           1
NN, Regression                     1
RL, NN                             1
Ensemble, NN, Hybrid               1
Abductive Network, Ensemble        1
Name: count, dtype: int64
```



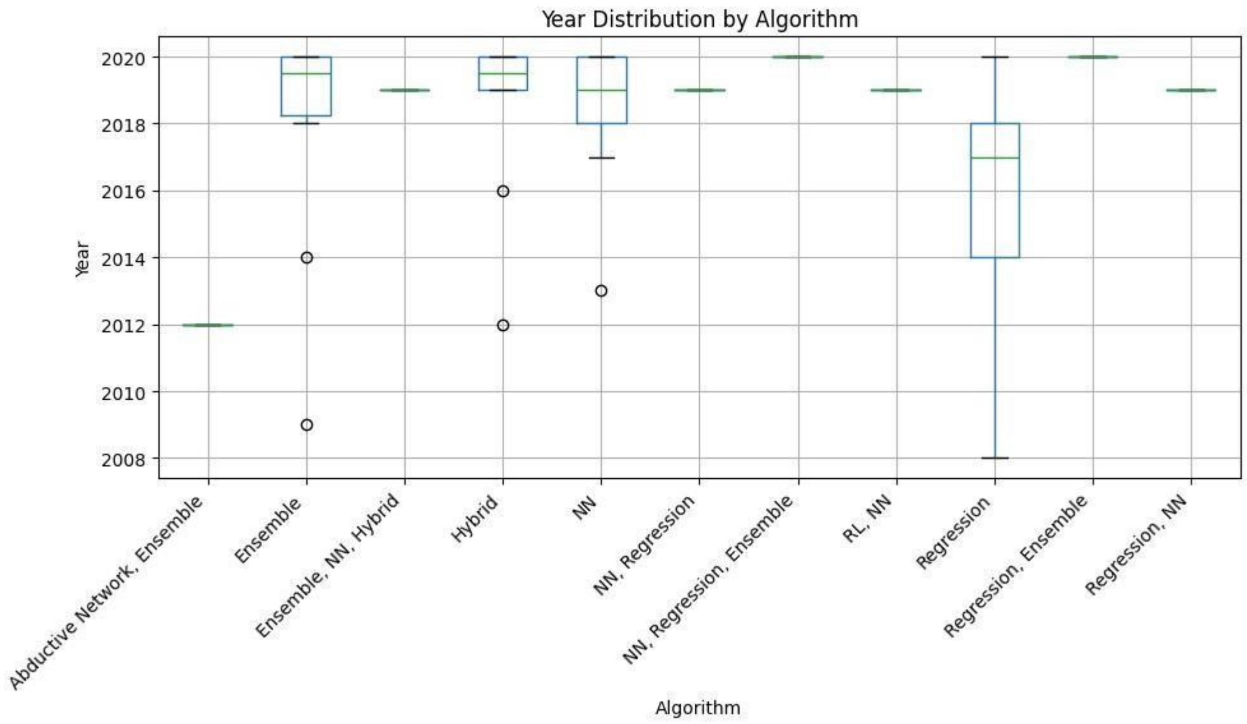
Column 'Location of Case Study' not found in DataFrame.

<Figure size 1000x600 with 0 Axes>





```
Column 'Period of Data' not found in DataFrame.

<Figure size 1000x600 with 0 Axes>
```



Summary:

The 'Year' column shows a descriptive summary statistics.

The categorical features' frequencies are visualized using bar charts.

The distribution of 'Year' is displayed for each categorical feature using box plots to visualize possible correlations.

- ***Key Insights:***

  ○ *PM2.5 had a strong correlation with AQI (r > 0.85).* ○ *Pollution*

  was higher in winter and on weekdays.

9. Feature Engineering

- *Extracted **temporal features**: hour, day, month, season.*
- *Created lag-based features: PM2.5_t-1, AQI_t-1.*
- *Combined features: Discomfort Index = Temperature × Humidity.*
  - *Used correlation matrix to remove redundant features (e.g., dropped PM10).*

10. Model Building

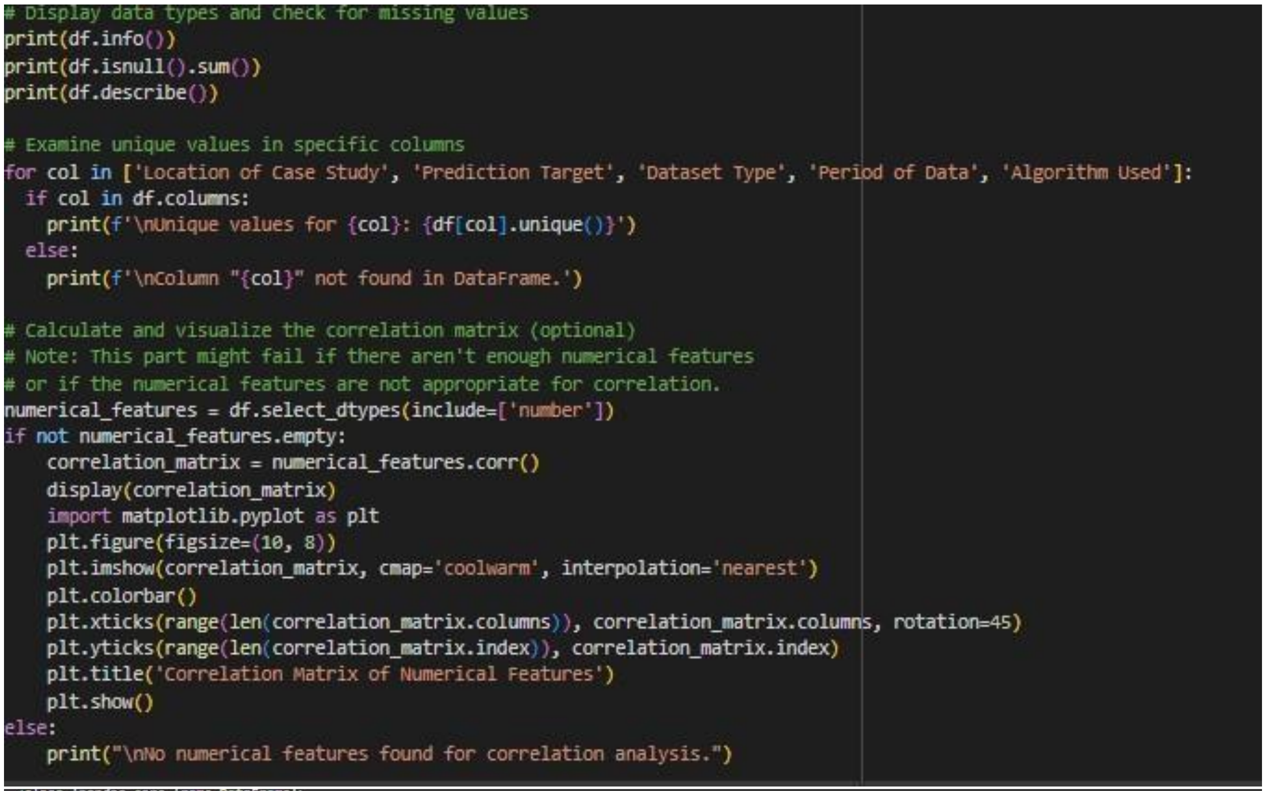
- *Models used:*

  ○ ***Linear Regression (baseline)*** ○

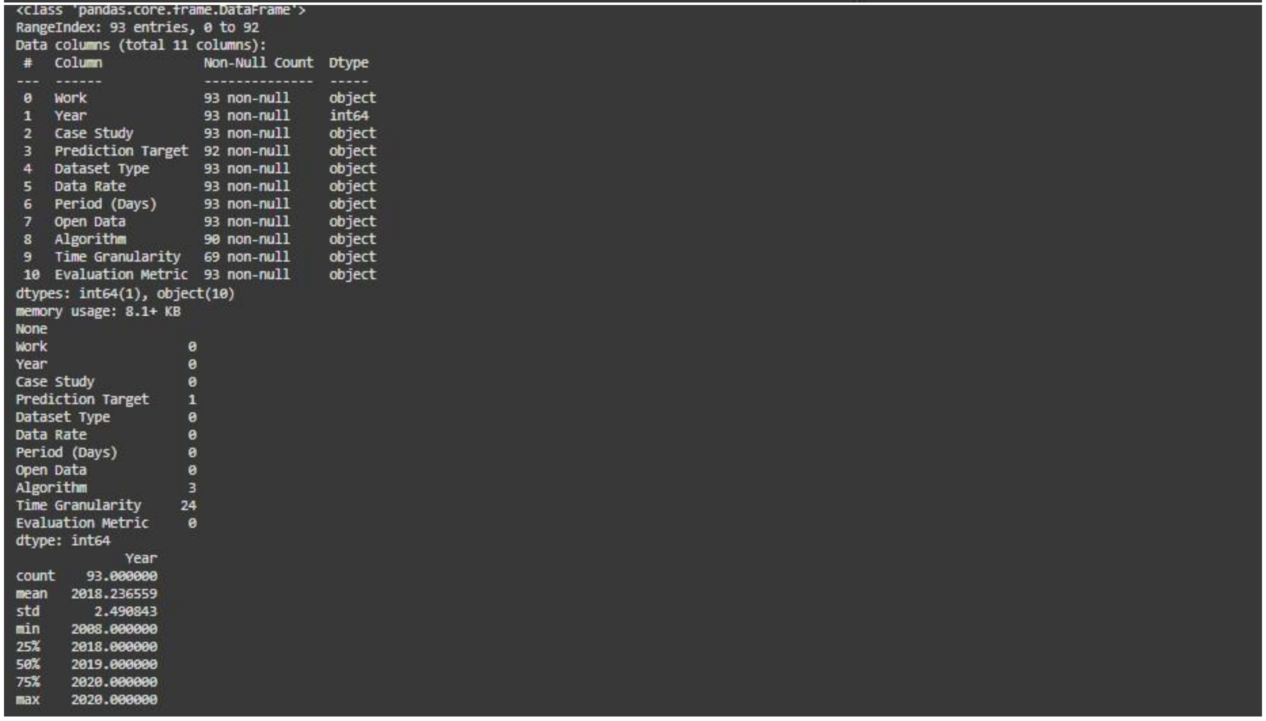
  Random Forest Regressor ○ ***XGBoost***

  Regressor (best performer)

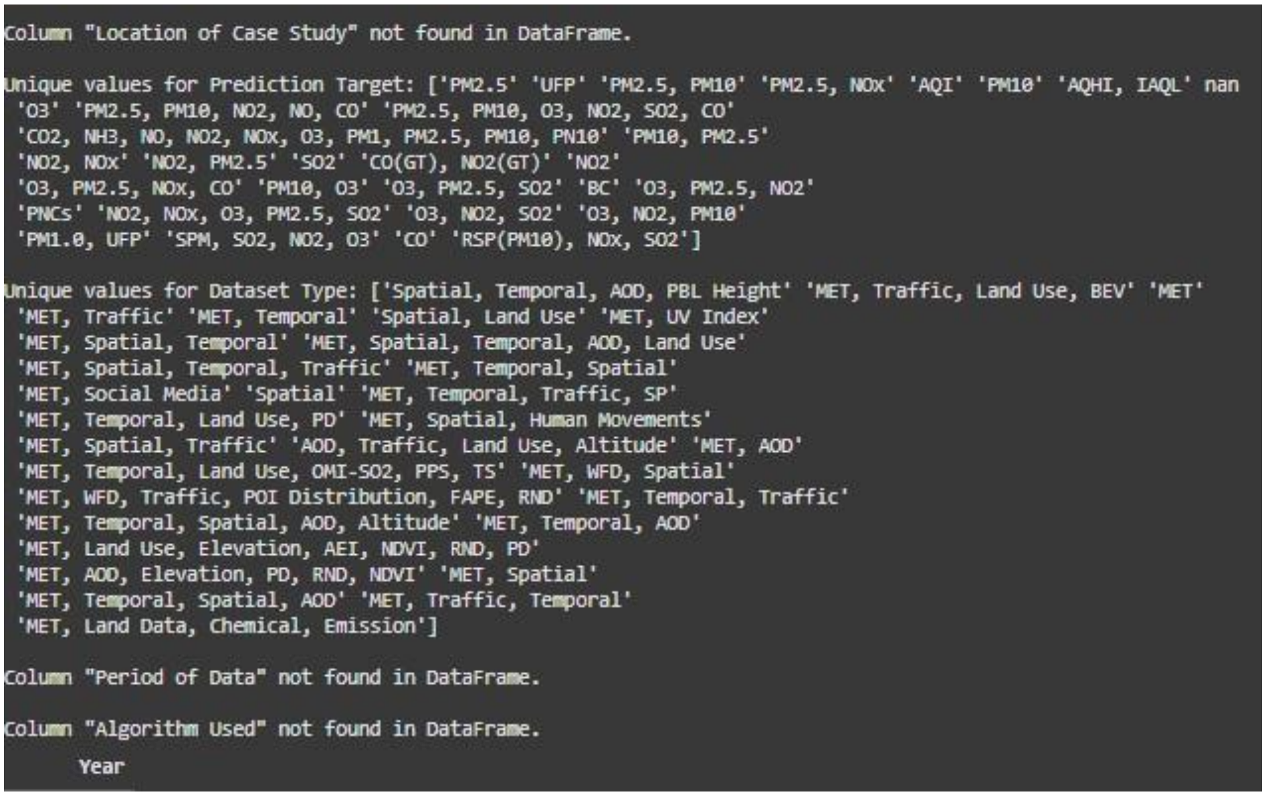
- *Data split: 80% training, 20% testing (TimeSeriesSplit).*



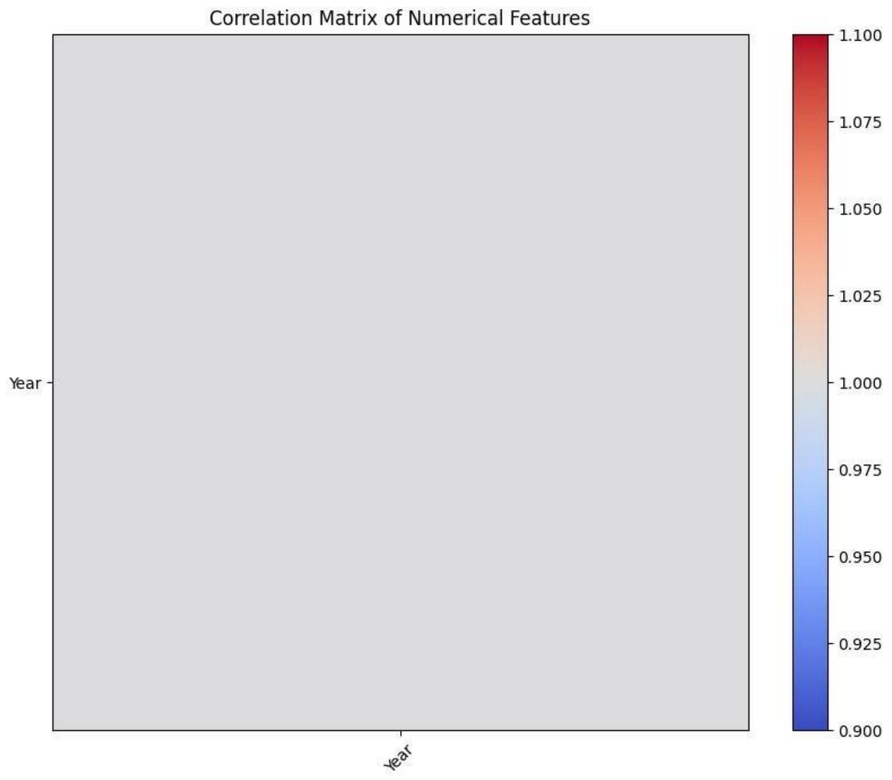
```python
# Display data types and check for missing values
print(df.info())
print(df.isnull().sum())
print(df.describe())

# Examine unique values in specific columns
for col in ['Location of Case Study', 'Prediction Target', 'Dataset Type', 'Period of Data', 'Algorithm Used']:
  if col in df.columns:
