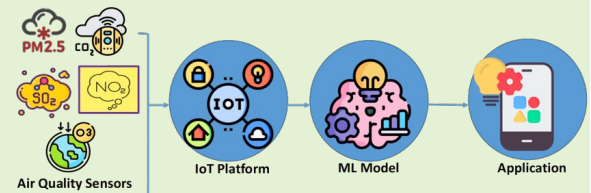


AI-IoT Driven Real-Time Air Pollution Monitoring and Mapping for Sustainable Urban Planning

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Abstract—Air pollution poses a critical threat to public health, environmental quality, and urban sustainability, driven by rapid urbanization, industrial activity, vehicular emissions, and inefficient waste management. Tackling this challenge demands robust monitoring, predictive modeling, pollution mapping, and effective management strategies. This study presents an AI-IoT Driven Real-Time Air Pollution Monitoring and Mapping System for sustainable urban planning, integrating IoT technology and machine learning for real-time monitoring of key air quality parameters, including PM_{2.5}, CO, NO₂, SO₂, O₃, and compute the Air Quality Index (AQI), a standardized scale ranging from Good (0–50) to Hazardous (301–500). We evaluate multiple machine learning algorithms, namely Random Forest, XGBoost, CatBoost, Gradient Boosting, and SVM, alongside a proposed stacked ensemble model, to support air pollution monitoring, predict pollution trends, identify high-risk areas, and generate actionable mitigation insights. The stacked ensemble achieves the highest performance with 98.73% ($\pm 0.21\%$) cross-validation accuracy. The system further delivers real-time alerts to residents and authorities, enabling avoidance of polluted zones and timely interventions. In addition, adaptive route optimization and IoT-enabled waste monitoring ensure timely waste collection, reducing emissions from unmanaged waste and supporting urban planning. Together, these capabilities form an integrated, data-driven framework for improving urban air quality and enabling evidence-based smart city planning.

Index Terms—Air quality index (AQI), IoT, air pollution monitoring, smart city, machine learning, ensemble model, pollution mapping, real-time environmental monitoring, sustainable urban planning.



I. INTRODUCTION

URBAN air pollution is a pressing global issue, impacting public health, environmental quality, and urban sustainability. Rapid industrialization, rising vehicle emissions, urban growth, and poor waste management have worsened pollution levels, emphasizing the need for real-time monitoring systems [1]. Traditional monitoring methods, relying on manual data collection and fixed stations, often lack continuous, high-resolution insights, limiting timely decision-making and slowing progress toward improved living conditions and sustainability goals.

The emergence of Artificial Intelligence (AI) and Internet of Things (IoT) technologies offers a powerful solution to these challenges [2], [4], [6], [12]. AI-IoT based air quality monitoring systems employ distributed sensors to measure key pollutants, including PM_{2.5}, CO, NO₂, SO₂, O₃, and compute the **Air Quality Index (AQI)** in real time at low

cost. The AQI is a standardized scale used by governments and environmental agencies worldwide, to communicate air quality at a given time and location, with categories ranging from Good (0–50) to Hazardous (301–500). These systems provide automated, scalable, and decentralized monitoring. When combined with machine learning (ML), IoT platforms can analyze data to predict pollution trends, identify high-risk areas, and generate actionable insights for mitigation insights [3], [7].

IoT systems enable pollution mapping, visually identifying areas with high contamination levels. Such maps support policymakers and the public in targeting interventions and making informed health decisions. Real-time alerts via mobile or web platforms help individuals avoid hazardous areas. Additionally, adaptive management, such as optimizing waste collection routing, reduces emissions from inefficient waste-handling practices [8], [9].

This study proposes an **AI-IoT Driven Real-Time Air Pollution Monitoring and Mapping System** for sustainable urban air quality planning. The system integrates real-time monitoring, ML-based predictions, pollution mapping, user alerts, and adaptive waste management. IoT sensors collect data on both waste levels and pollutants, transmitting it to a cloud platform [5]. Machine learning algorithms analyze this data to detect pollution hotspots, optimize waste collection, and forecast air quality, delivering timely notifications to users [10].

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A key feature is AI-IoT based waste monitoring, which enhances urban cleanliness, reduces transport-related emissions, supports pollution hotspot mapping for safer routing, and classifies air quality to guide public health interventions. The architecture integrates sensor modules, cloud data processing, and ML analytics, enabling real-time monitoring, prediction, and actionable insights via an interactive dashboard for authorities and citizens. This study demonstrates how IoT and ML enable smarter air quality monitoring, reduce emissions, support sustainable urban growth, and improve living conditions. Key contributions of this study include:

- A stacked ensemble learning approach that improves the accuracy and robustness of air quality predictions.
- Integration of IoT sensors and machine learning to monitor and predict real-time air pollution levels across standard health categories (Good, Hazardous, Moderate, Unhealthy, *etc.*).
- A dynamic pollution mapping interface with color-coded visuals and mobile/web alerts when pollution exceeds safe thresholds.
- A unified cloud platform for data collection, analysis, visualization, and decision support to enhance urban air quality sustainability.

The paper is structured as follows: § II reviews existing IoT-based solutions, § III outlines the IoT sensors and cloud framework, § IV discusses the ML methodology, § V presents experimental results, and § VI explores implications and future research directions. § VII summarizes the study's contributions and societal relevance.

