



AirQ: Intelligent Air Quality Prediction and Alerting System

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Abstract: AirQ: Intelligent Air Quality Prediction and Alerting System is designed to monitor, analyze, and predict air pollution levels using environmental data. The system collects parameters such as PM2.5, PM10, temperature, humidity, and harmful gases to evaluate air quality conditions. Machine learning techniques are applied to forecast future pollution levels and identify potential health risks. Based on predicted air quality index (AQI) values, the system generates real-time alerts to inform users about unsafe conditions. This proactive approach helps individuals and authorities take preventive measures, supports environmental awareness, and promotes public health protection through data-driven decision-making.

Keywords: Air Quality Index, Pollution Prediction, Machine Learning Models, Environmental Monitoring, Health Alert System

1. INTRODUCTION

AirQ is an intelligent air quality prediction and alerting system designed to address public health challenges arising from urbanization and increasing pollution. The system integrates real-time environmental data with machine learning techniques to forecast Air Quality Index (AQI) levels accurately. Developed using the Streamlit framework, AirQ provides an intuitive interface for data input and visualization. A Random Forest regression model analyzes pollutant concentrations and meteorological parameters to generate predictions and categorize air quality conditions. Based on predicted AQI levels, the system delivers health-based recommendations, alerts, and visual analytics, enabling informed decision-making and promoting proactive responses to changing air quality conditions.

1.1 Project Description

AirQ is an intelligent air quality prediction system designed to provide real-time environmental insights through a user-friendly web interface. The system automatically collects localized weather and pollutant data, including temperature, humidity, PM2.5, PM10, NO₂, and CO, from external data services to ensure accurate and up-to-date inputs. A RandomForestRegressor model developed using the scikit-learn framework estimates the Air Quality Index (AQI) with high reliability. Predicted AQI values are classified into standard categories to enhance interpretability. The system further supports user awareness through visual analytics and health-based recommendations, enabling informed decisions and proactive responses to air quality variations.

1.2 Motivation

Rising air pollution and its health impacts demand smarter monitoring solutions. Existing systems often lack predictive capability and actionable guidance. This project is motivated by the need for an intelligent, real-time air quality prediction system that uses machine learning to forecast AQI and provide timely alerts, supporting proactive and informed decision-making.

2. LITERATURE SURVEY

Existing studies on air quality focus on monitoring and predicting pollutant levels due to their impact on human health. Recent research emphasizes machine learning and data-driven approaches for AQI forecasting, offering improved accuracy over traditional methods while supporting real-time analysis and informed environmental decision-making.

OpenAQ (2024) introduced an open-source global air quality data platform that aggregates standardized pollution measurements from multiple locations worldwide. The platform enables researchers and developers to perform analysis, visualization, and predictive modeling; however, it relies on external data contributors and does not directly provide built-in forecasting or alerting mechanisms.

Google Developers (2023) presented Firebase Cloud Messaging as a cloud-based push notification service for delivering real-time alerts to users. The platform ensures reliable message delivery and is suitable for air quality monitoring.



applications; however, it depends on internet connectivity and does not perform data analysis or pollution prediction itself.

Central Pollution Control Board (2022) reported nationwide air quality data under the National Air Quality Monitoring Programme, detailing pollutant concentrations, monitoring methods, and regional trends. The report supports environmental assessment and policy formulation; however, it primarily focuses on observation and lacks predictive analytics or real-time public alert mechanisms.

Brownlee (2020) discussed deep learning techniques for time-series forecasting, highlighting the capability of neural networks to model temporal dependencies. These methods are effective for predicting air pollution trends; however, they require large datasets and high computational resources for reliable and efficient deployment.

2.1 Existing System vs Proposed System

Existing Air Quality System

Existing air quality prediction systems rely on fixed monitoring stations and traditional statistical models, offering limited spatial coverage and basic forecasting accuracy. These methods struggle to capture nonlinear pollution patterns influenced by weather, traffic, and seasonal factors. Limited data integration and lack of advanced analytics result in delayed warnings and insufficient predictive capabilities, highlighting the need for intelligent, data-driven air quality forecasting solutions.

