International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-15

https://doi.org/10.70917/ijcisim-2026-0983
Article

Real-Time Air Quality Monitoring in Industrial Zones Using IoT-Powered AI Systems

Leena Arya [1,*], Shashi Mehrotra [2], CH. Sabitha [3], Mandalapu Sivaparvathi [4], Venkata Rajani Katuri [5], Ravi Rastogi [6] and Katepalli Srivalli Rani [7]

[1] Department of Computer Science & Engineering, Professor, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur District, AP – 522302, India; leenaarya18@gmail.com https://orcid.org/0000-0002-9249-732X
[2] Department of Computer Science and Engineering, SRM Institute of Science and Technology, Delhi NCR Campus, Modinagar, Ghaziabad – 201204, India; sethshashi11@gmail.com https://orcid.org/0000-0003-3907-5790
[3] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh – 522302, India; sabithakiran.ch@kluniversity.in
[4] Department of Computer Science and Engineering, MAM Women's Engineering College, Kesanupalli Village, Narasaraopet, District Palnadu, Andhra Pradesh – 522601, India; sivaparvathi1242@gmail.com
[5] Department of Computer Science and Engineering, Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad, Telangana – 500029, India; kvrajanirajesh@gmail.com https://orcid.org/0009-0008-1790-7027
[6] Department of Computer Science and Engineering, JIMS Engineering Management Technical Campus, 48/4, Knowledge Park III, Greater Noida, District Gautam Budh Nagar, Uttar Pradesh – 201303, India; ravikumarrastogi@gmail.com https://orcid.org/0000-0002-1118-3020
[7] Department of Mechanical Engineering, M.B.T.S Government Polytechnic, Guntur, AP-522005, India; srivalli.mech@gmail.com https://orcid.org/0000-0002-0551-708X
* Correspondence author: leenaarya18@gmail.com

Abstract: Air pollution in industrial zones poses significant risks to human health and the environment, making real-time monitoring essential for effective mitigation. Traditional air quality monitoring methods are deficient mainly in terms of spatial coverage and temporal resolution, making it challenging to trace the dynamic changes in the levels of pollutants. Development and implementation of real-time customized industrial area air quality monitoring using Internet of Things, sensors and artificial intelligence analytics. An IoT-enabled sensor network continuously measures key pollutants: PM2.5 and PM10, NO2, SO2, CO, and VOCs. The data is also processed through AI algorithms and LSTM networks to detect anomalies in pollutant level prediction. The experimental findings were a Root Mean Square Error (RMSE) of 2.2 and an R^2 of 0.90, better than the regular multivariate linear regression model. The alert mechanism of the system responded within an average of 5 seconds with low false positives below 3%, thus providing reliable real-time monitoring. Users gave a high satisfaction rating (average score of 4.7/5) about the system interface, especially on ease of navigation and clarity of information. These findings suggest a practical approach to monitoring and managing air quality in the industrial environment using IoT and AI technology integration to support improvement in public health and environmental sustainability and ensure minimal deployment challenges and cost-effectiveness.

Keywords: Air quality sensors; polluting gas; Predictive analytics for pollution; Machine-learning; Smart industrial zones

1. Introduction

Air pollution is a serious environmental issue, particularly in industrial areas where factories, refineries, and manufacturing plants release harmful chemicals that may endanger nearby residents [1]. Monitoring and controlling air quality in these areas is important for protecting public health and meeting environmental standards.

Traditional air quality monitoring techniques, which rely on manual sampling and laboratory analysis, cannot respond quickly enough to provide real-time information [2]. Additionally, this might be too costly, time-consuming, and labour-intensive to deploy quickly and effectively to identify hotspots or changes in air quality [3]. It is difficult to identify localized pollution hotspots or abrupt changes in pollutant levels since they only offer crude measures devoid of spatial and temporal granularity [4]. Furthermore, traditional systems lack the predictive ability to foresee possible hazards because they are reactive by nature, indicating pollution levels only after examination [5]. Because of this, they are unable to facilitate prompt adherence to environmental rules, automated control, or proactive interventions in dynamic industrial settings [6].

The Internet of Things (IoT) and Artificial Intelligence (AI) have changed environmental monitoring by allowing real-time data collection, analysis, and response [7]. Sensors in industrial areas now give continuous, detailed information on important air quality indicators such as particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO), and volatile organic compounds (VOCs) [8]. These sensors send their data straight to cloud platforms for further analysis [9].

Wireless communication and IoT systems enable large networks of air quality monitors to be deployed in smart cities and industrial areas [10]. Research shows that having a strong network and the right technology are important for using IoT sustainably [11]. Machine learning models also make air quality forecasts more accurate by using optimization and regularization methods [12].