II. RELATED WORK

Air pollution is a critical environmental issue affecting urban sustainability, public health, and climate change. With rapid urbanization and industrialization, the need for real-time air quality monitoring and predictive systems has become increasingly important. The integration of the Internet of Things (IoT), machine learning (ML), and Geographic Information Systems (GIS) has enabled advanced solutions for pollution tracking and management. This chapter reviews existing research on IoT-based air quality monitoring systems, pollution prediction models, spatial mapping techniques, and adaptive management strategies. The deployment of IoT-enabled sensor networks for air quality monitoring has gained significant attention in recent years. Studies by [11], [12] and [13] highlight the effectiveness of low-cost, portable sensors in measuring pollutants such as $PM_{2.5}$, PM_{10} , CO , SO_2 , NO_2 , and O_3 . These systems leverage wireless communication protocols (e.g., LoRaWAN, Wi-Fi, Zigbee) to transmit real-time data to cloud platforms for analysis [14]. Several researchers have proposed edge computing architectures to reduce latency and enhance data processing efficiency [15]. Additionally, IoT-based systems have been integrated with mobile applications to provide user-friendly interfaces for pollution data visualization [16]. However, challenges such as sensor calibration, data accuracy, and power consumption remain critical concerns [17]. Machine learning models have been widely adopted for predicting air pollution levels [18] based on historical and

real-time data. Traditional statistical models such as ARIMA (Auto-Regressive Integrated Moving Average) have been used for time-series forecasting [19]. However, deep learning techniques, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have demonstrated superior performance in capturing complex pollution patterns [20]. Hybrid models combining ensemble methods (e.g., Random Forest, XGBoost) with deep learning have also been explored to improve prediction accuracy [21]. Furthermore, transfer learning approaches have been applied to generalize models across different geographical regions [22]. Despite advancements, challenges such as data sparsity, model interpretability, and computational costs persist.

Geospatial techniques play a crucial role in visualizing and analyzing air pollution distribution. GIS-based interpolation methods, such as Kriging and Inverse Distance Weighting (IDW), have been used to generate pollution heatmaps [23]. Recent studies have incorporated real-time satellite data (e.g., Sentinel-5P) alongside ground-based IoT sensors to enhance spatial resolution [24], [25]. Mobile and web-based dashboards with interactive pollution maps enable policymakers and citizens to identify pollution hotspots and take preventive measures [26], [27]. However, challenges in data fusion [28] from heterogeneous sources and dynamic urban environments require further research.

Adaptive air quality management systems leverage real-time data to dynamically adjust pollution control strategies. Studies by [29]–[31] propose rule-based and AI-driven decision-making frameworks for traffic regulation and industrial emission control. Additionally, personalized alert systems using SMS, mobile notifications, and email have been implemented to inform users about hazardous air quality levels [32]–[34]. Behavioral studies indicate that real-time alerts significantly influence public awareness and mitigation actions [35]. However, ensuring timely and accurate alerts while minimizing false alarms remains a challenge.

Existing IoT-based air quality studies show progress but lack robust sensor fusion, lightweight edge ML, scalable adaptive frameworks, and long-term urban prediction; this research proposes a smart IoT-enabled monitoring and prediction system to address these gaps. The system fuses multi-sensor data, uses ensemble forecasting, enables real-time GIS mapping, and delivers adaptive alerts, offering a comprehensive, user-centric solution for effective air quality monitoring and sustainable urban management.

III. MATERIALS

This section describes the hardware, software, and data acquisition resources used to develop the Smart IoT-Enabled Air Quality Monitoring System.

A. IoT devices and sensors

The proposed IoT-based system integrates environmental and meteorological sensors for real-time monitoring. PMS5003 measures particulate matter, MQ-7 detects CO , electrochemical sensors measure NO_2 , SO_2 , and O_3 , while

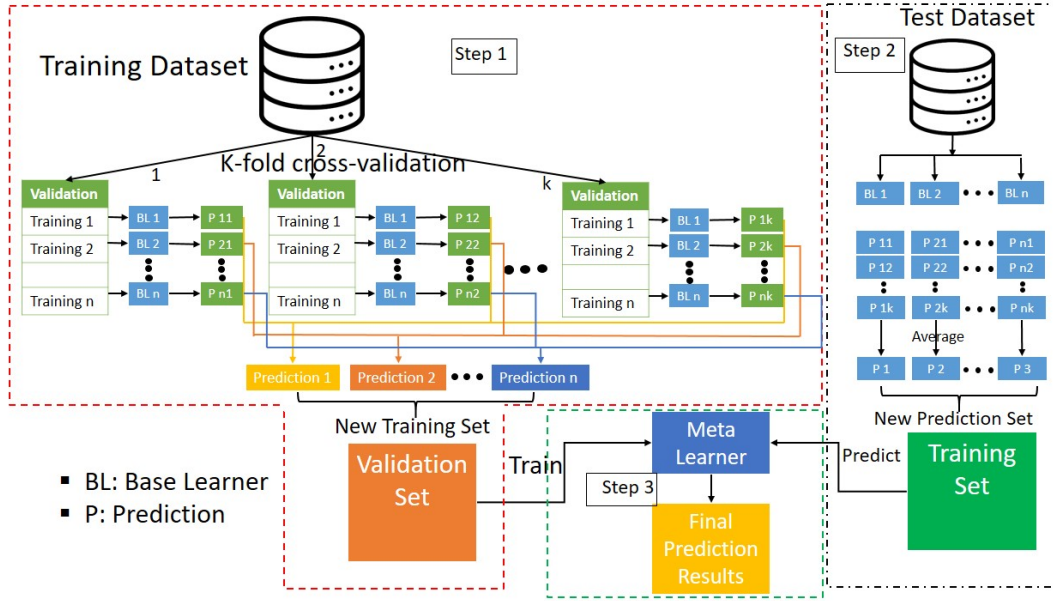


Fig. 1: Stacked Ensemble Learning Model for Pollution Prediction and Urban Sustainability Planning

anemometer and DHT11 capture wind, temperature, and humidity. An Arduino Uno processes data, triggers alerts, and transmits readings to an IoT platform for continuous monitoring.

B. Data Transmission and Processing

In this study, IoT sensors transmit real-time air quality and meteorological data include $PM_{2.5}$, CO , NO_2 , SO_2 , O_3 , temperature, humidity, wind speed and direction via the lightweight MQTT protocol to a cloud server, ensuring low-latency, reliable communication with minimal bandwidth overhead.