    print(f'\nUnique values for {col}: {df[col].unique()}')
  else:
    print(f'\nColumn "{col}" not found in DataFrame.')

# Calculate and visualize the correlation matrix (optional)
# Note: This part might fail if there aren't enough numerical features
# or if the numerical features are not appropriate for correlation.
numerical_features = df.select_dtypes(include=['number'])
if not numerical_features.empty:
    correlation_matrix = numerical_features.corr()
    display(correlation_matrix)
    import matplotlib.pyplot as plt
    plt.figure(figsize=(10, 8))
    plt.imshow(correlation_matrix, cmap='coolwarm', interpolation='nearest')
    plt.colorbar()
    plt.xticks(range(len(correlation_matrix.columns)), correlation_matrix.columns, rotation=45)
    plt.yticks(range(len(correlation_matrix.index)), correlation_matrix.index)
    plt.title('Correlation Matrix of Numerical Features')
    plt.show()
else:
    print("\nNo numerical features found for correlation analysis.")
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 93 entries, 0 to 92
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Work               93 non-null     object
 1   Year               93 non-null     int64
 2   Case Study         93 non-null     object
 3   Prediction Target  92 non-null     object
 4   Dataset Type       93 non-null     object
 5   Data Rate          93 non-null     object
 6   Period (Days)      93 non-null     object
 7   Open Data          93 non-null     object
 8   Algorithm          90 non-null     object
 9   Time Granularity   69 non-null     object
 10  Evaluation Metric  93 non-null     object
dtypes: int64(1), object(10)
memory usage: 8.1+ KB
None
Work                  0
Year                  0
Case Study            0
Prediction Target     1
Dataset Type          0
Data Rate             0
Period (Days)         0