Many IoT-based air quality monitoring systems have been created for industry and smart cities [13]. With AI, these systems can predict pollution trends and help automate decisions in industrial environments [14]. Real-time AI-powered IoT systems have greatly improved the monitoring and forecasting of industrial air pollution [15].

Advanced machine learning and anomaly detection make pollutant predictions more reliable and systems stronger [16]. Crowdsensing and distributed sensing platforms expand environmental coverage and get more people involved in urban monitoring [17]. Reviews of IoT, big data, and machine learning show their big impact on air pollution monitoring [18].

Keeping data quality high and regularly calibrating IoT air quality systems is important for reliability and for reducing false alarms [19]. Secure, privacy-focused IoT designs protect environmental data during transmission and storage on cloud platforms [20]. AI-driven models for monitoring and predicting industrial pollution have worked well in manufacturing areas [21].

Recent reviews show that artificial intelligence is increasingly used in air pollution monitoring and forecasting to help make industry more sustainable [22]. For example, AI-based monitoring in the chrome plating industry shows that IoT-AI systems can operate across many industrial settings [23]. IoT-based environmental toxicology systems use AI to study pollutant exposure and health effects in real time [24].

Surveys on IoT-based air quality monitoring also discuss system design, deployment challenges, and future research needs to expand its use in industry [25].

Fig. 1 shows the architecture of the smart city air quality monitoring system, which integrates IoT-based sensing, edge processing, and cloud analytics to provide continuous, city-wide environmental surveillance. In the depicted layout, sensor nodes are strategically installed across multiple urban domains, including industrial plants, construction sites, landfills, vehicular corridors, residential neighborhoods, wastewater-treatment facilities, and airport zones, to ensure complete spatial coverage of key emission sources. Each sensing unit measures major pollutants such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and volatile organic compounds and transmits data wirelessly through gateways using protocols such as Wi-Fi, LoRa, or 5 G. At the edge layer, devices perform preliminary calibration correction, noise filtering, and anomaly detection before relaying validated data to the cloud platform, where artificial-intelligence models analyze temporal trends, predict pollution levels, and generate early-warning alerts. The architecture thus represents an integrated, scalable framework that links heterogeneous monitoring zones into a unified IoT-AI ecosystem, supporting real-time decision-making for sustainable urban and industrial air-quality management [1]-[6].