At the cloud server, data are stored, preprocessed, and analyzed using ML models including Random Forest, XGBoost, CatBoost, Gradient Boosting, and SVM, with flexible wireless connectivity across urban environments.

Results are displayed on an interactive dashboard enabling real-time monitoring, hotspot detection, trend analysis, and automated alerts for effective air quality management.

IV. METHODS

This section outlines the machine learning algorithms used to process sensor data and generate actionable insights for air quality management and pollution mitigation.

A. Proposed Machine Learning Model

The proposed model depicted in Figure 1 is a stacking ensemble with k -fold cross-validation where in each iteration, $K-1$ folds are used to train the base learners (BL1, BL2, ..., BL n), and the remaining fold serves as the validation set to generate out-of-fold predictions. XGBoost, CatBoost, and Gradient Boosting act as base learners, generating out-of-fold predictions used as meta-features. A logistic regression

meta-learner combines stacked base model outputs, using out-of-fold predictions to reduce overfitting and improve final prediction accuracy. Let the predicted probabilities (or outputs) of the three base learners for an input sample x be: $h_{BL1}(x), h_{BL2}(x), \dots, h_{BLn}(x)$. The meta-learner, Logistic Regression, computes a weighted linear combination of these meta-features defined as:

$$z = w_0 + w_1 \cdot h_{BL1}(x) + w_2 \cdot h_{BL2}(x) + \dots + w_n \cdot h_{BLn}(x) + b, \quad (1)$$

where weights $w_0, w_2, \dots, w_n$ indicate how much trust the meta-learner puts in each base model and the term b is the bias or intercept of the meta-learner. Then the predicted probability for the class is defined as:

$$\hat{y} = \sigma z. \quad (2)$$

where σ represents the logistic sigmoid function ensuring probabilistic output.

B. Proposed Framework

The IoT air quality monitoring system integrates real-time data collection, processing, and prediction. Distributed urban sensors measure $PM_{2.5}$, CO , NO_2 , SO_2 , O_3 , and meteorological parameters, transmitting data to a centralized IoT platform for real-time storage and analysis.

The IoT platform reliably aggregates sensor data via LoRa, ZigBee, or Wi-Fi, enabling ML models to classify air quality as either safe or harmful based on pollutant concentration levels, predict pollution trends, and identify hotspots.

Processed data is delivered through a user-friendly app, enabling real-time access, alerts, and trend analysis for citizens and authorities to avoid pollution and support informed urban planning decisions. The proposed framework is illustrated in Figure 2.

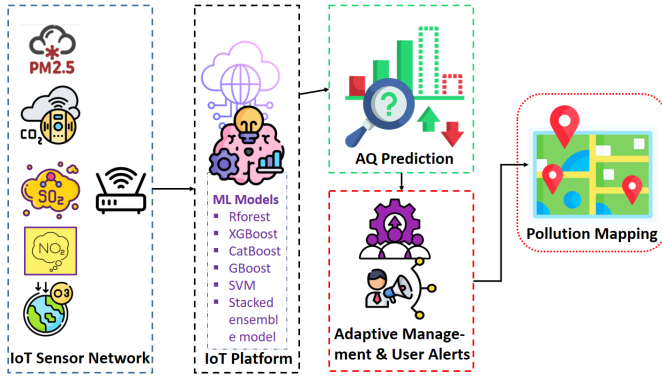


Fig. 2: Integrated IoT Framework for Air Quality Monitoring, Prediction, and Mapping

V. EXPERIMENTAL RESULTS

This section presents data collection process and the experimental evaluation of the proposed system. It reports the system's performance in terms of prediction accuracy, pollution level classification, real-time monitoring capability, and alert generation, along with comparative analyses against existing models. The results demonstrate the system's effectiveness in delivering reliable air quality forecasts and actionable insights for sustainable urban environmental management.

A. Experimental Setup

The experimental setup enables real-time air quality monitoring, pollution prediction, and adaptive waste management to support urban sustainability. As shown in Figure 3, multiple IoT sensors such as CO , NO_2 , SO_2 , $PM_{2.5}$, O_3 , DHT11, and anemometers are deployed across urban locations to continuously sense environmental conditions. Sensor data are transmitted to a central server via Wi-Fi, LoRa, or cellular networks.

The collected data are processed on a cloud-based platform, where both real-time and historical records are used to train machine learning models, including Random Forest, XGBoost, CatBoost, Gradient Boosting, SVM, and the proposed stacked ensemble model. These models predict air quality levels and identify pollution hotspots with high accuracy.

The results are visualized through a real-time dashboard and a mobile application that provides pollution maps and user alerts, enabling citizens and authorities to take timely preventive actions. Additionally, the system integrates adaptive waste management, where IoT-enabled waste sensors monitor bin fill levels to optimize collection routes and schedules, reducing emissions from inefficient waste handling.

By integrating real-time sensing, predictive analytics, and adaptive management, the proposed system offers a scalable and effective solution for improving air quality, supporting urban planning, and enhancing public health.

B. Data Collection and Pre-processing

The dataset contains 5,999 air quality records collected from IoT-enabled sensors deployed across multiple urban locations.

Each record includes timestamp, location, latitude, longitude, $PM_{2.5}$, CO , NO_2 , SO_2 , O_3 , temperature, relative humidity, wind speed, wind direction, AQI value, AQI category, binary label, sensor ID, and calibration factor. To ensure data reliability, all low-cost sensors were calibrated before deployment. PMS5003, MQ-7, and electrochemical sensors were collocated with a reference-grade monitoring station and corrected using regression-based calibration. Periodic recalibration addressed sensor drift and environmental effects. Measurement uncertainty was quantified from residual errors between calibrated sensors and reference data, and the resulting calibration factors were incorporated into the dataset to enhance robustness and transparency.