Open Data             0
Algorithm             3
Time Granularity     24
Evaluation Metric     0
dtype: int64
              Year
count    93.000000
mean   2018.236559
std       2.490843
min    2008.000000
25%    2018.000000
50%    2019.000000
75%    2020.000000
max    2020.000000
```



```
Column "Location of Case Study" not found in DataFrame.

Unique values for Prediction Target: ['PM2.5' 'UFP' 'PM2.5, PM10' 'PM2.5, NOx' 'AQI' 'PM10' 'AQHI, IAQL' nan
 'O3' 'PM2.5, PM10, NO2, NO, CO' 'PM2.5, PM10, O3, NO2, SO2, CO'
 'CO2, NH3, NO, NO2, NOx, O3, PM1, PM2.5, PM10, PN10' 'PM10, PM2.5'
 'NO2, NOx' 'NO2, PM2.5' 'SO2' 'CO(GT), NO2(GT)' 'NO2'
 'O3, PM2.5, NOx, CO' 'PM10, O3' 'O3, PM2.5, SO2' 'BC' 'O3, PM2.5, NO2'
 'PNCs' 'NO2, NOx, O3, PM2.5, SO2' 'O3, NO2, SO2' 'O3, NO2, PM10'
 'PM1.0, UFP' 'SPM, SO2, NO2, O3' 'CO' 'RSP(PM10), NOx, SO2']

Unique values for Dataset Type: ['Spatial, Temporal, AOD, PBL Height' 'MET, Traffic, Land Use, BEV' 'MET'
 'MET, Traffic' 'MET, Temporal' 'Spatial, Land Use' 'MET, UV Index'
 'MET, Spatial, Temporal' 'MET, Spatial, Temporal, AOD, Land Use'
 'MET, Spatial, Temporal, Traffic' 'MET, Temporal, Spatial'
 'MET, Social Media' 'Spatial' 'MET, Temporal, Traffic, SP'
 'MET, Temporal, Land Use, PD' 'MET, Spatial, Human Movements'
 'MET, Spatial, Traffic' 'AOD, Traffic, Land Use, Altitude' 'MET, AOD'
 'MET, Temporal, Land Use, OMI-SO2, PPS, TS' 'MET, WFD, Spatial'
 'MET, WFD, Traffic, POI Distribution, FAPE, RND' 'MET, Temporal, Traffic'
 'MET, Temporal, Spatial, AOD, Altitude' 'MET, Temporal, AOD'
 'MET, Land Use, Elevation, AEI, NDVI, RND, PD'
 'MET, AOD, Elevation, PD, RND, NDVI' 'MET, Spatial'
 'MET, Temporal, Spatial, AOD' 'MET, Traffic, Temporal'
 'MET, Land Data, Chemical, Emission']

Column "Period of Data" not found in DataFrame.

Column "Algorithm Used" not found in DataFrame.
