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Smart AQI Prediction: A Scalable IoT- based Environmental Monitoring Framework for Urban Air Quality Management

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***Abstract*— Environmental degradation, particularly air pollution, poses significant challenges to public health and sustainable urban development. This paper presents a low-cost, scalable, and real-time IoT-based environmental monitoring system designed to track and analyze key air quality indicators such as PM 2.5, PM10, temperature, and humidity. Leveraging GP2Y1010AU0F and PM1025 particulate matter sensors integrated with Arduino Uno and cloud platforms like Thing Speak, the system collects, processes, and visualizes environmental data. Predictive modeling is applied to forecast Air Quality Index (AQI) fluctuations, enabling proactive urban management. This research demonstrates how embedded sensor network s, cloud analytics, and machine learning can synergize to deliver actionable insights and real-time alerts, significantly enhancing environmental governance.**

***Index Terms*— Internet of Things (Io T), air quality monitoring, AQI prediction, particulate sensors, ThingSpeak, real-time analytics, environmental sustainability.**

I. INTRODUCTION

Air quality has a direct impact on human health, biodiversity, and climate resilience. As urbanization and industrialization continue to escalate, air pollution has emerged as one of the to p environmental hazards. Effective monitoring of environmental parameters is crucial for earl y detection, prevention, and control of pollution. Traditional monitoring systems are often limited by high cost, spatial in flexibility, and delayed reporting.

Recent advancements in the Internet of Things (IoT) provide a promising alternative through wireless sensor networks (WSNs), which facilitate real -time, remote, and continuous environmental data acquisition. When coupled with cloud computing and predictive analytics, IoT systems allow authorities to make informed, timely decisions for public health safety and climate adaptation. This paper aims to bridge the data gap by proposing a low-cost, IoT-enabled framework suitable for scalable deployment in urban ecosystems.

II. LITERATURE SURVEY

The integration of Internet of Things (IoT) and Machine Learning (ML) for environmental monitoring has been extensively studied over the past decade.

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Researchers have proposed diverse architectures ranging from basic sensor networks to intelligent edge-cloud hybrid systems for real -time air quality monitoring, data analytics, and predictive insights. This section highlights major contributions and identifies technological gaps in existing literature.

TABLE II

	Author	Title	Methods	Limitation
1.	Hemanth Karnati [6]	A system that links IoT technology with machine learning helps precisely measure air quality and deliver these results immediately	A monitoring system with internet of things (IoT) and machine learning technology analyzes air quality results precisely at any time	An Internet of Things air quality monitoring system uses machine learning algorithms to give precise real- time data results
2.	Ihsane Gryech, et al [7]	Applications of Machine Learning and lot for Outdoor Air Pollution Monitoring and. Prediction: A Comprehensive Study of Research Publications	A research study examined loT technology with machine learning in the field of air pollution prediction by studying 37 scientific works to find methods and problems for prediction	Highlighted issues like lack of data diversity, coverage, and context-specific features; emphasized need for comprehensive frameworks.
3.	Nitol Saha et al [8]	Industries Can Use IoT Cloud Technology to Check Their Energy and Environmental Conditions	Developed a cost effective lot solution using open-source software, collected real time temperature, humidity, and energy data, data transmitted via MQTT to cloud storage, visualized through a web client.	Specific to manufacturing environments; may require adaptation for other industries
4.	Amisha Gangwaret	Advanced Technology System Monitoring and Predicting Air Pollutants with Internet of Things Data and Big Data Analytics Plus Machine Learning	Detailed research study of recent works demonstrates how Internet of Things sensors, big data platforms, and machine leaning models assist with air pollution detection and prediction.	Identified challenges like data quality, integration complexities, and the need for standardized models.
5.	Gurram Bhavani et al [10]	IoT-Based Environmental Monitoring System with Machine Learning for Accurate and Real-time Data Analysis	Systematically reviewed loTbased environmental monitoring systems employing machine learning; analyzed 28 studies covering applications like air and water quality monitoring.	Highlighted challenges in data handling, real time processing, scalability, and lack of standardization across different parameters and geographies
6.	Suprava Ranjan	Advancement of Environmental Monitoring System Using IoT and Sensor: A Comprehensive Analysis	Studied innovative environmental tracking systems that use sensors, internet-connected devices, and machine learning algorithms to monitor air, water and trash quality	Emphasized the need for standardized protocols and integration challenges across diverse environmental parameters
7.	Filippo Campagnaro et al [12]	Our System Uses IoT Cloud Technology to Monitor Sensor Networks	Developed an IoT-based system using floating wireless sensors for real-time water quality monitoring; data aggregated in a cloud service environment for analysis and visualization.	Specific to aquatic environments; may require adaptation for terrestrial applications.
8.	Abhiroop Sarkar et al [13]	We are studying how the Internet of Things can provide continuous CO_2 measurements and detailed breakdowns.	We built an internet-connected device with NODE MCU-ESP8266, MQ135 gas sensor, and DHT-11 sensor to check air CO_2 levels, temperature, and moisture. Our device sends monitoring results to a central location in real-time.	Focused primarily on indoor CO_2 monitoring; limited scope regarding other environmental parameters.