Data are transmitted via Wi-Fi, LoRa, or cellular networks to a cloud server. The dataset includes 4,807 Harmful (80.12%) and 1,192 Safe (19.88%) instances and is further categorized into Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Hazardous classes. The data distribution is presented in the Table I. This distribution reflects real conditions, with rarer safe cases and more extremes; time-aware cross-validation ensured temporal consistency and prevented data leakage.

TABLE I: Distribution of Air Quality Data Samples Across Categories

Air Quality Category	Samples
Good	2,289
Moderate	2,604
Unhealthy for Sensitive Groups	664
Unhealthy	411
Very Unhealthy	27
Hazardous	4
Total	5,999

Each observation is enriched with derived Air Quality Index (AQI) values and corresponding health categories, along with binary classification labels for potential analytical applications. The dataset also includes sensor identification and calibration factors, ensuring transparency about data collection methodology and measurement reliability across the monitoring network.

The sub-index for each pollutant is calculated using the EPA linear breakpoint interpolation formula. After computing the AQI sub-index for all pollutants, the overall AQI is determined as the maximum of these values, representing the dominant pollutant. The final output reports both binary (Safe/Harmful) and multiclass (Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, Hazardous) AQI categories as predicted by the trained models.

The Sub AQI Formula (3):

$$QI_p = \frac{(I_{high} - I_{low})}{(C_{high} - C_{low})} \times (C_p - C_{low}) + I_{low} \quad (3)$$

where QI_p = Air Quality Index for pollutant p , C_p = Measured concentration of pollutant p , C_{low} and C_{high} = Concentration breakpoints that are closest to C_p , I_{low} and I_{high} = Corresponding AQI breakpoints for C_{low} and C_{high} .

The overall AQI is determined as the maximum value

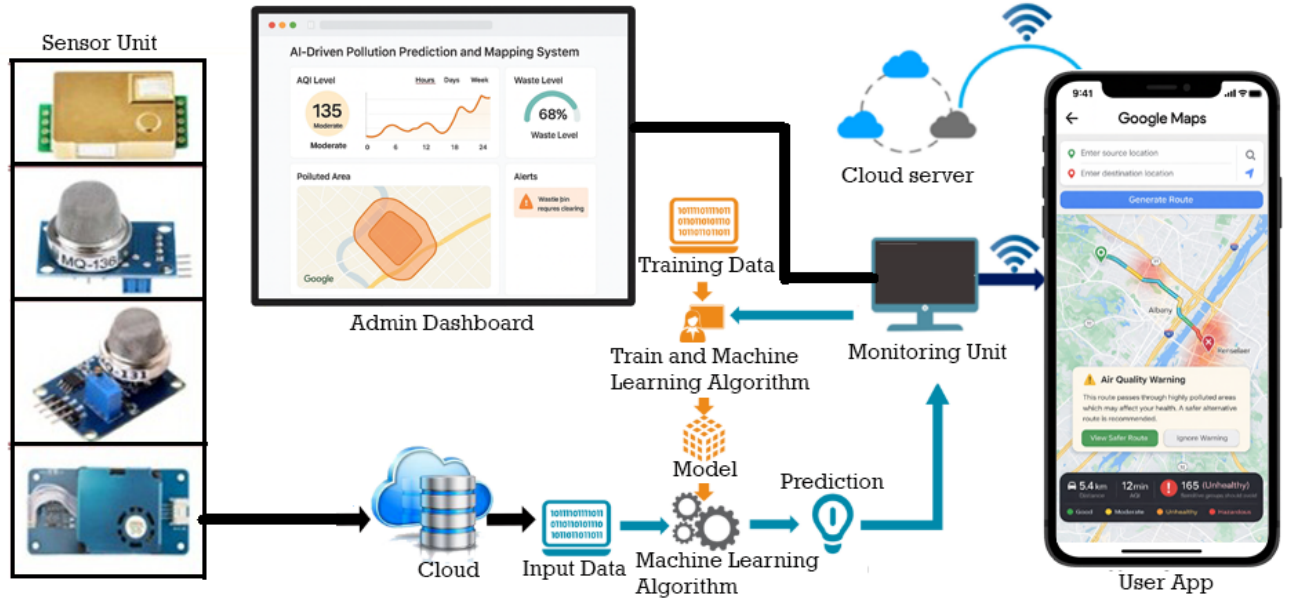


Fig. 3: Proposed architecture and working methodology for Pollution Prediction and Mapping

among all pollutants:

$$AQI = \max(QI_{PM_{2.5}}, QI_{PM_{10}}, QI_{CO}, QI_{NO_2}, QI_{SO_2}, QI_{O_3}) \quad (4)$$

A higher AQI value indicates poorer air quality and a greater potential health risk.

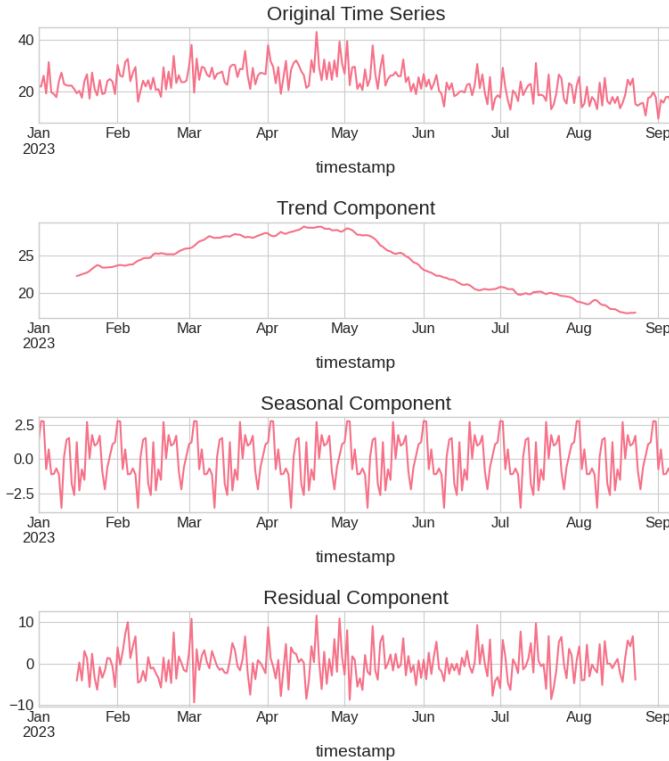


Fig. 4: Time Series Decomposition of the PM_{2.5} Air Quality Parameter.