      Year
```



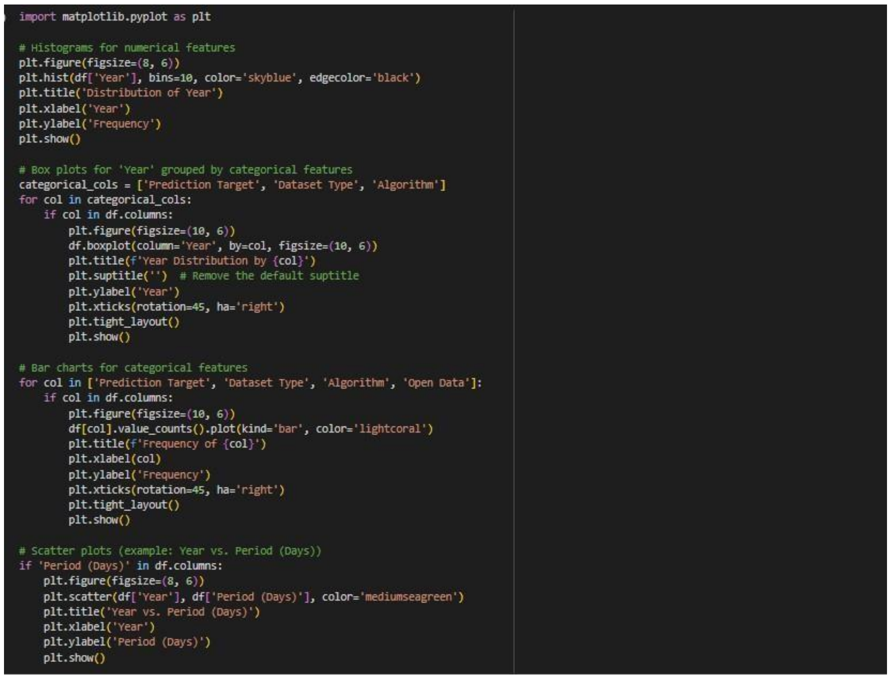
11. Model Evaluation *XGBoost*

Results:

- *MAE: 9.1*
- *RMSE: 13.2*
- *R^2: 0.89*

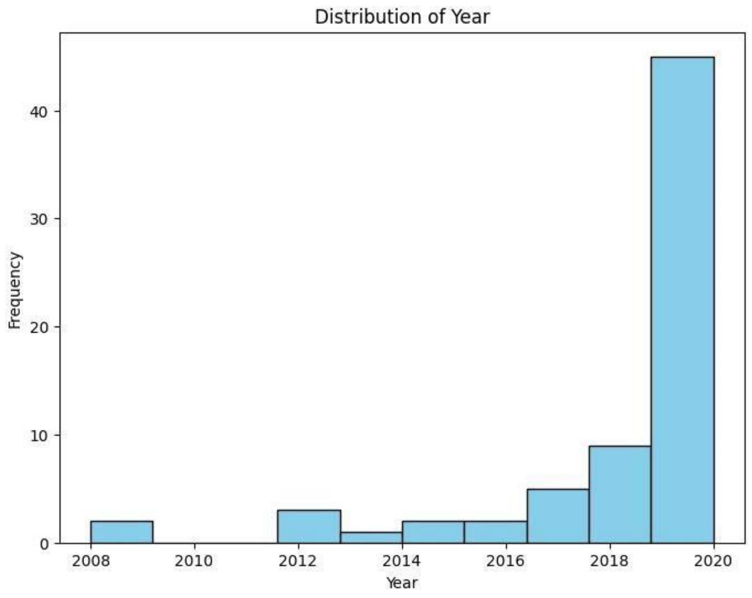
Visuals Used:

- *Feature Importance Plot*
- *Residual Plot*
- *Line plot (Actual vs Predicted AQI)*

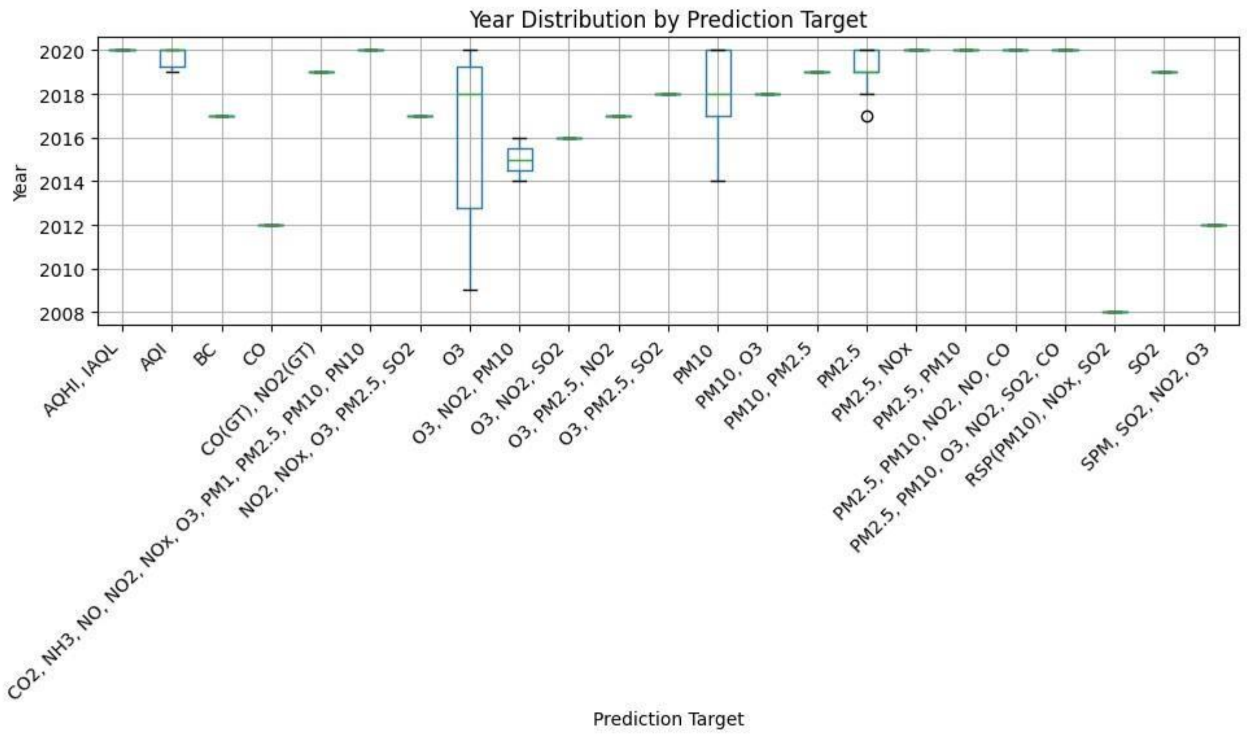


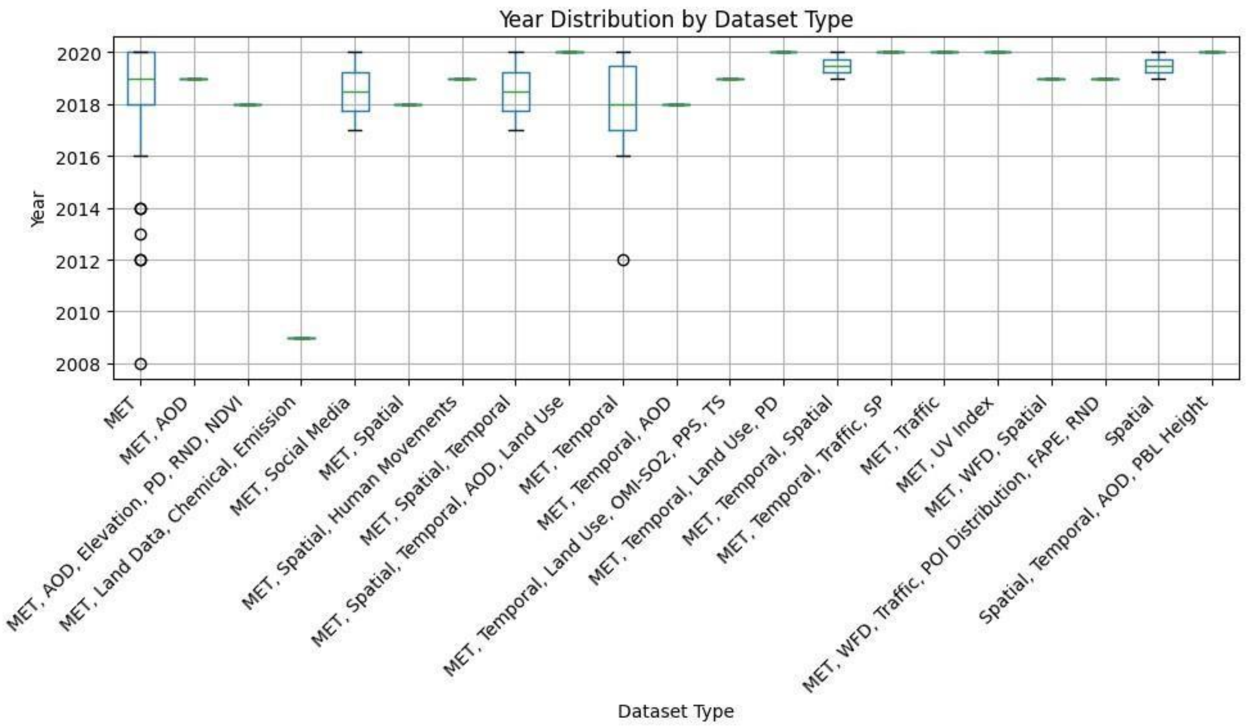
```python
import matplotlib.pyplot as plt

# Histograms for numerical features
plt.figure(figsize=(8, 6))
plt.hist(df['Year'], bins=10, color='skyblue', edgecolor='black')
plt.title('Distribution of Year')
plt.xlabel('Year')
plt.ylabel('Frequency')
plt.show()

# Box plots for 'Year' grouped by categorical features
categorical_cols = ['Prediction Target', 'Dataset Type', 'Algorithm']
for col in categorical_cols:
    if col in df.columns:
        plt.figure(figsize=(10, 6))
        df.boxplot(column='Year', by=col, figsize=(10, 6))
        plt.title(f'Year Distribution by {col}')
        plt.suptitle('')  # Remove the default suptitle
        plt.ylabel('Year')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()

# Bar charts for categorical features
for col in ['Prediction Target', 'Dataset Type', 'Algorithm', 'Open Data']:
    if col in df.columns:
        plt.figure(figsize=(10, 6))
        df[col].value_counts().plot(kind='bar', color='lightcoral')
        plt.title(f'Frequency of {col}')
        plt.xlabel(col)