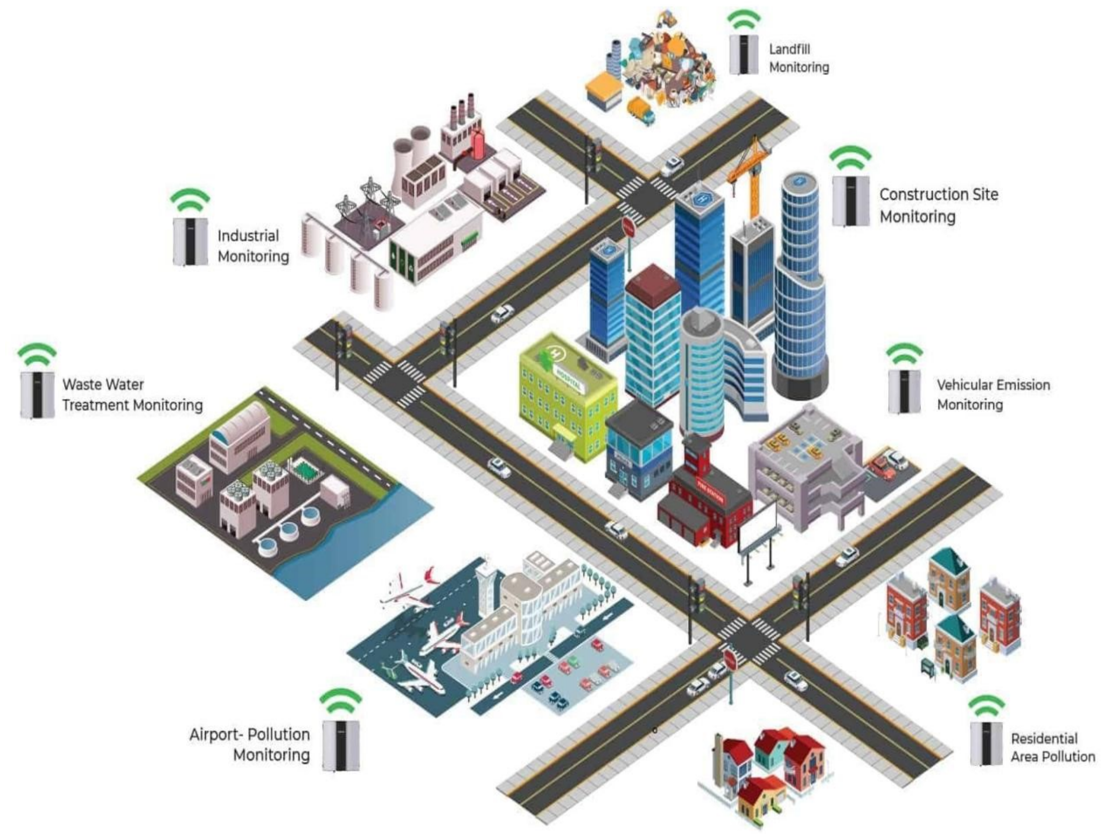

Figure 1. Smart City Air Quality Monitoring System Architecture

The World Health Organization (WHO) [1] estimates that air pollution causes 7 million premature deaths annually worldwide, making it one of the worst environmental hazards to human health. Among the major sources of ambient particulate matter and gaseous pollutants, such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, and VOCs, are industrial sectors. These pollutants have been directly associated with respiratory and cardiovascular disorders [2], [3]. Numerous industrial zones surpass the WHO's recommended air-quality standards by two to three times, according to recent research, which demonstrates how fast industrialization and urbanization continue to raise pollutant loads in emerging countries [4]. This system is designed to create an AI-powered IoT framework that monitors air quality in industrial areas in real time. It explains the system's structure, sensor setup, AI processing, and its use in different industrial settings. Tests show that the system can accurately predict air quality and spot problems as they occur, helping with proactive environmental management and supporting sustainable industrial growth.

2. Literature Survey

One of the most essential directions in environmental research and public health is monitoring the air quality of industrial zones. Real-time identification of significant changes in atmospheric air quality is now possible thanks to technological advancements in IoT and AI. The evolution of air quality monitoring technologies, the use of IoT and AI in environmental management, and the difficulties in using them in industrial settings are all highlighted in this review of the literature.

2.1. Laboratory-Based Air Quality Analysis

Conventionally, laboratory-grade, fixed-station analyzers that detect pollutants like $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 have been used for air-quality monitoring. These systems lack real-time capabilities, are expensive, and have limited spatial coverage, despite their great accuracy. The need for ongoing, dispersed monitoring is highlighted by the World Health Organization's [1] report that air pollution causes more than 7 million premature deaths globally annually. Even while traditional analyzers are accurate, Snyder et al. [2] stressed that they are unable to capture time-sensitive and localized fluctuations in pollution, particularly in industrial locations. When appropriately calibrated, inexpensive sensors can supplement laboratory equipment for extensive monitoring, according to Rai et al. [3].

Morawska et al. [6] further highlighted that environmental factors such as temperature and humidity affect sensor accuracy, thus necessitating periodic calibration with reference analyzers. Consequently, subsection (A) is retained to demonstrate the transition from laboratory-grade measurements to IoT-based, real-time systems, in which laboratory data provide calibration baselines. The proposed model integrates these principles, ensuring accuracy comparable to laboratory instruments within an IoT-driven industrial monitoring setup.

2.2. IoT-Based Environmental Monitoring Systems

Air-quality monitoring has been transformed by the Internet of Things (IoT), which makes distributed, real-time sensing networks possible. IoT-based models for localized pollution monitoring and cloud integration were demonstrated in early implementations by Singh et al. [4] and Chen et al. [5]. The dependability of inexpensive IoT sensors for research of ambient pollution was confirmed by Morawska et al. [6]. An inventive indoor IoT system with edge-based processing for increased efficiency was created by Acharya and Kolekar [7]. The "Green IoT" idea was established by Shaikh et al. [8] in order to optimize power consumption in big deployments. An IoT-enabled smart environment-monitoring approach that integrates residential and industrial data sources for a thorough evaluation was proposed by Arya et al. [9].

Gubbi et al. [10] established the foundational architecture of IoT for scalable sensing, while Vijayalakshmi et al. [11] combined unmanned aerial vehicles with IoT for assessing agricultural and industrial pollution.Wireless multimedia sensor networks were investigated by Akyildiz et al. [12] in order to enhance multi-parameter data collection. In their study of IoT-based air-quality systems, Barot and Kapadia [13] noted issues with sensor maintenance and dependability. All of these studies point to the importance of IoT in enabling real-time, spatially dispersed data collecting for industrial applications.