Raw sensor data undergo preprocessing to ensure quality

and reliability, including noise filtering, missing value imputation, and outlier detection, with anomalies corrected or removed using predefined pollutant concentration thresholds. Given a raw observation vector $x = \{x_1, x_2, \dots, x_n\}$, normalization is applied using min-max scaling:

$$x'_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

This transformation ensures uniform feature scaling across heterogeneous sensor measurements. After cleaning, data are normalized to align feature scales, then organized and stored in a cloud database for machine learning analysis.

To avoid label leakage, AQI values and AQI categories are not used as input features in any machine learning model. These variables are derived outcomes calculated using the EPA breakpoint formulation and are employed solely as ground-truth labels for supervised training and evaluation. Model inputs consist exclusively of raw pollutant concentrations $PM_{2.5}$, CO , NO_2 , SO_2 , O_3 and meteorological parameters (temperature, humidity, wind speed, and direction). AQI-related attributes are explicitly excluded from the feature set, ensuring that model performance reflects genuine learning rather than circular inference.

This preparation provides high-quality data for Random Forest, XGBoost, CatBoost, Gradient Boosting, SVM, and the stacked ensemble, improving prediction accuracy, hotspot identification, and overall system performance.

Although AQI can be calculated using the EPA breakpoint formula, real-world sensor data are noisy and influenced by meteorological and multi-pollutant interactions. Machine learning is therefore used to enhance classification robustness rather than replace EPA calculations. By learning nonlinear patterns from pollutants, weather parameters, and AQI values, the models provide stable binary and multiclass predictions, especially near threshold boundaries and in mixed-pollutant

conditions.

C. Data Analysis and Description

A comprehensive exploratory and temporal analysis was conducted, including descriptive statistics, visual exploration, and time series decomposition, to identify patterns, correlations, trends, and seasonal variations supporting accurate predictive modeling and meaningful environmental insights.

Figure 5 presents EDA results, showing monthly AQI distributions. Unhealthy and Moderate categories dominate, while Good and Very Unhealthy occur less frequently, indicating seasonal pollution fluctuations influenced by meteorological or anthropogenic factors.

The top-right plot shows PM2.5 peaking during early morning hours (0–7 h) and decreasing later, likely due to daytime atmospheric mixing.

The bottom-left correlation matrix shows weak positive correlations of PM2.5 with NO₂ ($r = 0.18$) and O₃ ($r = 0.16$), while other pollutant pairs exhibit negligible correlations, indicating largely independent variation patterns.

The bottom-right plot shows temperature versus PM2.5 across AQI categories, where higher PM2.5 aligns with Unhealthy and Very Unhealthy conditions, while Good air quality appears at moderate temperatures, suggesting temperature influences particulate dispersion or formation.

Figure 4 decomposes PM2.5 (January–September 2023) into trend, seasonal, and residual components. Peaks occur during March–May, with a pre-monsoon rise and post-monsoon decline. Strong seasonal patterns and minimal residuals indicate captured variability, supporting reliable forecasting and anomaly detection.

Diurnal analysis of PM2.5 shows elevated concentrations during early morning hours, followed by a gradual decline due to enhanced daytime atmospheric dispersion.

Inter-pollutant relationships were quantified using the Pearson correlation coefficient:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

PM2.5 exhibited weak positive correlations with NO₂ and O₃, suggesting partial common emission sources.

Furthermore, time series decomposition was applied to PM2.5 to separate its underlying components:

$$X_t = T_t + S_t + R_t$$

where T_t , S_t , and R_t denote the trend, seasonal, and residual components, respectively. The results indicate strong seasonality and a pronounced pre-monsoon peak, supporting the suitability of temporal models for forecasting and anomaly detection.

Overall, this preprocessing and analytical framework establishes a robust foundation for accurate machine learning based air quality prediction and environmental decision support.

D. Model Evaluation Metrics

Before applying the proposed model to simulated data, it is necessary to evaluate its predictive capability using multiple performance metrics. Relying solely on accuracy can lead to misleading conclusions, especially in imbalanced datasets. Therefore, we assess model performance using four standard classification metrics: Accuracy, Precision, Recall, and F1-Score.

E. Results Analysis

This section presents a comprehensive evaluation of machine learning models and the proposed stacked ensemble for AQI prediction. Two tasks are assessed: multiclass AQI classification (Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, Hazardous) and binary Safe–Harmful classification. Performance is analyzed in terms of accuracy, consistency, interpretability, and temporal generalization. Random Forest, XGBoost, CatBoost, and Gradient Boosting were trained using time-aware cross-validation and combined through a stacked ensemble with a meta-classifier. Average cross-validation results are summarized below.

TABLE II: Cross-validation performance comparison of different models for multiclass AQI prediction.

Model	Mean CV Accuracy	Std. Dev.
Random Forest	0.9771	±0.0095
XGBoost	0.9833	±0.0020
CatBoost	0.9818	±0.0058
Gradient Boosting	0.9862	±0.0030
Stacked Ensemble	0.9883	±0.0024

The stacked ensemble outperformed all individual models, achieving 98.83% accuracy. It effectively reduced bias and variance, capturing nonlinear relationships among pollutants and meteorological factors to provide a comprehensive spatiotemporal understanding of air quality dynamics.