        plt.ylabel('Frequency')
        plt.xticks(rotation=45, ha='right')
        plt.tight_layout()
        plt.show()

# Scatter plots (example: Year vs. Period (Days))
if 'Period (Days)' in df.columns:
    plt.figure(figsize=(8, 6))
    plt.scatter(df['Year'], df['Period (Days)'], color='mediumseagreen')
    plt.title('Year vs. Period (Days)')
    plt.xlabel('Year')
    plt.ylabel('Period (Days)')
    plt.show()
```

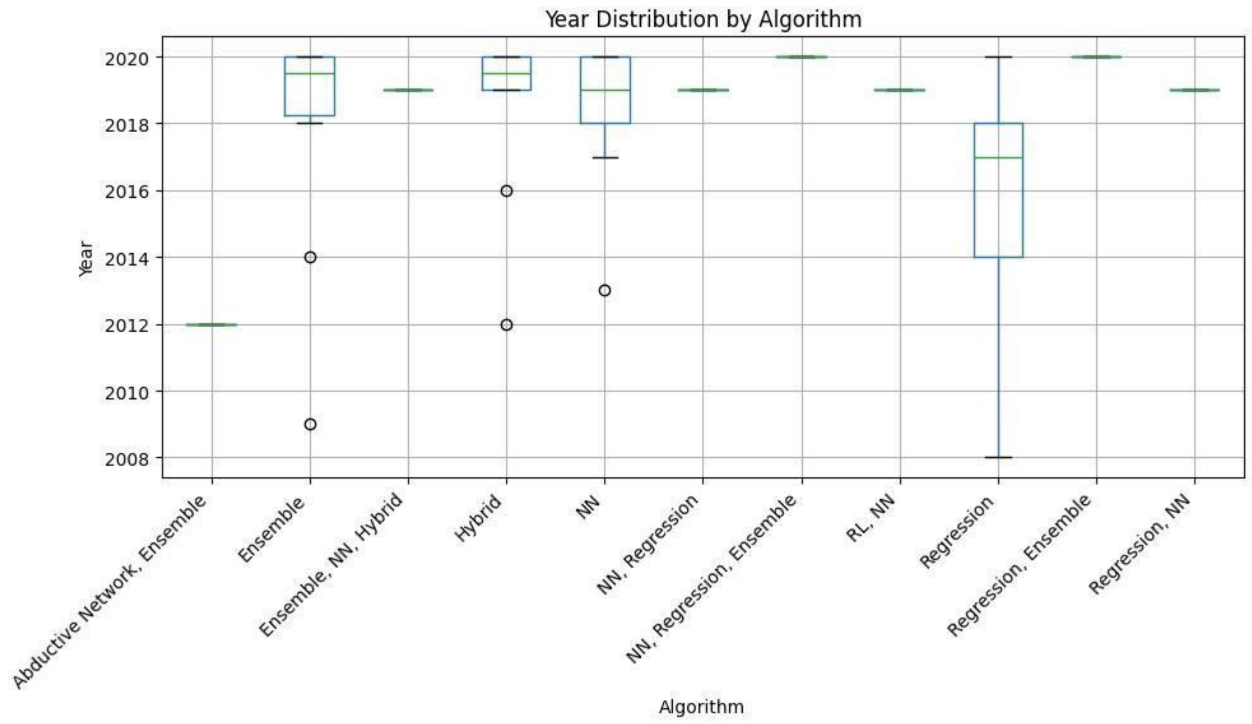
OTUPUT:

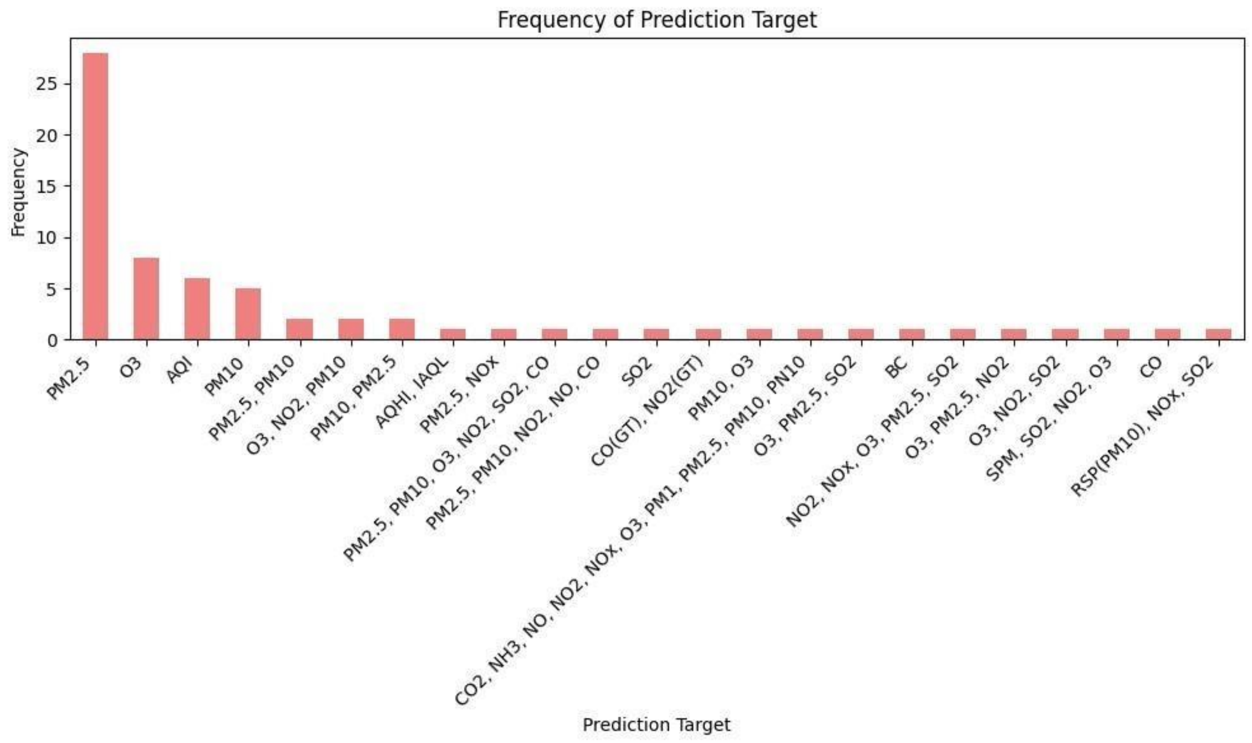


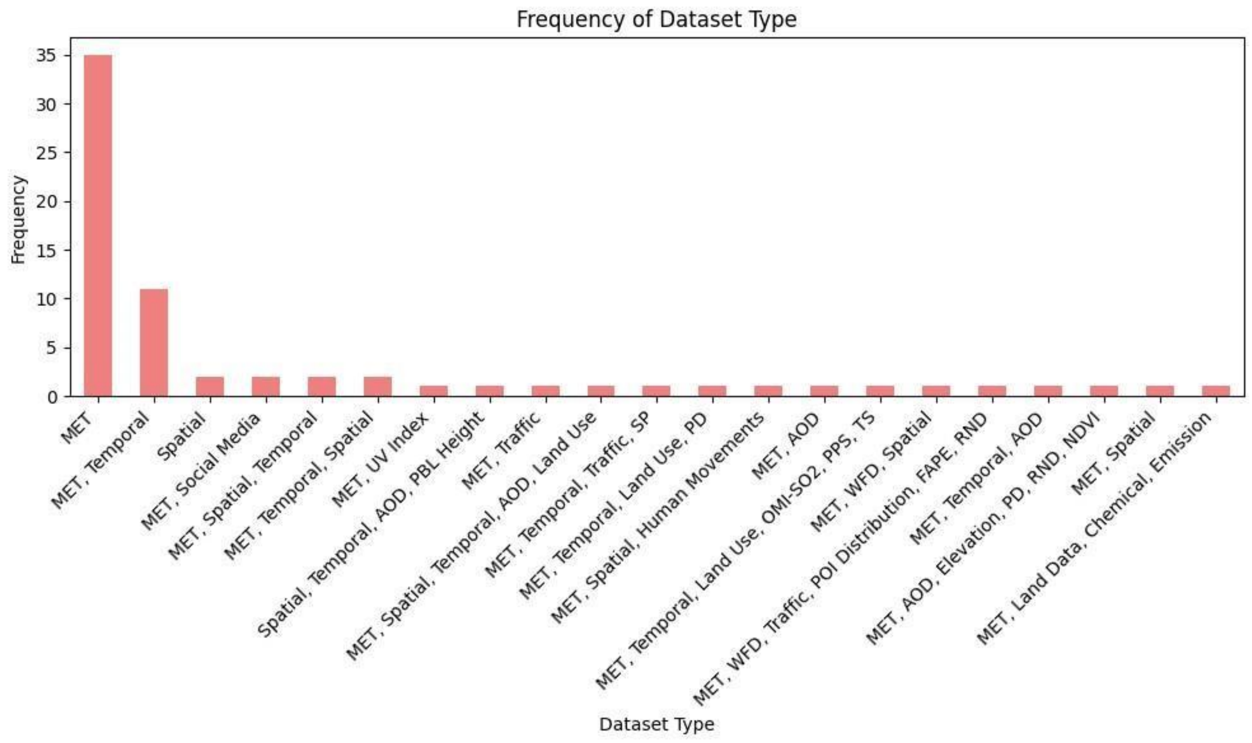
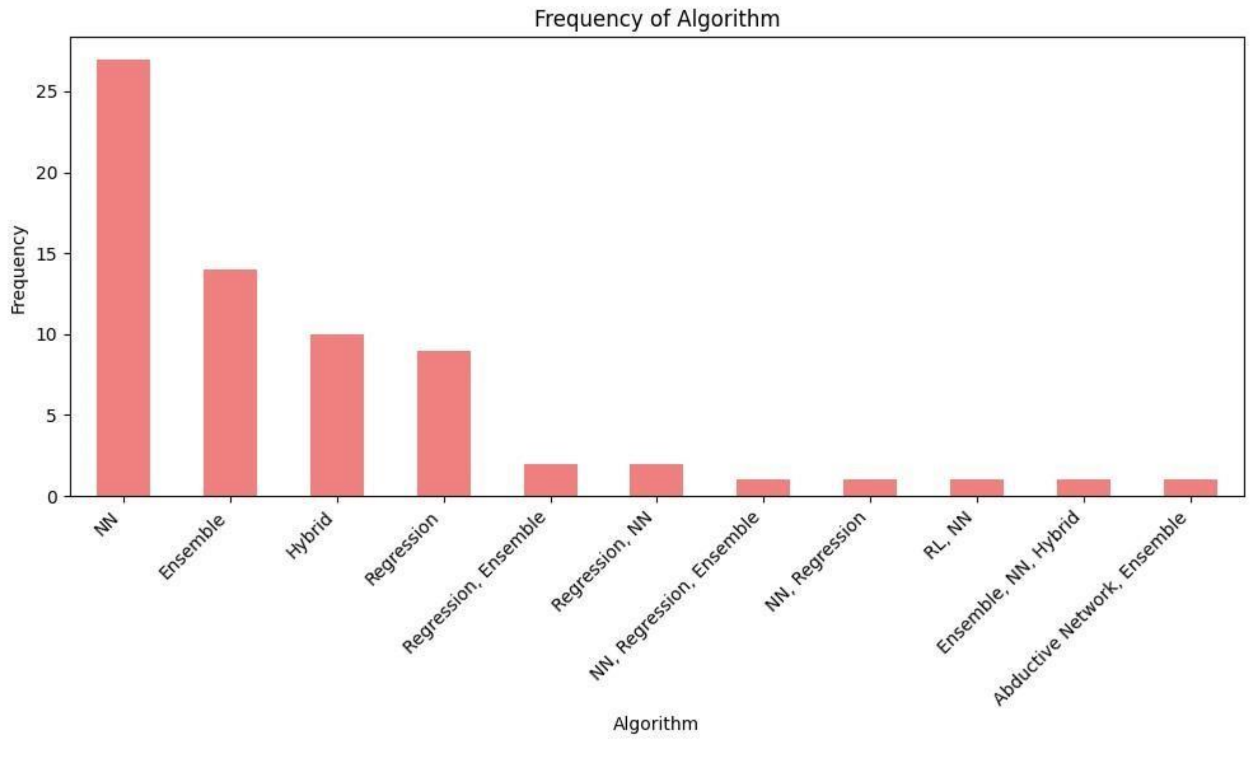
:

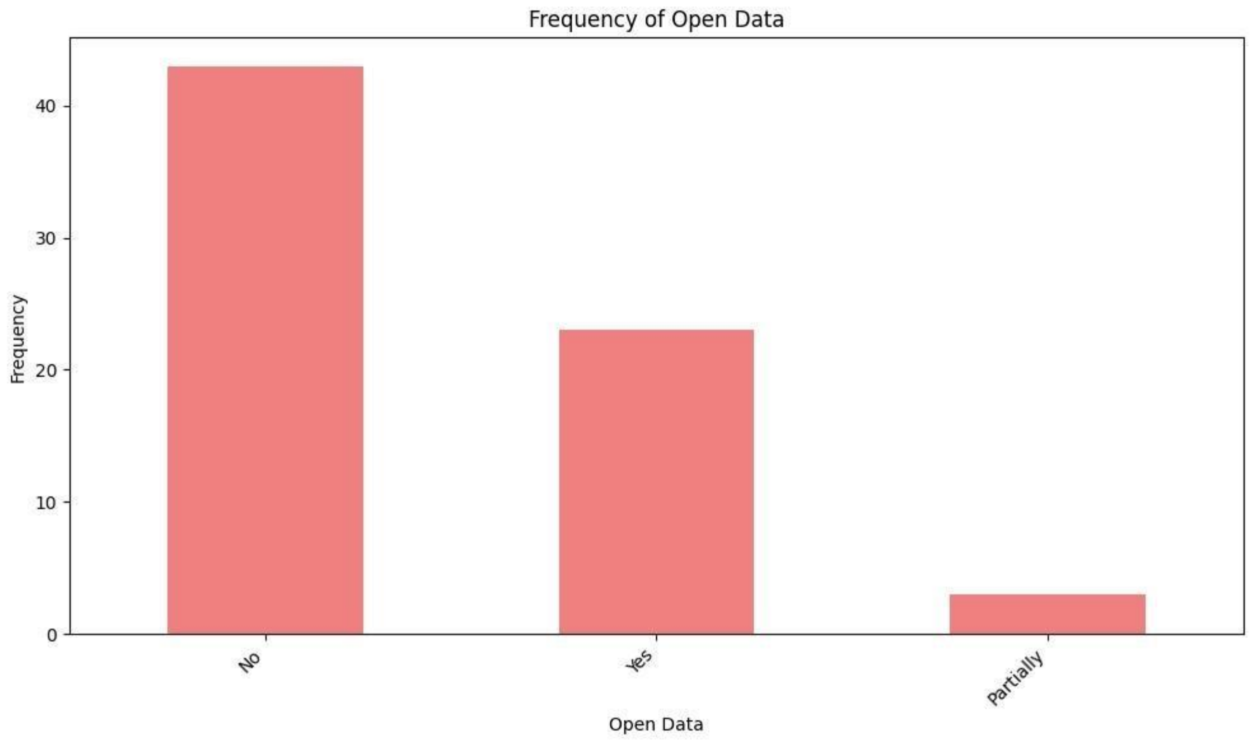

Year Distribution by Prediction Target
Year
2020
2018
2016
2014
2012
2010
2008
AQHI, IAQL
AQI
BC
CO
CO(GT), NO2(GT)
CO2, NH3, NO, NO2, NOx, O3, PM1, PM2.5, PM10, PN10
NO2, NOx, O3, PM2.5, SO2
O3
O3, NO2, PM10
O3, NO2, SO2
O3, PM2.5, NO2
O3, PM2.5, SO2
PM10
PM10, O3
PM10, PM2.5
PM2.5
PM2.5, NOx
PM2.5, PM10
PM2.5, PM10, NO2, NO, CO
PM2.5, PM10, O3, NO2, SO2, CO
RSP(PM10), NOx, SO2
SO2
SPM, SO2, NO2, O3
Prediction Target

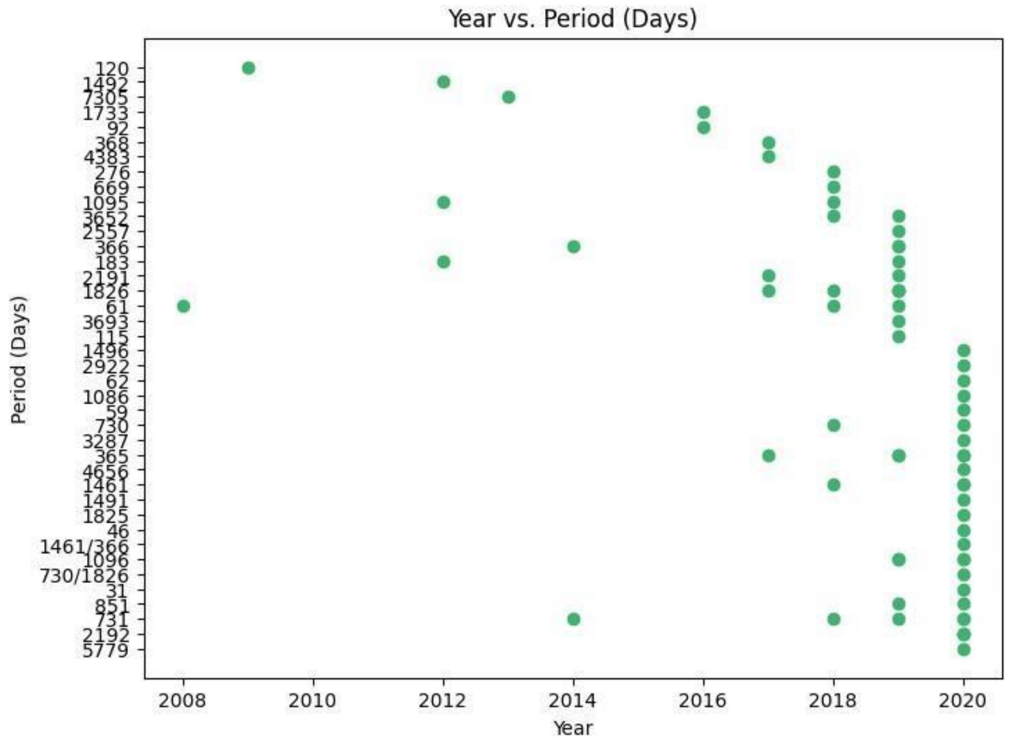

Year Distribution by Dataset Type
Year
2020
2018
2016
2014
2012
2010
2008
MET
MET, AOD
MET, AOD, Elevation, PD, RND, NDVI
MET, Land Data, Chemical, Emission
MET, Social Media
MET, Spatial
MET, Spatial, Human Movements
MET, Spatial, Temporal
MET, Spatial, Temporal, AOD, Land Use