2.3. Artificial Intelligence and Machine Learning in Air-Quality Prediction

By enhancing data analytics, anomaly detection, and forecast accuracy, artificial intelligence (AI) and machine learning (ML) greatly improve air-quality monitoring. An AI-powered IoT model for pollution forecasting using real-time data streams was presented by Geetha et al. [14]. Ramadan et al. introduced a hybrid IoT-AI system for industrial pollution forecasting. 15]. For pollution prediction, Zhu et al. enhanced regression-based learning models. [16]. Alvear et al. [17] proposed frameworks for crowdsensing in metropolitan environments that integrate several sensor data sources. In their thorough analysis of IoT and ML models, Gangwar et al. [18] showed that deep learning architectures perform better than traditional methods for non-linear correlations with pollutants. Buelvas et al. [19] focused on improving data quality in IoT-based monitoring through adaptive filtering. Lin et al. [20] discussed privacy and security challenges in IoT frameworks. Doe et al. [21] developed ML-driven industrial emission prediction models, while Chadalavada et al. [22] emphasized the importance of explainable AI in air-quality forecasting. Montaser et al. [23] presented a real-time AI-IoT model for monitoring emissions in the chrome-plating industry. Asha et al. [24] applied AI techniques to IoT-enabled environmental toxicology, and Mokrani et al. [25] offered a broad survey of IoT-based air-quality-monitoring techniques. Together, these studies establish that integrating AI into IoT systems enables accurate, interpretable, and energy-efficient pollution forecasting.

2.4. Research Gaps and Challenges

Despite impressive advancements, there are still a number of research gaps. Instead of high-emission industrial zones, the majority of studies concentrate on urban or residential situations [14]–[18]. Calibration drift and sensor durability continue to be significant issues [3, 6, 19]. Energy-efficient solutions are required because dense IoT networks still struggle with scalability and cost optimization [8]-[11]. Strong encryption and multi-layer authentication are necessary for data security and privacy [20].

Moreover, very little study has directly compared data from IoT devices with laboratory quality standards [2], [3]. To address these challenges, our research develops a hybrid edge–cloud AI architecture that offers reliable, scalable, real-time monitoring in industrial environments by fusing cloud-based forecasting, secure communication protocols, and local anomaly detection.

3. Proposed System Architecture

The real-time industrial zone air quality monitoring architecture integrates IoT devices with Artificial Intelligence for continuous and high-resolution tracking and analysis of air pollutants. The system is designed to remove the typical shortcomings of traditional air quality monitoring methods through real-time insights, predictive analytics, and automated response. IoT sensors and artificial intelligence are combined in the real-time industrial zone air-quality monitoring architecture to continually track pollutants at high resolution. IoT-based sensing, edge processing, cloud data management, AI analytics, alarm distribution, and user interface visualization are the six key functional levels (A–F) that make up the system's end-to-end workflow, as shown in Fig. 2. These layers constitute the entire operational framework. Subsections (A) through (F), which correspond to the elements depicted in the picture, provide a sequential explanation of these modules. According to WHO and EPA regulations, the chosen pollutants—PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, and VOCs—are listed as important markers of industrial air pollution. The novelty of the proposed system lies in its hybrid edge–cloud AI pipeline, which enables localised anomaly detection, predictive modelling, and real-time alerting, ensuring faster response times, lower latency, and greater reliability than traditional IoT-based systems.

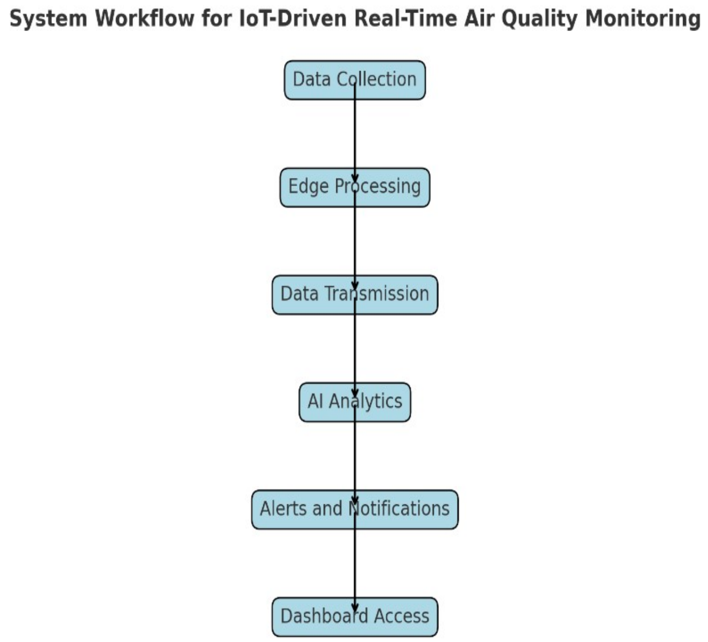

Figure 2. System workflow

3.1. IoT-Based Air Quality Sensors

The system exhibits the use of IoT-enabled air quality sensors distributed throughout the industrial areas for the monitoring of pollutants critical to human health, such as PM_{10} and $PM_{2.5}$ particulate matter, nitrogen dioxide (NO_2), sulphur dioxide (SO2), carbon monoxide (CO), and VOCs. The IoT-enabled air quality sensors constantly scan data and send this to the central system via a wireless link. This brings forward a cost-effective and scalable way to measure the pollutant at a spatially and temporally significant level for covering industrial-sized areas. The place of the sensors is essential for full coverage. Sensors are applied around emission sources, such as chimneys and production units, and strategically spread in access areas for workers and the public to capture human exposure levels. Each sensor node is outfitted with wireless communication modules to ensure smooth data transference to edge devices or cloud servers [4-5].