Figure 6a compares Accuracy, Precision, Recall, and F1-Score for multiclass AQI prediction across all models. All achieved values above 0.97, indicating reliable performance. Among base learners, Gradient Boosting showed the best balance (0.986 across all metrics), followed closely by XGBoost and CatBoost, while Random Forest remained competitive. The proposed stacked ensemble outperformed all models, achieving the highest scores (Accuracy 0.988, Precision 0.989, Recall 0.988, F1 0.988). This balanced improvement highlights effective bias–variance reduction and confirms the suitability of stacked ensembles for stable, practical air quality monitoring.

The confusion matrix shown in Figure 7 summarizes the classification performance of the stacking ensemble across six AQI categories. The strong diagonal dominance confirms the model's high predictive reliability. In particular, 449 of 458 samples in class 0(Good) and all samples in classes 1(Hazardous) and 5(Very Unhealthy) are correctly classified, while class 2(Moderate) also achieves near-perfect recognition with 521 correct predictions. Minor misclassifications are mainly observed between neighboring AQI levels such as class 0(good) and class 2(Moderate), and class 3(Unhealthy for

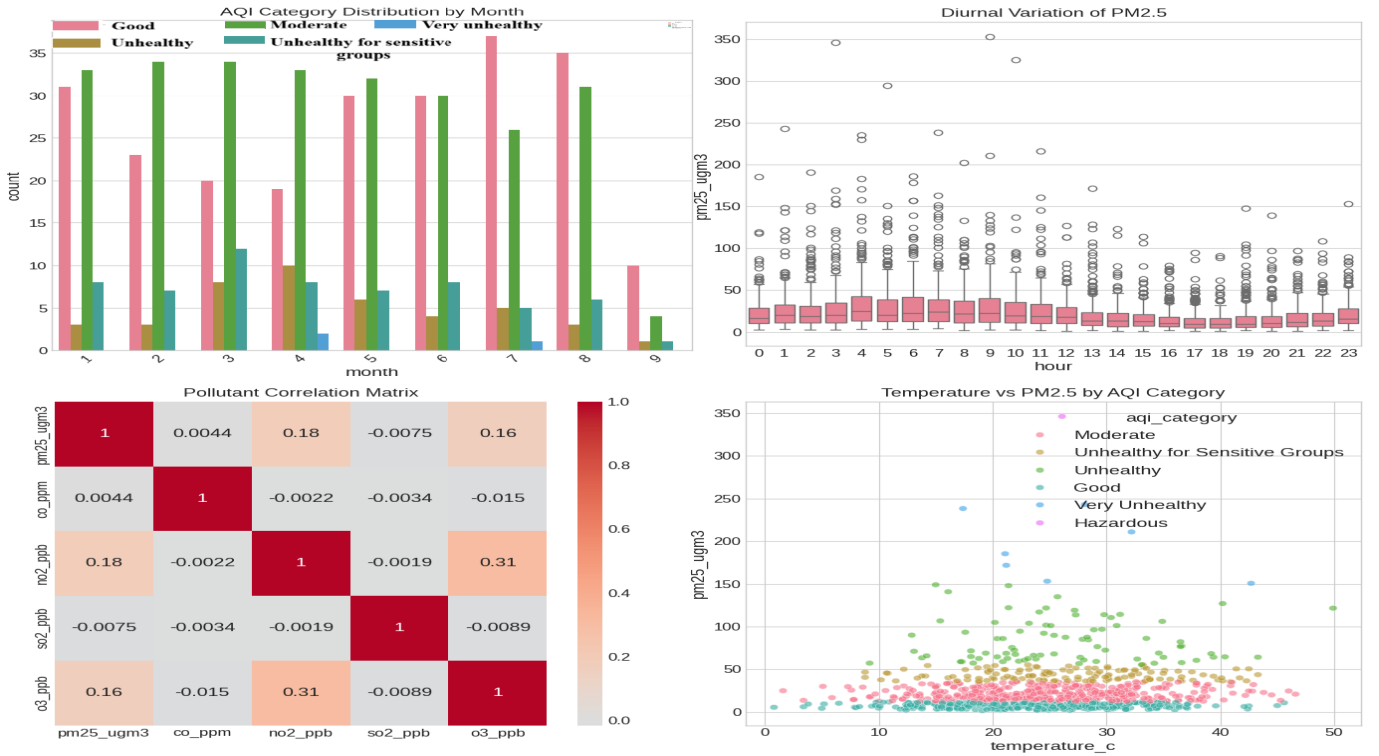


Fig. 5: Exploratory data analysis (EDA) visualizations of the air quality dataset.

Sensitive Groups) and class 4(Unhealthy) indicating natural overlap in air-quality transitions rather than systematic model bias. Despite severe class imbalance, the ensemble successfully identifies rare classes, including all instances of class 1 ($n = 1$) and class 5 ($n = 5$), demonstrating the robustness of the proposed framework in handling skewed environmental data distributions.

Table III presents a performance comparison of machine learning models using six metrics: Accuracy, Precision, Recall, F1-Score, Cross-Validation Stability, and Complexity for multiclass AQI prediction. Among all models, the Stacked Ensemble achieves the best overall results, with the highest Accuracy (0.988), Precision (0.989), Recall (0.988), and F1-score (0.988), as well as the strongest CV stability (0.999), demonstrating superior generalization and robustness. XGBoost and Gradient Boosting also show strong predictive capability, but fall slightly behind the ensemble in all major metrics. Random Forest exhibits comparatively lower precision and recall, while Gradient Boosting, despite high predictive scores, shows the lowest complexity score (0.700), indicating higher computational cost. In contrast, the Stacked Ensemble attains a high complexity score (0.950), reflecting a favorable trade-off between performance and computational efficiency.

The proposed stacked ensemble achieved the best overall performance, with 0.988 accuracy and 0.999 CV stability, indicating consistent results across folds. Although complexity was higher (0.950), superior stability and precision justify the computational cost, demonstrating strong generalization for reliable real-time air quality monitoring and decision support.

