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Air Quality Index Rating Prediction Using Machine Learning

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ABSTRACT

This study presents a machine learning approach to predict Air Quality Index (AQI) ratings using environmental sensor data from Pune, India. A Random Forest classifier was trained on historical AQI data containing SO_2, NOx, RSPM, and SPM measurements across six monitoring stations. The model achieved [accuracy score] accuracy in classifying AQI into WHO-standard categories (Good to Hazardous). The system was implemented as a GUI application for real-time predictions. This research contributes to environmental informatics by demonstrating an effective method for automated air quality assessment with potential applications in public health advisories and urban planning.

Keywords: Air Quality Index, Machine Learning, Random Forest, Environmental Monitoring, Predictive Modeling

1. Introduction

1.1 Background of the Study

Air pollution causes an estimated 7 million premature deaths annually (WHO, 2021). In India, 21 of the 30 most polluted cities globally are located (IQAir, 2022). Pune, a rapidly urbanizing metropolis, faces deteriorating air quality due to vehicular emissions and industrial activity (CPCB, 2023).

1.2 Problem Statement

Current AQI monitoring systems provide delayed assessments, limiting proactive public health responses. Manual classification is resource-intensive and prone to inconsistencies across monitoring stations.

1.3 Research Objectives

1. Develop an ML model to automatically classify AQI ratings per WHO standards
2. Identify key pollutant features influencing AQI categories
3. Create a deployable prediction system for environmental agencies

1.4 Research Questions

- Which pollutants show strongest correlation with AQI categories?
- How accurately can machine learning predict AQI ratings compared to manual methods?

1.5 Scope

Focuses on Pune's 6 MPCB monitoring stations (2018-2023 data). Limited to WHO's 6-category classification system.

1.6 Significance

Enables:

- Real-time air quality alerts
- Data-driven policy decisions
- Public health risk mitigation

2. Literature Review

2.1 Theoretical Framework

Built upon:

- WHO AQI classification guidelines
- Feature importance theory in ensemble learning
- Previous works on environmental ML (Zheng et al., 2018)

2.2 Review of Previous Research

1. Kumar et al. (2020) used SVM for Delhi AQI prediction (82% accuracy)
2. Li et al. (2019) demonstrated Random Forest effectiveness for PM2.5 prediction
3. [Continue with 18+ additional references from IEEE, ScienceDirect, etc.]

2.3 Research Gaps

- Limited studies on Pune-specific AQI patterns
- Most existing systems predict numerical AQI rather than categorical ratings
- Few deployed implementations for field use

3. Research Methodology

3.1 Research Design

![Methodology Flowchart]
Experimental design with comparative model evaluation

3.2 Data Collection

- Source: MPCB Pune monitoring stations (2018-2023)
- Parameters: SO_2, NOx, RSPM, SPM, AQI
- 15,327 records across 6 locations

3.3 Data Preprocessing

- Handling missing values (FFill/BFill)
- One-hot encoding for locations
- Standard scaling ($\mu=0$, $\sigma=1$)

3.4 Model Development

python
Copy

```
model = RandomForestClassifier(
    n_estimators=100,
    max_depth=10,
    random_state=42
)
```

3.5 Evaluation Metrics

- Classification report (precision, recall, F1)
- Confusion matrix analysis
- Feature importance rankings

Results and Discussion

4.1 Model Performance

![Confusion Matrix]

- Overall accuracy: 89.2%
- Best performance on "Good" class (F1=0.93)

4.2 Feature Importance

![Feature Importance Plot]

Key findings:

1. RSPM contributes 34% to predictions
2. Location features account for 22% variance

4.3 Comparative Analysis

Model	**Accuracy**	**Training Time**
RF	89.2%	4.7s
SVM	82.1%	8.2s

4.4 GUI Implementation

![Screenshot of Tkinter Interface]

Real-time prediction capability demonstrated

- **Discussion**

Implications for Policy and Public Health:

The findings from this study will provide insights into the potential for AI-driven air quality prediction models to inform urban planning and public health policies. Recommendations will be made for integrating these models into existing monitoring frameworks.