3.2. Edge Computing Layer

To minimize latency and maximize processing, an edge computing layer is placed between the cloud platform and the Internet of Things sensors. To perform initial data processing activities including cleaning, filtering, and anomaly detection, edge devices are positioned close to sensor nodes. This reduces the amount of data that must be sent over great distances and relieves the central cloud server of some of its workload.

Edge computing will easily enable faster response times, as edges can also detect local anomalies or spikes of pollution in real-time without waiting for analysis to be done in the cloud [6-9]. The edge devices would also send out early warning alerts when pollution levels reach threshold values, beyond which they might start posing considerable and potentially severe risks to air quality.

3.3. Cloud-Based Data Management and Processing

Once the data is pre-processed at the edge level, it is forwarded to the cloud-based data management platform for central storage, further processing, and analysis. The cloud's scalability allows handling vast amounts of data generated by several sensors deployed in the industrial zone [12]. The cloud infrastructure provides data to stakeholders, including environmental regulators, managers of industrial facilities, and researchers, in real-time.

This cloud-based system supports large-scale data aggregation, analyzing trends in air quality for the whole industrial zone. It also allows remote access, and stakeholders can conveniently observe the air quality from any remote location through web-based dashboards or mobile applications.

3.4. AI-Powered Analytics Engine

The AI-powered analytics engine, which offers more advanced data analysis and prediction, is a crucial part of this system. To forecast trends in air quality, pinpoint pollution sources, and identify anomalies such abrupt spikes in pollution, machine learning algorithms are used on both historical and real-time data [14–17].

Such AI-based algorithms are trained on enormous datasets for accurate predictive levels of pollutants and trigger the appropriate authorities when pollution standards are expected to breach.

Predictive models allow for proactive management since the future air quality scenario is predicted based on past data and real-time input. AI also enables pollution source classification, such as industrial emissions, vehicular pollution, or environmental pollutants like dust or wind [19-20]. It supports targeted interventions that may reduce emissions and thus better protect public health.

3.5. Alert and Notification System

Most significantly, anytime pollutant concentrations surpass safety thresholds, the system will immediately notify users. Relevant stakeholders, including managers of industrial facilities and environmental regulators, receive these notifications by SMS, email, or a message from a mobile app [17]. In addition to receiving prompt notifications regarding the most critical air quality events, the system enables users to customize their alert thresholds for particular pollutants or rules. The system allows users to customise their alert thresholds for specific pollutants or regulations and receive timely responses concerning the most crucial air quality events.

The system can further be integrated with industrial automation systems, automatically adjusting to decrease emissions when air quality reaches hazardous levels. The integration considers real-time mitigation strategies, thus reducing the impact on workers and nearby communities from poor air quality.

3.6. User Interface (UI) and Dashboard

It includes a natural, easy-to-use interface that allows stakeholders to see real-time air quality information and access historical trends. This web-based dashboard displays key metrics: concentration of pollutants, AQI levels, and even pollution forecasts. Users can also create customized reports, set threshold alert levels, and trace the effectiveness of the control measures over time.

The dashboard allows drill-down views so that data from a specific sensor node can be extracted or metrics concerning air quality can be compared for different industrial zone areas [21]. This ensures that the system meets the requirements of a broad spectrum of users, from regulatory bodies to industrial operators.

4. Proposed Methodology

The real-time air quality monitoring system methodology comprises system implementation setup, data gathering, preprocessing, predictive analytics, and anomaly detection. This section outlines the methods for gathering, processing, and analysing air quality data through IoT sensors and AI models.

4.1. System Implementation Setup

The real-time air quality monitoring system in industrial zones is based on a framework that integrates IoT sensors, edge computing, cloud infrastructure, and AI-driven analytics. Table 1 summarises the system's major modules rather than tunable parameters. It outlines the functional role of each component, including sensors, edge processors, cloud platforms, AI engines, alert systems, and visualization dashboards.