Table IV reports the multiclass AQI classification performance of the proposed stacked ensemble. Precision, recall,

and F1-scores exceed 0.97 across all categories. Perfect scores (1.00) for Hazardous and Very Unhealthy demonstrate robustness to class imbalance, while Good and Moderate achieve F1-scores of 0.99. Slight recall reductions for Unhealthy (0.97) and Unhealthy for Sensitive Groups (0.98) reflect minor misclassifications near overlapping AQI thresholds.

The model achieved 0.99 accuracy, with macro and weighted Precision (0.99–1.00), Recall (0.99), and F1 (0.99), confirming balanced, reliable performance across both common and rare AQI classes for real-world monitoring.

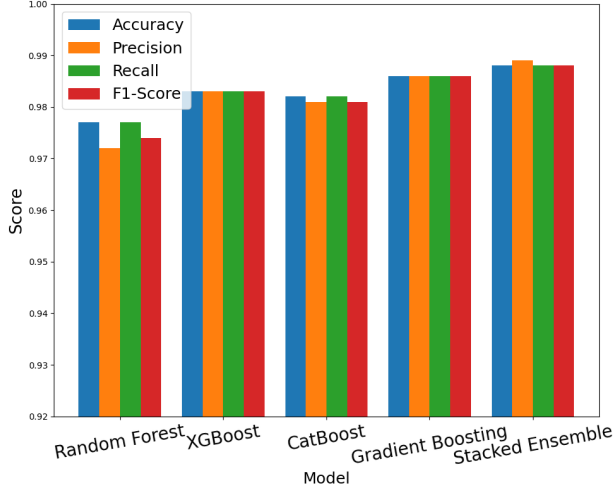
For binary AQI classification into Safe and Harmful, the stacked ensemble achieved 99.85% (± 0.0019) accuracy, outperforming Random Forest and XGBoost at 99.60%.

Figure 6b compares multiclass and binary AQI prediction accuracies of all models. Blue bars show multiclass accuracy across six AQI categories, while orange bars represent binary Safe–Harmful accuracy. Among base learners, Gradient Boosting achieved the highest multiclass accuracy (98.62%), followed by XGBoost (98.33%), CatBoost (98.18%), and Random Forest (97.71%). The proposed stacked ensemble outperformed all models, reaching 98.83% multiclass and 99.85% binary accuracy. All models performed better in binary tasks, indicating lower complexity in Safe–Harmful classification. High binary accuracies (99.42%–99.85%) confirm strong detection of harmful conditions. The ensemble’s superior performance demonstrates robust generalization by effectively capturing nonlinear pollutant interactions and temporal air quality variations.

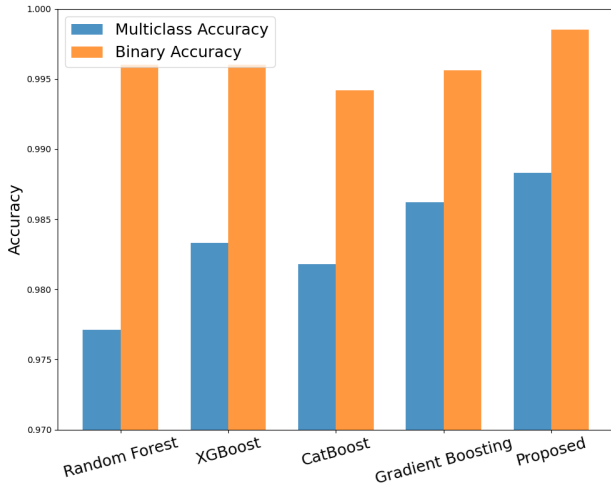
Comparative evaluation shows Gradient Boosting as the strongest individual model for capturing nonlinear pollutant interactions. The stacked ensemble achieved highest accu-

TABLE III: Performance comparison of machine learning models across evaluation metrics

Model	Accuracy	Precision	Recall	F1-Score	CV Stability	Complexity Score
Random Forest	0.977	0.972	0.977	0.974	0.990	0.800
XGBoost	0.983	0.983	0.983	0.983	0.998	0.900
CatBoost	0.982	0.981	0.982	0.981	0.994	0.850
Gradient Boosting	0.986	0.986	0.986	0.986	0.997	0.700
Stacked Ensemble (Ours)	0.988	0.989	0.988	0.988	0.999	0.950



(a) Comparative evaluation of each applied model's accuracy, precision, recall, and F1-score in the multiclass AQI

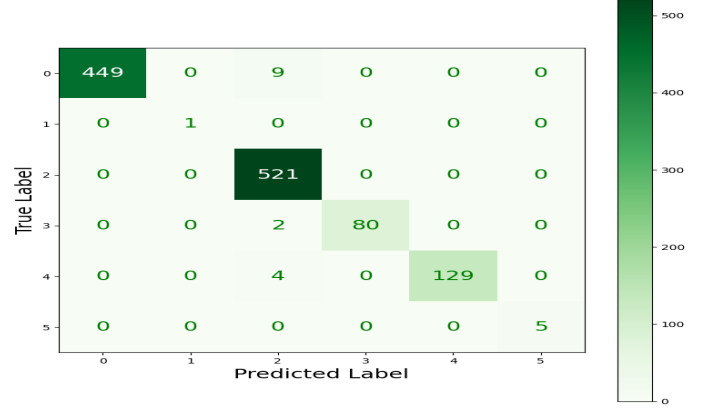


(b) Comparative performance of the applied machine learning models in terms of their multiclass and binary classification

Fig. 6: Comparative performance of multiclass and binary AQI prediction across different models.

racy by integrating diverse learners, improving robustness and generalization. Temporal features enhanced prediction by capturing cyclic and seasonal patterns, while time-aware cross-validation confirmed stability without overfitting or data leakage.

Overall, the results demonstrate the strong performance and reliability of the proposed framework. The stacked ensemble achieved 98.83% accuracy for multiclass AQI prediction and 99.85% for binary classification, as shown in Figure 6. Its

**Fig. 7:** Confusion Matrix Illustrating Multiclass AQI Prediction Performance**TABLE IV:** Classification report for the proposed Stacked Ensemble model (Multiclass AQI prediction).

