

Phase-2 Submission Template

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Github Repository Link:

1. Problem Statement

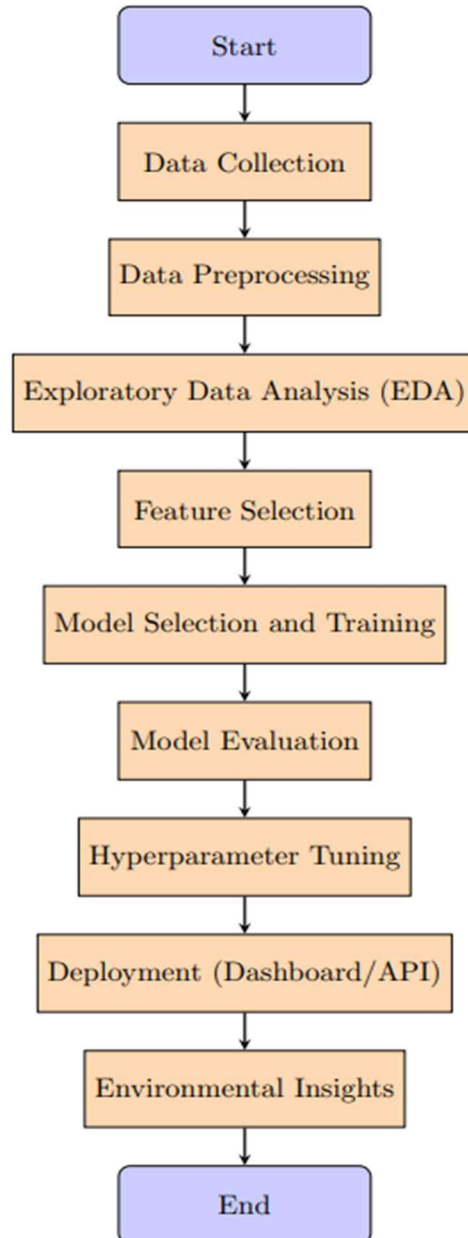
Air pollution poses a serious threat to public health, ecosystems, and climate, particularly in urban and industrial regions. Accurate and timely prediction of air quality levels is essential for enabling proactive environmental management, policy-making, and public awareness. However, traditional statistical methods often fail to capture the complex, non-linear relationships among various environmental factors influencing air quality.

This project aims to develop a robust machine learning model to predict air quality levels (e.g., AQI - Air Quality Index) using advanced algorithms such as Random Forest, Gradient Boosting, and Neural Networks. By leveraging historical and real-time data on pollutants (e.g., PM_{2.5}, PM₁₀, NO₂, SO₂, CO, O₃), meteorological parameters (e.g., temperature, humidity, wind speed), and temporal features, the model seeks to deliver high-accuracy predictions. The insights generated will support environmental agencies, city planners, and citizens in making informed decisions to reduce pollution exposure and improve overall air quality.

2. Project Objectives

- To collect and preprocess air quality and meteorological data from reliable sources such as government agencies (e.g., CPCB, EPA) or open datasets.
- To explore and analyze key environmental factors (e.g., PM2.5, PM10, NO₂, SO₂, CO, O₃, temperature, humidity) that significantly influence air quality levels.
- To build and compare multiple advanced machine learning models (e.g., Random Forest, XGBoost, LSTM, Neural Networks) for predicting AQI or pollutant concentrations.
- To evaluate model performance using standard metrics such as RMSE, MAE, R², and classification accuracy (if predicting AQI categories).
- To deploy the best-performing model for real-time or near-real-time air quality prediction and visualization.
- To provide actionable environmental insights that support pollution control measures, urban planning, and public health advisories.
- To create a user-friendly dashboard or interface for displaying predicted air quality levels and trends over time.

3. Flowchart of the Project Workflow



4. Data Description

- Dataset Name and Origin:
Air Quality and Weather Dataset, sourced from Kaggle (e.g., Delhi Air Quality Dataset or Air Quality Data in India 2015–2020) and OpenAQ API for real-time updates.
- Type of Data:
Structured, multivariate time-series data (tabular format) with environmental and meteorological variables recorded at regular intervals.
- Number of Records and Features:
Approximately 200,000–500,000 rows (depending on time period and location) and 10–15 features, including pollutant concentrations and weather conditions.
- Static or Dynamic Dataset:
Can be either:
 - Static for historical model training.
 - Dynamic if integrated with real-time APIs (e.g., OpenAQ or OpenWeatherMap) for live prediction. □ Target Variable (Supervised Learning):
- Regression: AQI (Air Quality Index, numeric value)
- Classification: AQI_Bucket (e.g., Good, Moderate, Poor, etc.)