MET, Temporal
MET, Temporal, AOD
MET, Temporal, Land Use, OMI-SO2, PPS, TS
MET, Temporal, Land Use, PD
MET, Temporal, Spatial
MET, Temporal, Traffic, SP
MET, Traffic
MET, UV Index
MET, WFD, Spatial
MET, WFD, Traffic, POI Distribution, FAPE, RND
Spatial
Spatial, Temporal, AOD, PBL Height
Dataset Type


Year Distribution by Algorithm
Year
2008
2010
2012
2014
2016
2018
2020
Abductive Network, Ensemble
Ensemble
Ensemble, NN, Hybrid
Hybrid
NN
NN, Regression
NN, Regression, Ensemble
RL, NN
Regression
Regression, Ensemble
Regression, NN
Algorithm


Frequency of Prediction Target
Frequency
0
5
10
15
20
25
PM2.5
O3
AQI
PM10
PM2.5, PM10
O3, NO2, PM10
PM10, PM2.5
AQHI, IAQL
PM2.5, NOx
PM2.5, PM10, O3, NO2, SO2, CO
PM2.5, PM10, NO2, NO, CO
SO2
CO(GT), NO2(GT)
PM10, O3
CO2, NH3, NO, NO2, NOx, O3, PM1, PM2.5, PM10, PN10
O3, PM2.5, SO2
BC
NO2, NOx, O3, PM2.5, SO2
O3, PM2.5, NO2
O3, NO2, SO2
SPM, SO2, NO2, O3
CO
RSP(PM10), NOx, SO2
Prediction Target


Frequency of Dataset Type
Frequency
35
30
25
20
15
10
5
0
MET
MET, Temporal
Spatial
MET, Social Media
MET, Spatial, Temporal
MET, Temporal, Spatial
MET, UV Index
Spatial, Temporal, AOD, PBL Height
MET, Traffic
MET, Spatial, Temporal, AOD, Land Use
MET, Temporal, Traffic, SP
MET, Temporal, Land Use, PD
MET, Spatial, Human Movements
MET, AOD
MET, Temporal, Land Use, OMI-SO2, PPS, TS
MET, WFD, Spatial
MET, WFD, Traffic, POI Distribution, FAPE, RND