Class Label	Prec.	Recall	F1	Support
0 (Good)	1.00	0.98	0.99	458
1 (Hazardous)	1.00	1.00	1.00	1
2 (Moderate)	0.98	1.00	0.99	521
3 (Unhealthy for Sensitive Groups)	1.00	0.98	0.99	82
4 (Unhealthy)	1.00	0.97	0.98	133
5 (Very Unhealthy)	1.00	1.00	1.00	5
Accuracy			0.99	1200
Macro Avg.	1.00	0.99	0.99	1200
Weighted Avg.	0.99	0.99	0.99	1200

balanced performance across tasks confirms superior generalization over base learners. Time-aware validation ensured fair evaluation, with misclassifications mainly between adjacent AQI levels. Incorporating meteorological and temporal features improved stability and interpretability, while high sensitivity to harmful conditions supports practical use in real-time monitoring, smart cities, and environmental policy.

Table V compares recent IoT-enabled air quality monitoring systems, highlighting differences in sensors, learning methods, features, and performance. The proposed system integrates multiple gas sensors ($PM_{2.5}$, CO , NO_2 , SO_2 , O_3) with a stacked ensemble model, enabling real-time monitoring, pollution mapping, user alerts, and adaptive waste management, achieving 98.73% ($\pm 0.21\%$) cross-validation accuracy. Earlier studies [11], [13] focus on basic monitoring, while [14] reports 92% accuracy using Random Forest. Works [15], [20] explore edge or deep learning without full user-centric integration, and [24], [29] emphasize geospatial or UAV-IoT applications

TABLE V: Comparative Performance Analysis of IoT-Based Air Quality Monitoring Systems

Study	Focus Area	Sensors Used	ML Algorithms	Key Features	Performance
Proposed System	Air quality monitoring, pollution prediction, waste management	PM2.5, CO, NO ₂ , SO ₂ , O ₃ , Anemometer and DHT11	Proposed Stacked Ensemble Model	Real-time monitoring, pollution mapping, adaptive waste management, user alerts	98.73% (+/- 0.21%) Cross-validation accuracy, 98.83% test accuracy
Kumar, A et al. [11]	Basic air quality monitoring	PM2.5, CO ₂	None	Real-time sensor data collection	implementation with low-cost components
Guerrero Ulloa et al. [13]	Indoor air quality control	MQ135, MQ7, temperature	Basic threshold alerts	Indoor AQ automation	Very satisfied: 43.59%, Satisfied: 48.72%
Kumar, T et al. [14]	Urban air quality monitoring	NO ₂ , SO ₂	Random detection	~92% classification accuracy	
Chan. Y. W et al. [15]	Edge-based AQM	PM2.5, CO ₂	Lightweight ML	Edge computing for low latency	Functional up to 1.65 km
Zhang, H et al. [19]	AQI forecasting	Historical AQI data	Fuzzy time series	Short-term AQI prediction	MAPE (Mean Absolute Percentage Error) 4.49% ~ 6.44%
Nguyen, T. P. et al. [20]	Indoor AQ prediction	Indoor sensors	Hybrid deep learning	Metaheuristic optimization	Cosine Proximity (CP) improved by 0.02% ~ 0.57%
Moraga,A. et al. [29]	Smart city emissions	Traffic/emission data	LLM + UAV-IoT	Congestion/emission reduction	Inference latency: 8.4 ms per query

without reporting performance metrics.

VI. DISCUSSION AND FUTURE RESEARCH

The objective of this study was to design and develop a Smart IoT-Enabled Air Quality Monitoring and Prediction System to address rising urban air pollution and support sustainable city planning. The results show that integrating multi-parameter IoT sensing with advanced machine learning enables reliable real-time monitoring, accurate pollution prediction, and optimized waste management.

The system deploys CO, NO₂, SO₂, PM_{2.5}, and O₃ sensors, transmitting continuous data via Wi-Fi, LoRa, and cellular networks. These streams provide actionable insights into pollution levels and temporal trends. Machine learning models, including XGBoost, CatBoost, Gradient Boosting, SVM, and a stacked ensemble, were applied for air quality classification and prediction. The ensemble achieved near-perfect performance across accuracy, precision, recall, and F1-score, confirming the complementary strengths of its base learners and the robustness of the decision process, while highlighting scope for reducing false positives under diverse conditions.

Beyond air monitoring, the system integrates IoT-based waste monitoring to optimize collection routes and schedules, reducing emissions from inefficient waste handling. A cloud-based backend supports scalable storage, processing, visualization, and mobile alerts, ensuring real-time access for authorities and citizens.

Future work will focus on expanding sensor coverage, integrating satellite and weather data, improving scalability, adopting advanced spatiotemporal and deep learning models, and enhancing energy efficiency. Overall, the proposed framework demonstrates strong potential for real-time pollution management, informed policymaking, and healthier, more sustainable urban environments.

VII. CONCLUSION

This study proposes a AI-Driven Pollution Prediction and Mapping System for Sustainable Urban Planning that integrates IoT sensing with machine learning to address urban air pollution. Distributed sensors continuously measure $PM_{2.5}$, CO, NO₂, SO₂, O₃, humidity, and wind parameters, transmitting data via Wi-Fi, LoRa, or cellular networks for real-time analysis, pollution mapping, and user alerts. The system also incorporates IoT-based waste monitoring to optimize collection routes and reduce emissions. For prediction, XGBoost, CatBoost, Gradient Boosting, SVM, and a stacked ensemble were evaluated. The proposed ensemble, combining boosting models with a logistic regression meta-learner, achieved the best performance (98.83% accuracy, 98.9% precision, 98.8% recall, 98.8% F1-score). Its novelty lies in unifying sensing, analytics, mapping, and adaptive waste management. While results are strong, further work is needed on sensor calibration, generalization, privacy, and large-scale deployment.

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