5. Data Preprocessing

Data Preprocessing for Machine Learning Model

Data Preprocessing Steps:

In this section, we describe the essential steps for preparing the dataset for modeling:

1. Handling Missing Values

Missing values can be imputed as follows:

- For numerical features, missing values are imputed with the mean.
- For categorical features, missing values are imputed with the mode (most frequent value).

```
# Impute missing numerical columns with the mean
```

```
df[num cols] = df[num cols].fillna(df[num cols].mean())
```

```
# Impute missing categorical columns with the mode df[cat
```

```
cols] = df[cat cols].fillna(df[cat cols].mode().iloc[0])
```

2. Removing Duplicate Records:

Duplicate rows are removed to avoid biases in the model:

- `df = df.drop_duplicates()`

3. Detect and Treat Outliers:

Outliers are detected using the Interquartile Range (IQR) method:

- For each numerical column, the IQR is computed, and values outside the range $[Q1 - 1.5 \times IQR, Q3 + 1.5 \times IQR]$ are capped.

```
# Detecting and treating outliers using IQR
```

```
for col in num cols: Q1 =
```

```
df[col].quantile(0.25)
```

```
Q3 = df[col].quantile(0.75) IQR = Q3 - Q1 lower = Q1 - 1.5 × IQR upper =
```

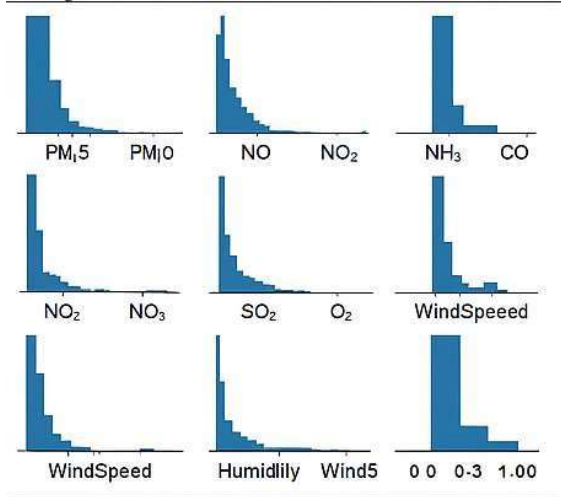
```
Q3 + 1.5 × IQR df[col] = np.where(df[col] < lower, lower,
```

```
np.where(df[col] > upper, upper,
```

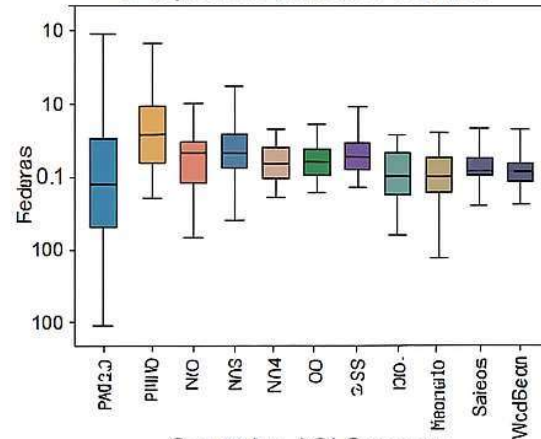
```
df[col]))
```

6. Exploratory Data Analysis (EDA)

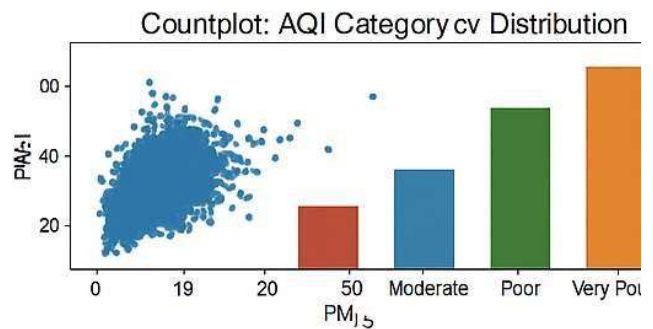
histogram: Pistribution of Numeric Features