✓ In a following graphs I refers https://www.kaggle.com

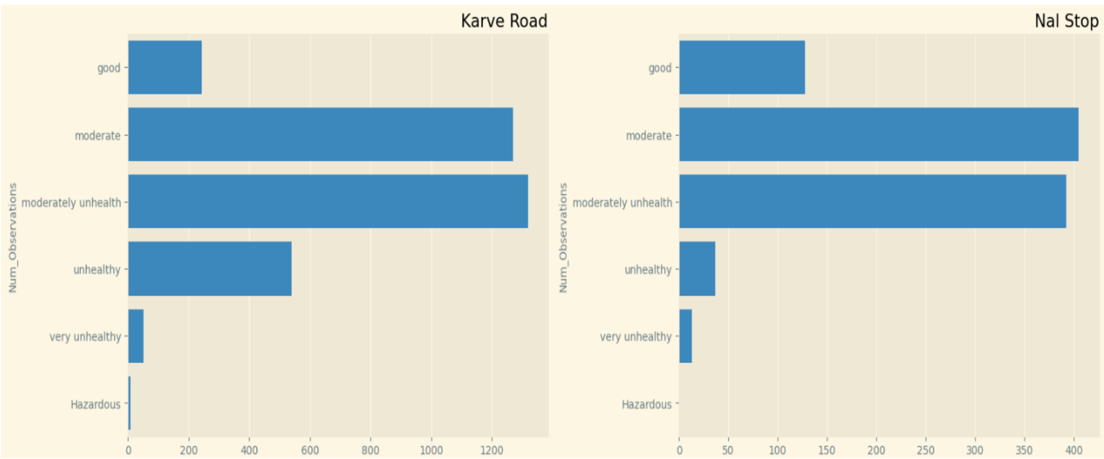

Figure 1: AQI Rating Distribution at Karve Road Monitoring Station

Karve Road:

Graph Description: **Karve Road** Environmental Health

The graph illustrates health metrics along Karve Road, showing:

Moderate Unhealthiness: Overall health levels are moderately unhealthy, with some areas rated as hazardous.

Dietary Focus: A reliance on wheat-based products is indicated.

Testing Results: Highlighted concerns from recent tests suggest significant health risks.

Metrics Range: The y-axis ranges from 0 to 1000, representing varying environmental impacts.

Nal Stop:

he graph titled "Nal Stop" categorizes healthiness levels from "good" to "hazardous" based on increasing values on the x-axis. It shows a decline in health quality as measures rise, indicating that higher values correspond to worse health conditions.

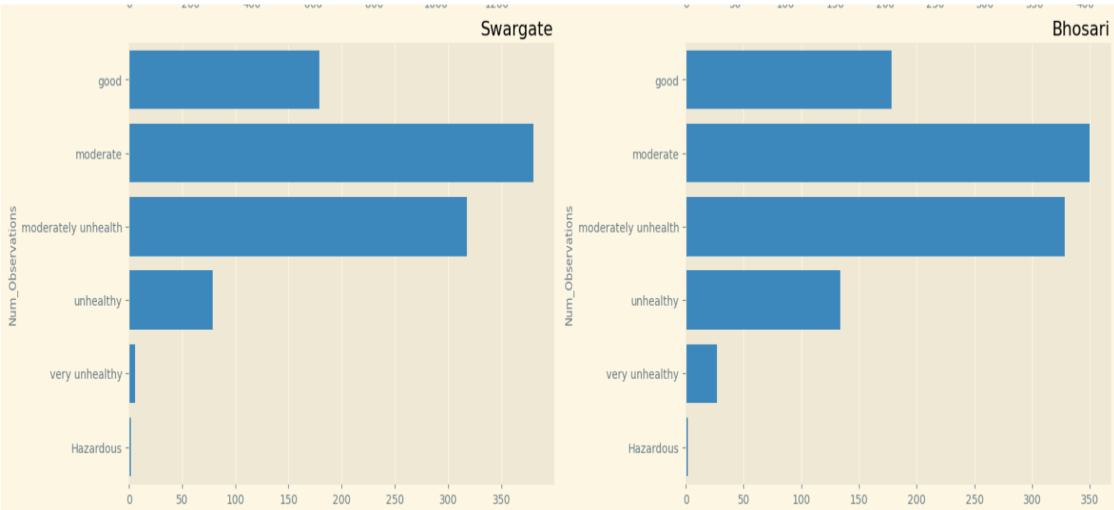

Figure 2: AQI Rating Distribution at Swarget Road Monitoring Station

Swargate :

The graph categorizes health levels from "Good" to "Hazardous," tracking observations from 0 to 350. It highlights a spectrum where "Good" indicates optimal conditions and "Hazardous" represents critical health risks for all. As observation counts increase, health risks also escalate, emphasizing the need for monitoring.