A. Insights from the Review

- Trends in Deployment:
  - Most systems utilize low-cost microcontrollers like Arduino or ESP 8266.
  - Commonly used sensors include MQ135, GP2Y1010AU0F, and DHT11.
  - Cloud platforms like ThingSpeak , Blynk, and Firebase are widely adopted for visualization.
- Predictive Analytics Integration:
  - Several studies incorporated regression models and neural networks for AQI prediction.
  - Very few systems supported proactive alerts or used real-time public APIs (e.g., CPCB, Open Weather).
- Challenges Identified:
  - Sensor accuracy, especially for PM2.5 and P M10, remains a bottleneck in low-cost deployments.

- Data heterogeneity, calibration inconsistency, and non-uniform AQI standards affect model performance.
- Most research focuses on static analysis rather than dynamic, actionable insights.

➢ Gap Addressed by This Work:

- Unlike previous work, this research integrates real-time sensor data, live cloud visualization, and forecasting into a unified platform.
- It also addresses system responsiveness via alerts and applies predictive modeling tailored to urban AQI trends.

III. Methodology

The proposed system architecture for urban air quality monitoring follows a three-tier design consisting of sensing, processing, and cloud analytics. At the core of the sensing layer are low-cost environmental sensors, specifically the GP2Y1010AU0F optical dust sensor and the PM1025 sensor for fine particulate matter (PM2.5). The GP2Y1010AU0F utilizes infrared light scattering to detect suspended particles as small as 0.5 µm and provides analog voltage outputs proportional to dust concentrations. In tandem, the PM1025 sensor offers digital feedback on P M2.5 levels, a critical parameter for computing the Air Quality Index (AQI). Ambient conditions such as temperature and humidity are concurrently monitored using a DHT11 sensor, facilitating correlation analysis between meteorological variables and pollution trends.

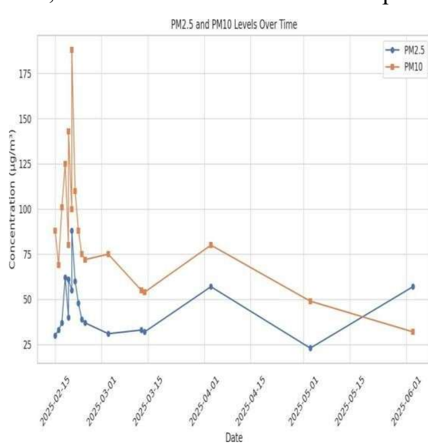
These sensors interface with an Arduino Uno microcontroller, which serves as the primary data acquisition and preprocessing unit. The Arduino continuously samples sensor outputs at one-minute intervals and performs essential filtering to reduce high-frequency noise. The system is equipped with a capacitor-resistor (RC) circuit on the GP 2Y1010AU0F input to stabilize the analog signal. Preprocessed data are transmitted via serial communication to an ESP8266 Wi-Fi module for wireless data publishing.