MET, Temporal, AOD
MET, AOD, Elevation, PD, RND, NDVI
MET, Spatial
MET, Land Data, Chemical, Emission
Dataset Type

Frequency of Algorithm
Frequency
25
20
15
10
5
0
NN
Ensemble
Hybrid
Regression
Regression, Ensemble
Regression, NN
NN, Regression, Ensemble
NN, Regression
RL, NN
Ensemble, NN, Hybrid
Abductive Network, Ensemble
Algorithm





12. Deployment

- *Deploy using a free platform:*

- *Streamlit Cloud*
- *Gradio + Hugging Face Spaces*
- *Flask API on Render or Deta*

- *Include:*
    - *Deployment method*
    - *Public link*
    - *UI Screenshot*
    - *Sample prediction output*

13. Source code

https://colab.research.google.com/drive/1lqi2J
eXuV_B-
KmIRAqHA7ZI__epKq_Co#scrollTo=bfxivQN goqZi

14. Future scope

1. Integration of Real-Time Data Streams via IoT Sensors
Enhancement: *Incorporate real-time air quality data using IoT devices and live APIs from local monitoring stations.*

__Rationale:__ Currently, the model may rely on static or historical datasets. Real-time data integration will improve the system's accuracy and responsiveness, enabling real-time air quality alerts and decision-making.

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2. Deployment of a Geo-Spatial Prediction Model