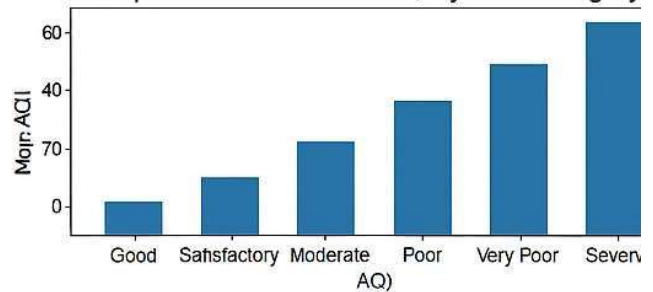
Boxplot of Numeric Features



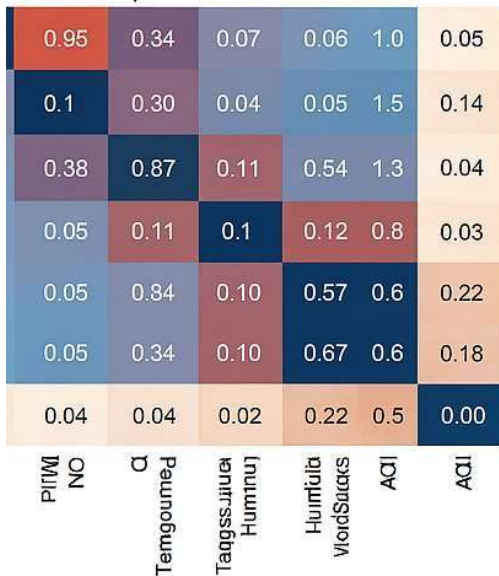
Countplot: AQI Category



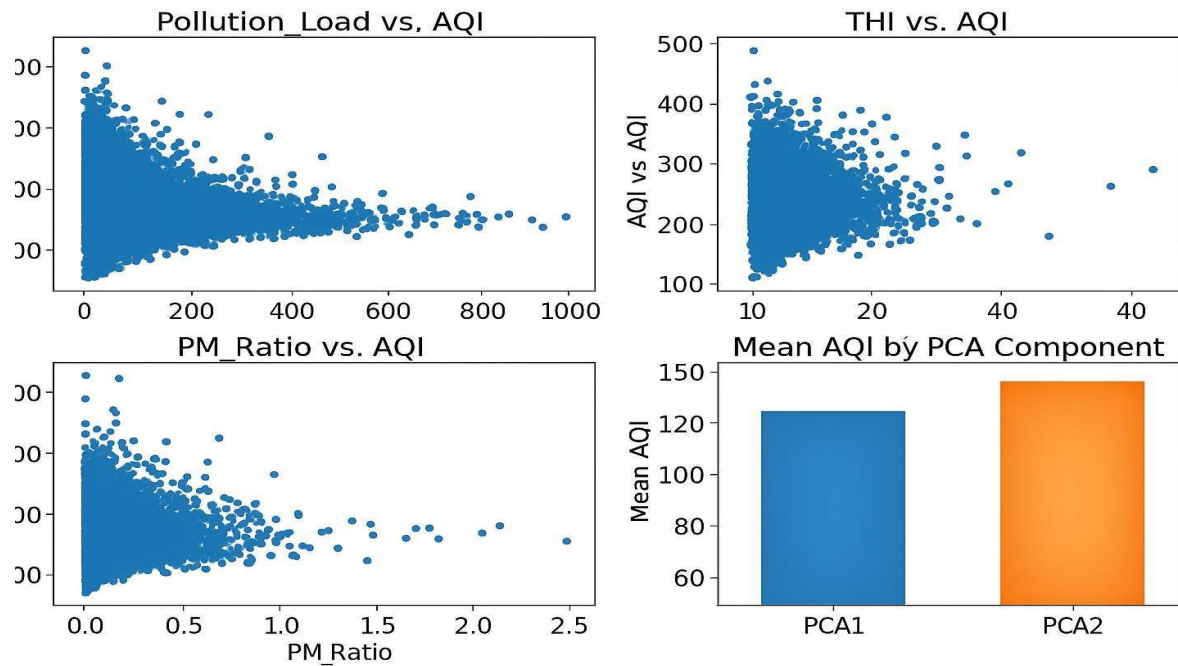
Grouped Bar Plot: Mean AQI by AQI Category