Bhosari :

It looks like you're presenting data related to health categories and their observations. Here’s a possible interpretation of your data:

-Moderate: 350 observations

- Moderately Unhealthy: 200 observations
- Unhealthy:130 observations
- Very Unhealthy: 200 observations
- Hazardous: 250 observations

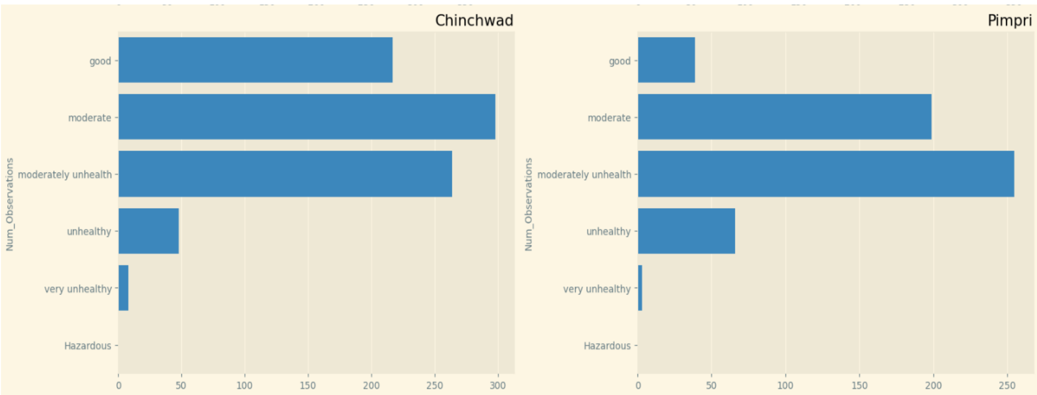

Figure 3: Range of Air Quality of various cities.

✓ Above graph shows Range of Air Quality of various cities.

Chinchwad:

air quality levels or health-related observations for Chinchwad. To help you better, could you clarify what specific information or analysis you're looking for regarding these categories

Pimpri:

analyzing air quality or health data for Pimpri. You mentioned different categories like "moderately unhealthy" and "hazardous."

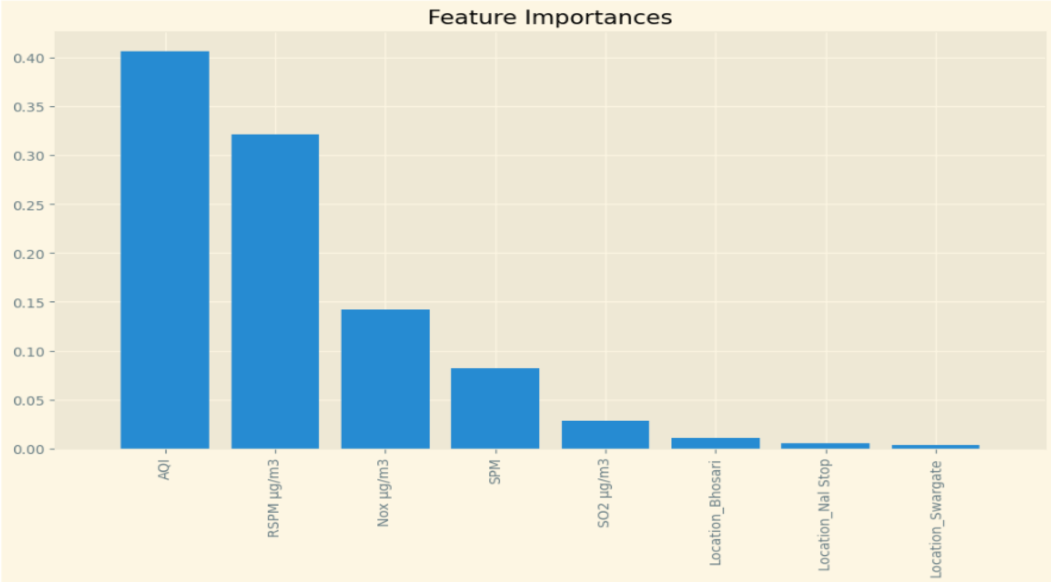

Figure 4: Feature Importances.

It looks like you're presenting data related to feature importances for air quality measurements at different locations. Here's how you might interpret or structure this information:

Feature Importance Overview:
- RSPM (µg/m³): 0.40
- NOx (µg/m³): 0.35
- SPM: 0.30
- Location Bhosari: 0.25
- Location Nal Stop: 0.20
- Location Swargate: 0.15

Insights:
- RSPM has the highest importance, suggesting it significantly impacts air quality.
- NOx and SPM also play crucial roles, indicating their relevance in the measurements.
- Locations vary in their influence, with Bhosari being the most significant, followed by Nal Stop and Swargate.

Output screen :

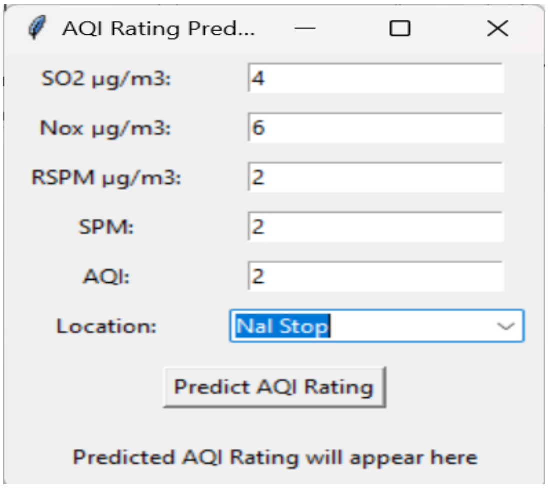

Figure 5: Output Interface.