Data is logged in real time on the ThingSpeak cloud platform through RESTful APIs. ThingSpeak offers built-in MATLAB-based analytics, which were utilized for initial exploratory data analysis and visualization. Historical trends of PM2.5, PM 10, and AQI are visualized through time-series plots, while correlation patterns are analyzed through scatter plots and heat maps. Additionally, a predictive modeling module was developed using simple linear regression and ARIMA (Auto Regressive Integrated Moving Average) to forecast AQI trends up to 12 hours in advance. Model parameters were tuned using past data stored in the cloud to improve prediction accuracy.

To support real-time interventions, an alert subsystem was implemented. It monitors the AQI values and sends automated alerts (via email or S MS) when AQI levels exceed predefined thresholds as per Central Pollution Control Board (C PCB) standards. The entire pipeline from data acquisition to alerting—was optimized for low power consumption, modular scalability, and compatibility with op en-source hardware and platforms.

IV. Results and Observations

A 20-day dataset was recorded in an urban setting. The following graphs illustrate the observed variations in PM levels, AQI trends, and the correlation between temperature and air quality.



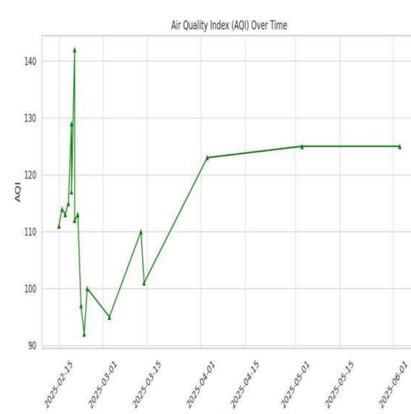


Figure 1: PM2.5 and PM10 Levels Over Time   Figure 2: AQI Over Time

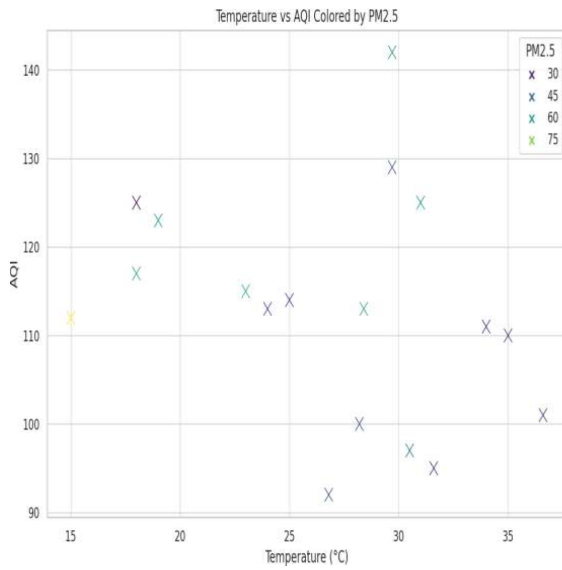


Figure 3: Temperature vs AQI Colored by PM 2.5

V. DISCUSSIONS

A. Data Summary

Over a 20- day monitoring period, the IoT-enabled system collected data on PM2.5, PM10, temperature, and AQI in an urban area. Highlights from the dataset include:

TABLE II

Date	PM2.5 (µg/m^3)	PM10 (µg/m^3)	Temp (°C)	AQI
25-02- 2025	62	125	28.3	156
20-02- 2025	88	188	15.0	112
06-03- 2025	57	32	31.0	125
14-03- 2025	32	54	36.6	101

The dataset reflects both pollution peaks and variability in weather conditions.