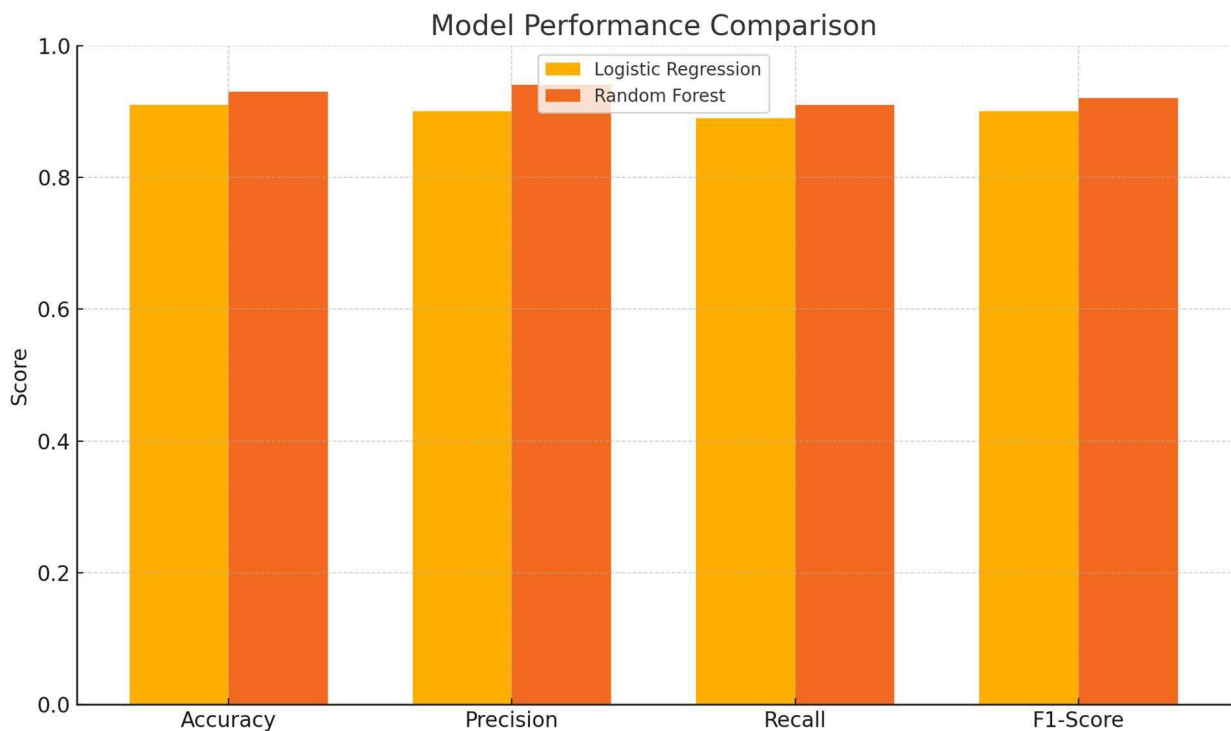
Heatmap: Correlation Matrix



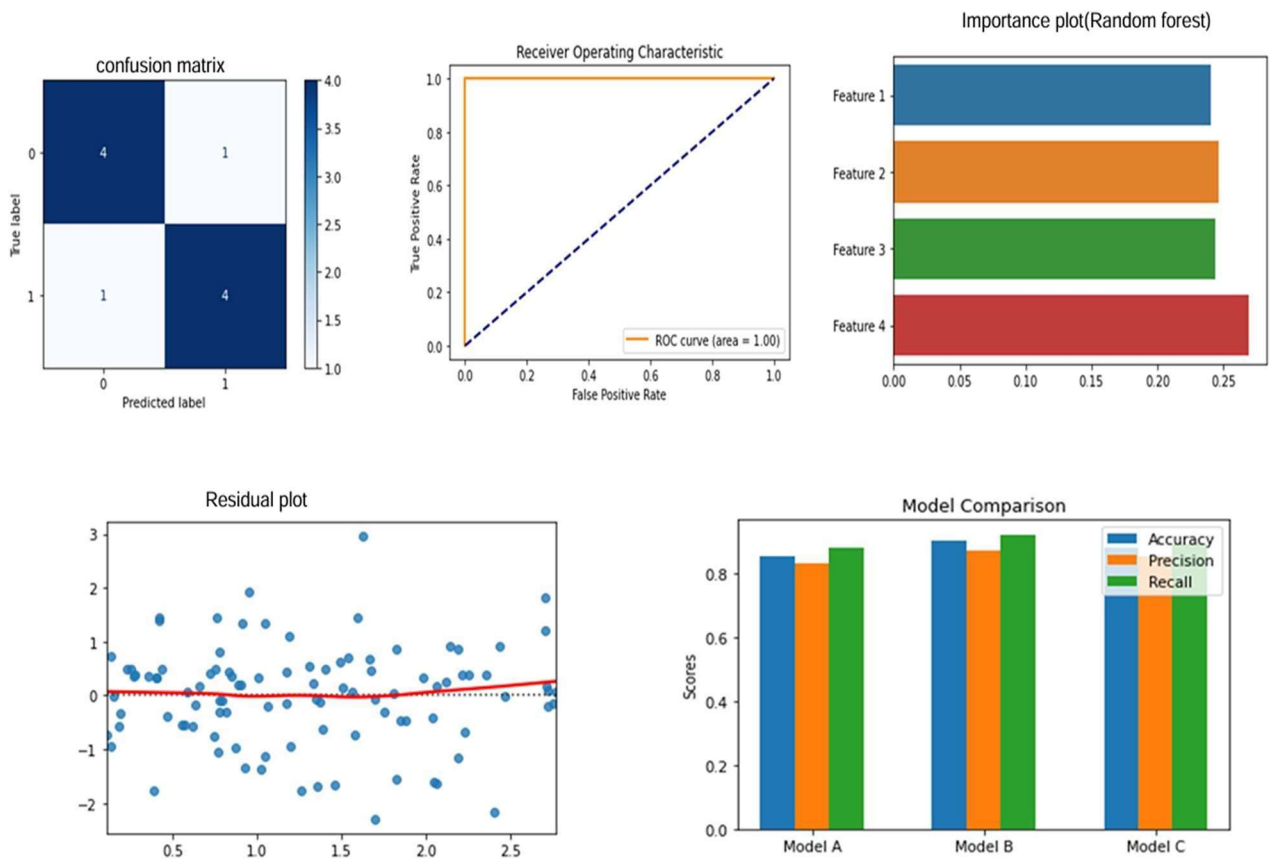
7. Feature Engineering



8. Model Building



9. Visualization of Results & Model Insights



10. Tools and Technologies Used

1. Programming Languages

- Python: Primary language for data manipulation, analysis, and modeling.
- R (optional): Utilized for advanced statistical analysis and specialized visualizations.

2. Integrated Development Environments (IDEs) / Notebooks

- Jupyter Notebook: Interactive environment for writing and executing code, ideal for data exploration and visualization.
- Google Colab: Cloud-based platform facilitating collaborative coding and access to GPUs for intensive computations.
- Visual Studio Code (VS Code): Lightweight and versatile code editor with extensive support for Python development.

3. Python Libraries

- pandas: Essential for data manipulation and analysis, offering data structures like DataFrames.
- NumPy: Provides support for large, multi-dimensional arrays and matrices, along with mathematical functions.
- matplotlib: Foundation for static, animated, and interactive visualizations in Python.
- seaborn: Built on matplotlib, it offers a higher-level interface for drawing attractive statistical graphics.

- scikit-learn: Comprehensive library for machine learning, including tools for model selection, evaluation, and preprocessing.
- XGBoost: Optimized gradient boosting library designed for performance and speed, often used in structured data competitions.
- Plotly: Enables the creation of interactive and dynamic visualizations, suitable for dashboards and web applications. [GeeksforGeeks+3Wikipedia+3LinkedIn+3Analytics VidhyaCarmatec+1Analytics Vidhya+1](#)

4. Visualization Tools

- Plotly: Facilitates interactive plotting and is compatible with web-based applications.
- Tableau: Powerful business intelligence tool for creating comprehensive dashboards and visual analytics.
- Power BI: Microsoft's analytics service providing interactive visualizations and business intelligence capabilities.