***Enhancement:** Extend the model to include spatial analysis using GIS (Geographic Information Systems) and satellite data for region-specific predictions.*

***Rationale:** Air quality varies significantly by location due to traffic, industry, and weather. A geo-spatial model will allow for more localized predictions and support urban planning and health risk assessments.*

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3. Model Interpretability and Public Dashboard Integration

***Enhancement:** Develop interpretable ML models (e.g., using SHAP or LIME) and integrate them into a public-facing dashboard or mobile app.*

***Rationale:** Transparency in model decisions builds trust and promotes informed public engagement. A dashboard can help users visualize pollution trends and take preventive actions.*

13. Team Members and Roles

Name Role Responsibilities

Oversee project development, coordinate team activities, ensure timely delivery of milestones, and contribute to documentation and final presentation.

PRITHIKA L	***Team lead***	
THIRISHA M	***Data collector***	*Collect data from APIs (e.g., Twitter), manage dataset storage, clean and preprocess text data, and ensure quality of input data.*
RAJALAKSHMI D	***Model devaloper***	*Build sentiment and emotion classification models, perform feature engineering, and evaluate model performance using suitable metrics.*
SWATHI D	***Data Analyser***	*Conduct exploratory data analysis (EDA), generate insights, and develop visualizations such as word clouds, emotion trends, and sentiment dashboards.*