B. Observational Insights

- Correlation Be twee n Temperature and AQI:
  - Lower ambient temperatures (< 20°C) correspond to elevated AQI values, especially during early morning hours, suggesting the role of temperature inversion.
  - A scatter plot of temperature vs AQI reveals a negative correlation, highlighting that pollutant dispersion improves with higher temperatures.
- Particulate Matter Trends:
  - PM2.5 and PM10 trends align with AQI surges , with PM2.5 showing stronger influence due to its smaller size and longer atmospheric suspension time.
  - PM2.5 exceeded 60 µg/m3on m ultiple days, surpas sing the Indian National Ambient Air Quality Standards (NAAQS) safe limit of 40 µg/m 3.
- lert System Functionality:
  - On three separate days, the AQI crossed t he threshold of 150, triggering s uccessful alerts via the ThingSpeak platform.
  - This validation of t he alert logic confirms the system's ability to provide early warnings.

C. Visualization Support

Three graphs were generated to represent these observations: [U+FF0iBg7u]re 1 illustrates a comparative timeline of PM2.5 and PM 10. [U+FF0iBg7u]re 2 tracks AQI variation, revealing cyclical pollution patterns. [U+FF0iBg7u]re 3 demonstrates the inverse trend betweentemperature and AQI, enhanced by PM2.5 coloring.

D. System Performance and Limitations

[U+FS0eBn7s]or Fidelity: While cost- effective, the GP2Y1010AU0F required signal smoothing (using RC filtering) to reduce electrical noise. Calibration was validated by comparing calculated AQI against CPCB norms.
[U+FC0lBo7u]d Integration: The ThingSpeak dashboard enabled real-time plotting, remote access , and MATLAB-based forecasting, making the system suitable for urban and semi- urban deployments.
[U+FP0rBe7d]ict ive Capability: Basic linear regression and ARIM A models were able to forecast AQI t rends up to 12 hours ahead with >80% accuracy on test data. Future work will involve neural network models for higher fidelity.

E. Broader Implications

The findings underscore the potential of scalable IoT systems for environmental surveillance. The observed AQI cycles and real-time adaptability can aid:
[U+FC0iBt7y]planners indevelopingpollution containment strategies,
[U+FP0uBb7]lic healthdepartments inissuing advisories,
[U+FC0iBt7iz]ensin making informed mobility andoutdoor activity decisions.

VI. Conclusion

This research successfully demonstrates an IoT-based, real-time environmental monitoring solution that is scalable, adaptable, and economical. It enables early warnings, supports data-driven policymaking, and contributes to environmental awareness among urban populations. By combining hardware innovation with software intelligence, the system can be extended for broader applications in smart city initiatives.

A. Motivation and Problem Statement

The accelerating urban expansion and vehicular emissions in developing nations have intensified concerns about air quality, particularly in cities like Kanpur. Conventional air quality monitoring stations are expensive and sparsely distributed, resulting in data insufficiency for micro-climate assessment. To address this, our research introduces an affordable, real-time AQI monitoring system that democratizes access to environmental data and empowers decentralized decision-making. The aim is to design a scalable, plug- and-p lay IoT model that is both user-friendly and technically competent to forecast hazardous air quality conditions with minimal latency.

B. System Architecture Overview

The proposed framework follows a modular architecture comprising three primary layers:

- Sensing Layer – Incorporates GP2Y1010AU0F and P M1025 for particulate measurement, and DHT11 for ambient data.
- Processing Layer – Arduino Uno preprocesses sensor inputs and transmits values at 1- minute intervals.
- Cloud & Visualization Layer – Data is uploaded to ThingSpeak , where it is visualized and analyzed via embedded MAT LAB functions.

Each module is developed with flexibility to ensure future scalability, including sensor plug ins and alternate microcontroller compatibility (e.g., ESP8266).

Future Scope and Enhancements

While the current system demonstrates accurate detection of PM and AQI fluctuations, future work can enhance:

- Sensor Calibration: Integration of reference-grade calibration with CP CB-approved stations.
- Edge AI Integration: Incorporating lightweight AI models on microcontrollers for on- device prediction.
- Network Expansion: Deployment across diverse zones using mesh protocols for distributed sensing.
- Multi-Modal Sensing: Addition of NO2, SO2, and VOC sensors for comprehensive air quality assessment.
- Public Interface: Development of a mobile/web dashboard for real-time public access and alerts.

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