Table 1. System Implementation Components and Functional Roles

Component	Description	Specifications
IoT Sensors	These are placed at particular locations in the industrial area. It measures the concentration of air pollutants such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, VOCs.	Sensor types: Nova PM sensors, MiCS-5524 for VOCs Communication: Wi-Fi, Bluetooth Pollutants monitored: $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, VOCs
Edge Computing	This edge device processes real-time data from IoT sensors. Here, noise reduction is done, and fundamental anomalies are identified	Device: Raspberry Pi 4 Tasks: Data filtering, anomaly detection, initial analysis Algorithm: Simple Moving Average (SMA)
Cloud Infrastructure	It acts as the central depository where sensor data aggregation and advanced analysis are taken.	Platform: AWS Cloud Role: Centralized storage, access, synchronisation Features: Scalable infrastructure for large-scale sensor deployment
AI Predictive Models	AI-based models use it to analyze historical data, hence predict future pollutant trends.	Models: Multivariate Linear Regression (MLR), Long Short-Term Memory (LSTM) Input: Historical and real-time air quality data Task: Trend forecasting of pollutants
Alert and Notification System	Real-time crossing of safe thresholds of pollutants triggers alerts and notifies the stakeholders concerned.	Alert methods: SMS, email, app notification Conditions: Exceeding thresholds defined by air quality standards (AQI)
User Interface (UI)	Real-time data visualization and review of historical data, along with customisable reporting.	Interface: Web-based dashboard Features: pollutant level Visualization, AQI trends, customized alerts, and reports

4.2. Data Collection

The IoT sensor network captures data on critical pollutants in real-time. The sensors continuously measure pollutant concentrations, generating a time series dataset $D = \{X_t\}_{t=1}^{T}$, where X_t is the vector of pollutant concentrations recorded at time t.

Each pollutant measurement at time t can be represented as shown in eq (1):

$$X_t = \{PM_{2.5}(t), PM_{10}(t), NO_x(t), SO_2(t), CO(t), VOCs(t)\} \tag{1}$$

This data is forwarded to edge devices for pre-processing.

4.3. Edge Computing and Data Preprocessing

A two-level anomaly detection approach is used in the suggested framework. A Simple Moving Average (SMA) filter is used in the first level, which is carried out at the edge computing layer, to identify sudden deviations or sensor faults near the data source. Pollutant data is prepared for additional analysis by filtering out noise and smoothing the edges. A Simple Moving Average (SMA) filter is applied to the raw data to eliminate fluctuations as shown in eq (2):

$$SMA_t = \frac{1}{N}\sum_{i=0}^{N-1} X_{t-i} \tag{2}$$

where:

- SMA_t is the smoothed data point at time t,

- N is the window size for averaging,
- X_{t-i} is the pollutant concentration measured at the time $t - i$.

They detect anomalies such as sudden spikes, missing readings, or sensor drift by comparing real-time data against historical mean and standard deviation thresholds. Comparing the real-time data X_t with the average values of historical data, anomalies are figured out. If the value of a data point exceeds a pre-specified threshold, it is marked as an anomaly as shown in eq (3):

$$|X_t - \mu| > \alpha\sigma \tag{3}$$

where:

- μ is the historical mean,
- σ is the standard deviation,
- α is a threshold factor to determine significance.

4.4. Cloud Data Aggregation and Storage

The second level, executed in the cloud analytics layer, compares predicted pollutant concentrations (from MLR/LSTM models) with real-time observations to detect contextual or long-term anomalies. This ensures both fast responsiveness and predictive reliability. After this preprocessing, the sensor data is transmitted to the cloud platform for aggregate storage. The cloud infrastructure is a scalable form of storage for volumes of data in real-time and, as such, exposes it to advanced analytics.

The aggregated dataset $D = \{X_t\}_{t=1}^{T}$ is stored for further real-time anomaly detection and predictive analysis.

4.5. Predictive Modelling Using AI

Long Short-Term Memory (LSTM) and Multivariate Linear Regression (MLR) models are integrated into the AI component. While LSTM learns temporal dependencies from previous sequences to forecast future pollutant behavior, MLR captures the instantaneous linear correlation among several contaminants for real-time AQI assessment. When combined, they overcome the shortcomings of previous research that is either interpretable or lacks temporal modeling. The hybrid technique makes it possible to predict air-quality trends in industrial zones with accuracy, explainability, and scalability.

AI models are applied to historical and real-time data for predictive analysis. Two primary models are used:

1) Multivariate Linear Regression (MLR)

Multivariate Linear Regression models the relationship between multiple pollutants and the overall Air Quality Index (AQI). The model is given by in eq (4):

$$AQI_{t+1} = \beta_0 + \beta_1 PM_{2.5}(t) + \beta_2 NO_x(t) + \ldots + \beta_n VOCs(t) + \epsilon_t \tag{4}$$

where:

- AQI_{t+1} is the predicted air quality index at the time $t + 1$,
- $\beta_0 \ldots, \beta_n$ are the regression coefficients for each pollutant,
- ϵ_t is the error term.