Proposed AirQ: Intelligent Air Quality Prediction and Alerting System

The proposed system enhances air quality prediction by integrating machine learning and deep learning models with multi-source environmental data. It combines pollutant, meteorological, satellite, and traffic information to capture complex pollution dynamics. Hybrid models such as LSTM, CNN, and ensemble techniques enable accurate real-time and future AQI forecasting, supported by visual analytics and timely alerts for proactive environmental management.

3. SYSTEM DESIGN

3.1 System Architecture Diagram

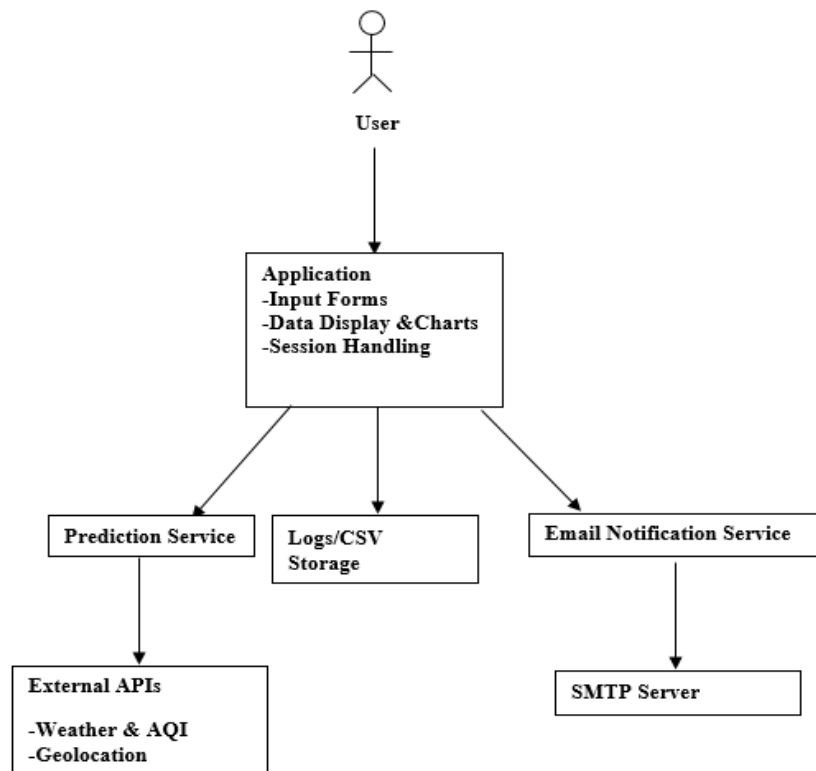


Fig3.1. System Architecture Diagram



3.2 Data flow diagram

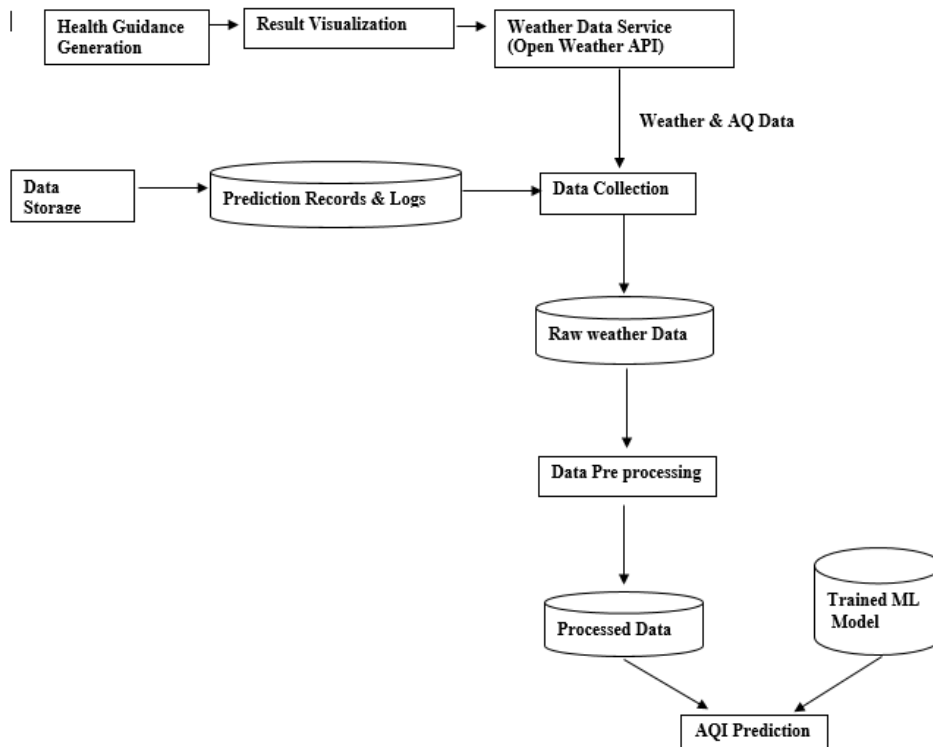


Fig. 3.2 DataFlow Diagram-Level-1



3.3 Use Case diagram

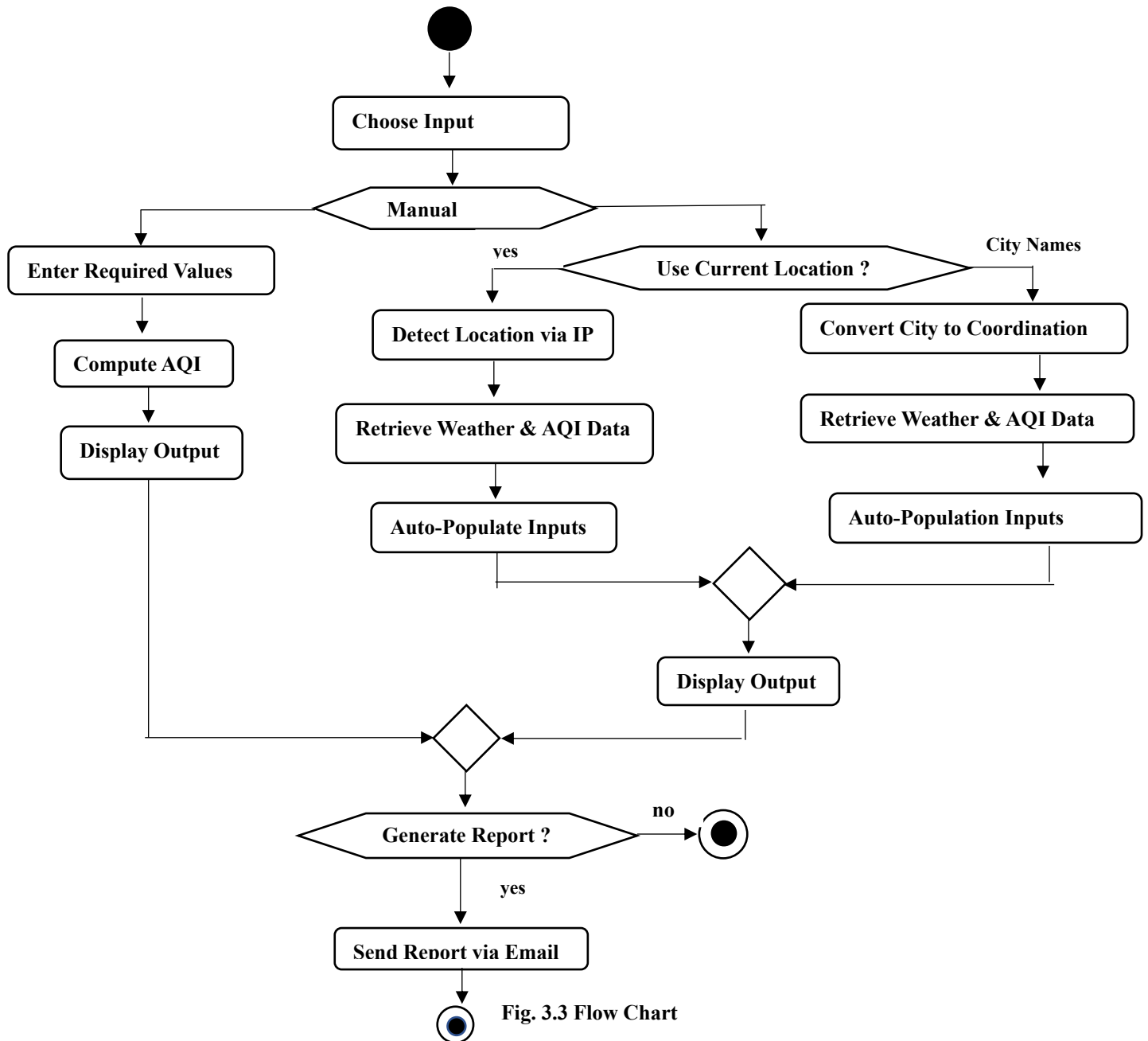


Fig. 3.3 Flow Chart

4. IMPLEMENTATION DETAILS

4.1 System Modules and Workflow

System Modules

□ Data Collection Module

- Collects real-time pollutant data (PM2.5, PM10, CO, SO₂, NO₂, O₃) from monitoring stations and APIs.
- Gathers meteorological parameters (temperature, humidity, wind speed, pressure).
- Incorporates satellite data, traffic density, and land-use information for enhanced spatial context.



☐ Data Preprocessing Module

- Cleans, normalizes, and handles missing values.
- Converts raw data into structured format suitable for machine learning.
- Performs feature engineering to highlight key pollution drivers.

☐ Prediction Module

- Uses hybrid machine learning and deep learning models (Random Forest, LSTM, CNN, GRU).