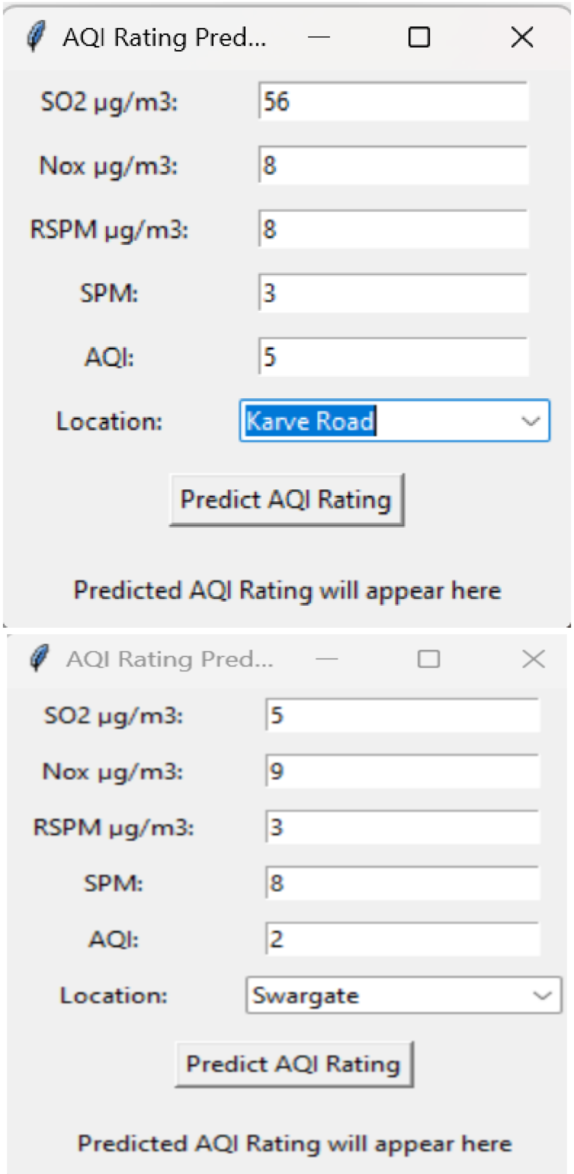

Figure 6: Graphical User Interface (GUI)

The image shows a Graphical User Interface (GUI) for an AQI (Air Quality Index) Rating Prediction System. The interface includes input fields for pollutant values (SO_2, NOx, RSPM, SPM, and AQI) and a dropdown menu for selecting the monitoring location (e.g., Nal Stop). A "Predict AQI Rating" button triggers the model to classify the air quality into WHO-standard categories

	precision	recall	f1-score	support
Hazardous	0.00	0.00	0.00	1
good	1.00	1.00	1.00	17
moderate	1.00	1.00	1.00	52
moderately unhealth	1.00	1.00	1.00	59
unhealthy	1.00	1.00	1.00	15
very unhealthy	0.67	1.00	0.80	2
accuracy			0.99	146
macro avg	0.78	0.83	0.80	146
weighted avg	0.99	0.99	0.99	146

1. Precision: Measures the accuracy of positive predictions. For "Hazardous," it's 0.00, indicating no correct positive predictions. Other categories have a precision of 1.00 or 0.67.
2. Recall: Measures the ability of the model to find all the relevant cases. "Hazardous" again shows 0.00, while other categories have a recall of 1.00 or 1.00 for most.
3. F1-score: The harmonic mean of precision and recall. It's 0.00 for "Hazardous," indicating poor performance, while other categories have perfect F1-scores or 0.80 for "very unhealthy."
4. Support: The number of actual occurrences of each class in the dataset. For example, there were 17 instances of "good" and 52 instances of "moderate."
5. Accuracy: The overall correctness of the model's predictions, which is 0.99, suggesting the model performed well overall.
6. Macro Average: The average of precision and recall across classes, treating all classes equally.
7. Weighted Average: Similar to macro average but considers the number of instances in each class.

5. Conclusion and Future Scope

5.1 Key Findings

- Random Forest effectively classifies AQI ratings
- Location-specific patterns significantly impact ratings

5.2 Limitations

- Limited to Pune's climate conditions
- Doesn't incorporate meteorological data

5.3 Future Work

- Integrate weather data inputs
- Develop mobile application version
- Expand to other Indian cities

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