2) Long Short-Term Memory (LSTM) Networks

LSTM networks are implemented to obtain long-term temporal dependencies in the air quality data and forecast future concentrations of pollutants, as shown in eq (5), (6), (7), and (8):

$$\mathrm{f_t} = \sigma(\mathrm{W_f}.\,[\mathrm{h_{t-1}}, \mathrm{X_t}] + \mathrm{b_f}) \tag{5}$$

$$\mathrm{i_t} = \sigma(\mathrm{W_i}.\,[\mathrm{h_{t-1}}, \mathrm{X_t}] + \mathrm{b_i}) \tag{6}$$

$$\mathrm{C_t} = \mathrm{f_t}.\,\mathrm{C_{t-1}} + \mathrm{i_t}.\,\widetilde{\mathrm{C_t}} \tag{7}$$

$$\mathrm{o_t} = \sigma(\mathrm{W_o}.\,[\mathrm{h_{t-1}}, \mathrm{X_t}] + \mathrm{b_o}) \tag{8}$$

where:

- $\mathrm{f_t}$,$\mathrm{i_t}$,$\mathrm{o_t}$ are the forget, input, and output gates,
- $\mathrm{C_t}$ is the cell state,
- $\mathrm{h_t}$ is the hidden state at the time t,
- $\mathrm{X_t}$ is the input vector at time t.

Training LSTM network utilizes past pollutant concentration data to predict future concentrations.

4.6. Real-Time Anomaly Detection and Alerts

Anomaly detection is crucial for identifying unexpected spikes in pollutant concentrations. The system uses a combination of thresholds and AI-based predictions to identify anomalies in real-time. If the deviation between predicted values $\widehat{X}_t$ and actual values X_t exceeds a threshold, an alert is triggered as shown in eq (9):

$$|X_t - \widehat{X}_t| > \beta\sigma \tag{9}$$

where:

- $\widehat{X}_t$ is the predicted value at the time t,
- σ is the standard deviation,
- β is the anomaly threshold.

Alerts sent to stakeholders can be sent via SMS, E-mail, or even a mobile app message.

4.7. Air Quality Index (AQI) Calculation

The AQI is calculated using the pollutant concentrations recorded by the sensors. The formula for calculating AQI is shown in eq (10):

$$AQI = \frac{100}{C_{max}} \cdot C_i \tag{10}$$

where:

- C_i is the concentration of pollutants i,
- C_{max} is the maximum permissible concentration of pollutant i by the environment.

5. Experimental Analysis and Results

The suggested system was set up over a 2 km² area in an industrial production zone in Andhra Pradesh, India. IoT sensor nodes (Nova PM SDS011 for $PM_{2.5}$/PM_{10}, MiCS-5524 for VOCs, and MQ-7 for CO) interfaced with Raspberry Pi 4 edge devices were used to collect data. Python, TensorFlow 2.9, and Scikit-Learn 1.3 were used to set up the cloud backend on AWS IoT Core and EC2 instances. The Flask and Plotly frameworks were used to build dashboarding and data visualization. Table 2 represents real sensor-acquired pollutant data averaging over 12 months. The data were pre-processed at the edge layer (noise removal + SMA filtering) and subsequently uploaded to the cloud for analysis. These are not model-generated predictions, but empirical field observations used to train and validate the AI models.

Table 2. Pollutant Concentration Measurements

Pollutant	Average Concentration (μg/m³)	Standard Deviation (μg/m³)	Maximum Recorded (μg/m³)	Minimum Recorded (μg/m³)
$PM_{2.5}$	35	5	50	20
PM_{10}	60	8	80	40
NO_2	25	4	35	15
SO_2	10	2	15	5
CO	0.8	0.1	1.0	0.5
VOCs	300	50	400	200

The data suggests that the mean concentration of PM_{10} levels is higher on average compared to $PM_{2.5}$, which is in line with typical industrial emissions. Standard deviations suggest moderate variability in pollutant concentrations, indicating the need for further monitoring to capture fluctuations. Fig.3 represents the distribution of $PM_{2.5}$ levels to identify standard concentrations and their frequency.