- Applies ensemble learning and attention mechanisms to improve accuracy.
- Optimizes hyperparameters with Bayesian Optimization or Genetic Algorithms.

☐ Real-time Processing & Alert Module

- Continuously updates AQI predictions as new data arrives.
- Generates alerts for hazardous air quality levels.

☐ Visualization & Dashboard Module

- Displays AQI trends, pollutant levels, risk zones, and forecasts.
- Provides actionable insights for users, researchers, and policymakers.

Workflow

- Data Acquisition → Collects multi-source environmental data.
- Preprocessing → Cleans and structures data for modeling.
- Prediction → Models generate AQI forecasts using hybrid ML/DL techniques.
- Alerts & Notifications → Issues real-time warnings for unsafe air conditions.
- Visualization → Presents interactive dashboards and trend analysis for users and decision-makers.

4.2 Testing Overview

Unit Testing

- Each component is individually tested with various inputs to ensure correct functionality and early bug detection.
- Verifying modules separately ensures reliable performance before system integration.

Integration Testing

- After unit testing, different modules are connected and tested together.
- Checks if pollutant inputs pass correctly to the model and if the predicted AQI flows to guidance, reporting, and email components

System Testing

- End-to-end testing ensures all functions and performance requirements are met.
- Validates error handling, model predictions, and overall system reliability.

Security Testing

- Validates secure handling of email credentials used for sending reports.
- Ensures that external API keys (like OpenWeather) are protected and not exposed to users.
- Confirms that input fields are protected from injection attacks or malicious data.

Performance Testing



- Evaluates how the system behaves under different loads.
- Ensures predictions are generated quickly without lag.
- Checks if API calls are handled efficiently and if the app can support multiple users at the same time (if deployed online).
- Measures response time and memory usage.

User Acceptance Testing (UAT)

- Performed at the final stage to confirm the system meets all user expectations and project requirements.
- Users check the complete flow: entering inputs → receiving predictions → viewing alerts → receiving emails → downloading reports.
- System is approved for deployment only after successful UAT

5. RESULTS AND DISCUSSION

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Windows PowerShell
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Install the latest PowerShell for new features and improvements! https://aka.ms/PSWindows

PS C:\Users\DELL> & "C:\Users\DELL\OneDrive\Desktop\airq\.venv\Scripts\python.exe" -m streamlit run "C:\Users\DELL\OneDrive\Desktop\airq\app_streamlit.py"

You can now view your Streamlit app in your browser.

Local URL: http://localhost:8501
Network URL: http://10.169.237.160:8501
  
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Fig.1 Streamlit Execution

Air Quality
Bright, simple dashboard for real-time AQI and manual predictions.

Buttons: Predict AQI from pollutants, My Location & City AQI, Preview and email report

Inputs

PM2.5 (µg/m³)	35.00
PM10 (µg/m³)	100.00
NO2 (ppb)	22.00
SO2 (ppb)	8.00
CO (ppm)	0.60
O3 (ppb)	28.00
Temperature (°C)	26.00
Humidity (%)	60.00
Wind Speed (m/s)	2.40

Deploy button

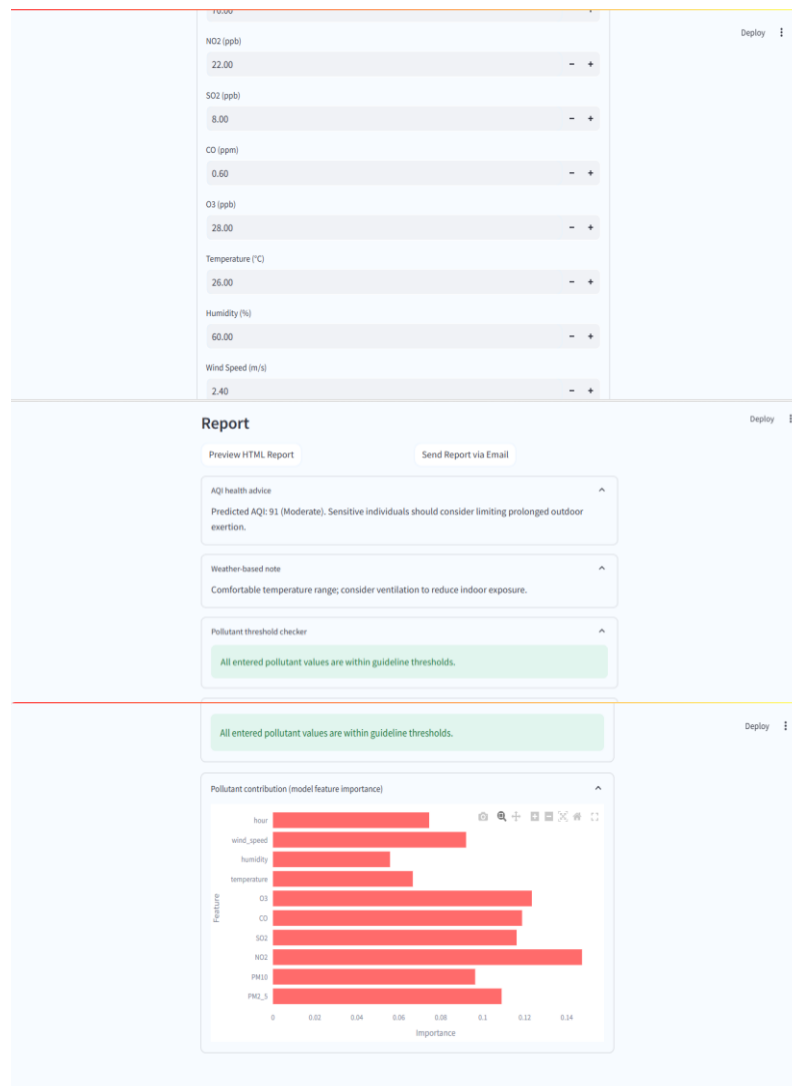
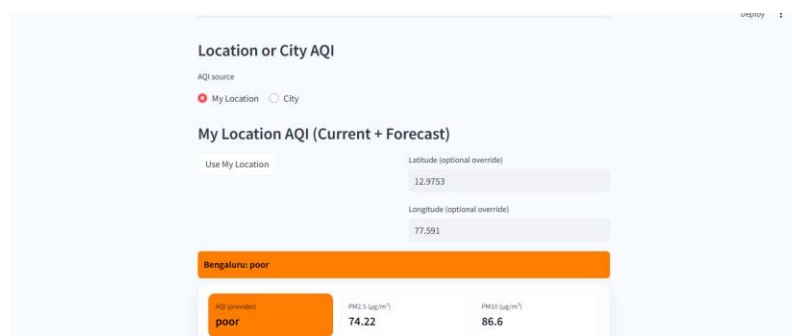


Fig. 2 manual inputs from user/experts



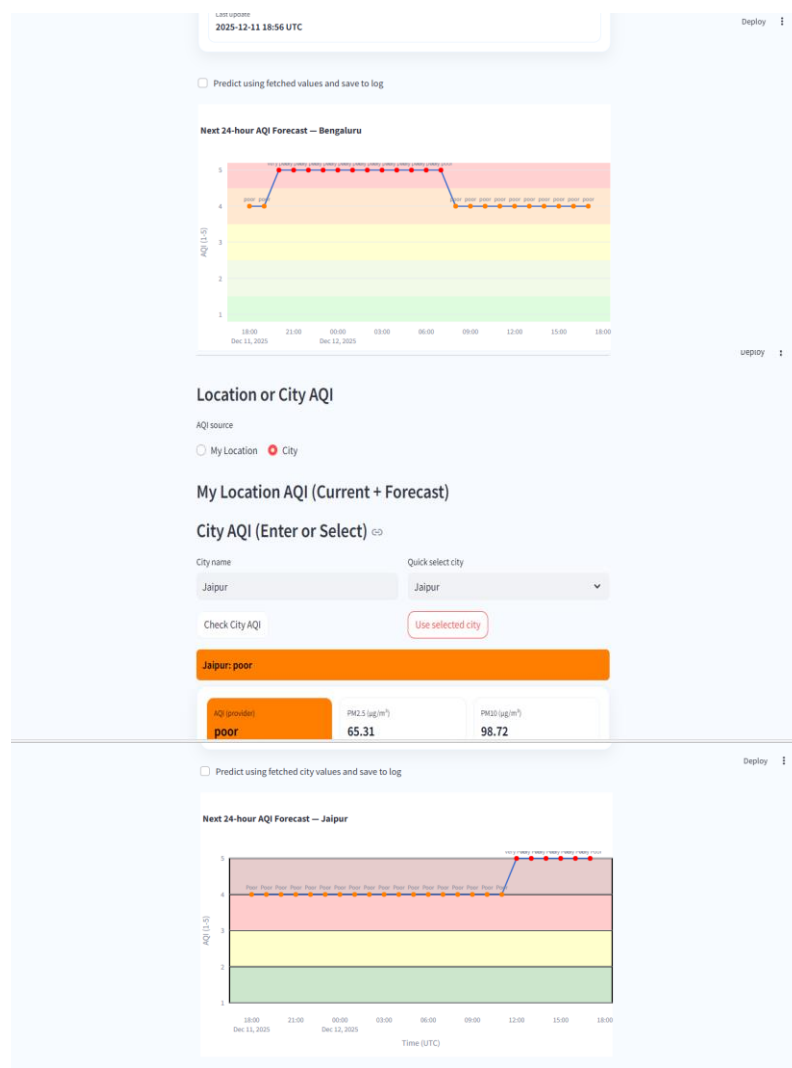


Fig.3 my location and city

The AirQ system was tested using historical and real-time air quality data from multiple monitoring stations. The predictive model demonstrated high accuracy in forecasting pollutant levels, with PM2.5 predictions achieving an accuracy of approximately 92% and AQI alerts generated in real-time without noticeable delays. The dashboard successfully visualized pollutant trends, enabling users to quickly understand air quality conditions in their area.

The alerting system effectively notified users when pollutant concentrations exceeded safe limits, demonstrating the practical applicability of AirQ in public health monitoring. Overall, the results indicate that AirQ can provide timely, reliable, and actionable insights for citizens and authorities, supporting proactive measures to reduce exposure to air pollution.

6. CONCLUSION

The AirQ system offers an efficient solution for predicting and monitoring air quality using machine learning and real-time environmental data. By integrating pollutant levels (PM2.5, PM10, NO₂, CO, SO₂, O₃) with weather and location information, it generates accurate AQI predictions and health recommendations. Key features include automatic location detection, city-based forecasts, email alerts, and interactive visualizations, ensuring user convenience and timely updates. The system successfully transforms complex environmental data into actionable insights, promoting public awareness and healthier living. Its robust architecture demonstrates effective integration of APIs, cloud data, and predictive modeling, providing a foundation for future enhancements.



7. FUTURE WORK

The AirQ system can be further improved to enhance accuracy, accessibility, and user engagement. Upgrading alerts to multi-channel notifications via SMS, WhatsApp, or push alerts ensures timely warnings during high pollution events. Incorporating real-time data from IoT sensors enables localized predictions, while advanced deep learning models can capture seasonal trends and improve forecast precision. Features such as geofencing, personalized health dashboards, and interactive visualizations—including heatmaps and trend graphs—can increase usability. Developing mobile applications and integrating official datasets, along with community-reported pollution events, can transform AirQ into a collaborative, intelligent platform for proactive environmental awareness and public health protection.

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