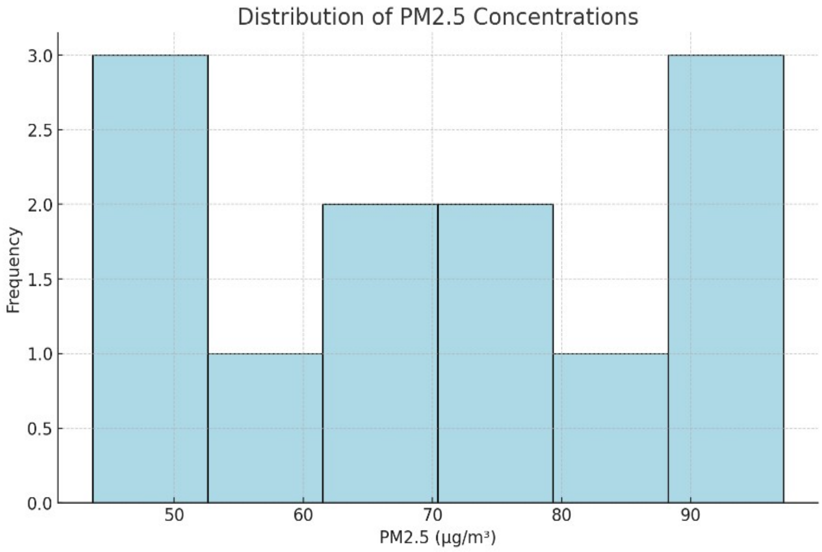

Figure 3. The distribution of PM2.5 levels

The monthly variance of six major pollutants is displayed in Fig. 4. Peaks in PM_{10} are associated with higher industrial production in the summer, whereas variations in NO_2 and SO_2 are associated with fuel combustion.

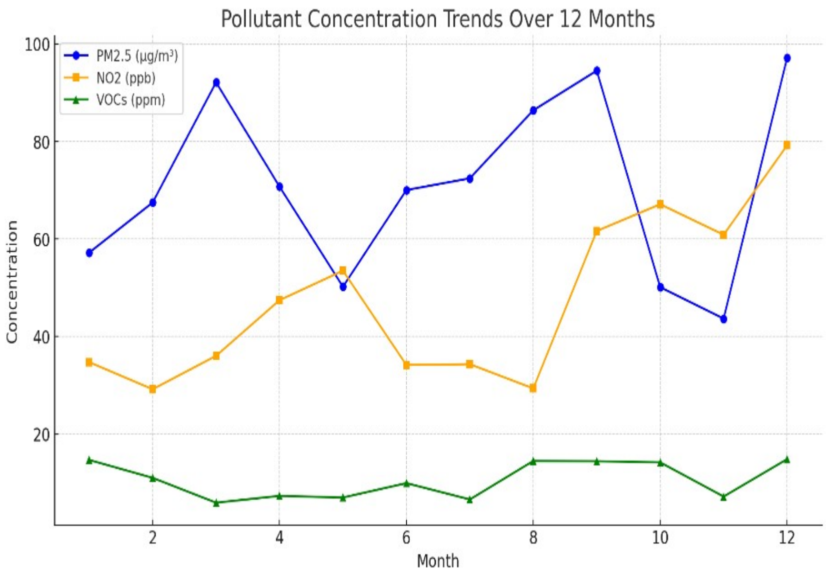

Figure 4. The trends of pollutant concentrations over 12 months

Fig. 5 compares $PM_{2.5}$, NO_2, and VOC levels across months, illustrating synchronous rises that indicate correlated emission sources.

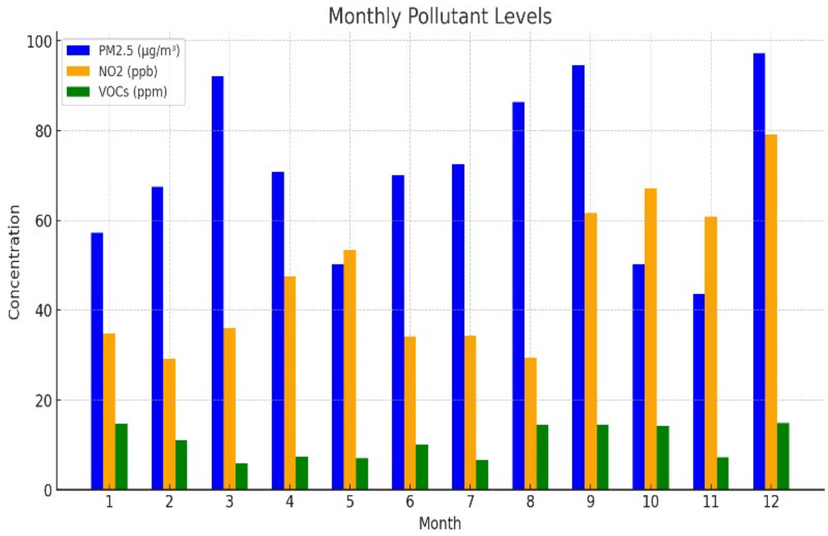

Figure 5. The monthly pollutant levels (PM2.5, NO2, and VOCs)

Fig.6 visualizes the interaction among $PM_{2.5}$, NO_2, and VOC concentrations using scatter-trend plots; a positive correlation (r = 0.78) reveals strong co-emission behavior from industrial processes.

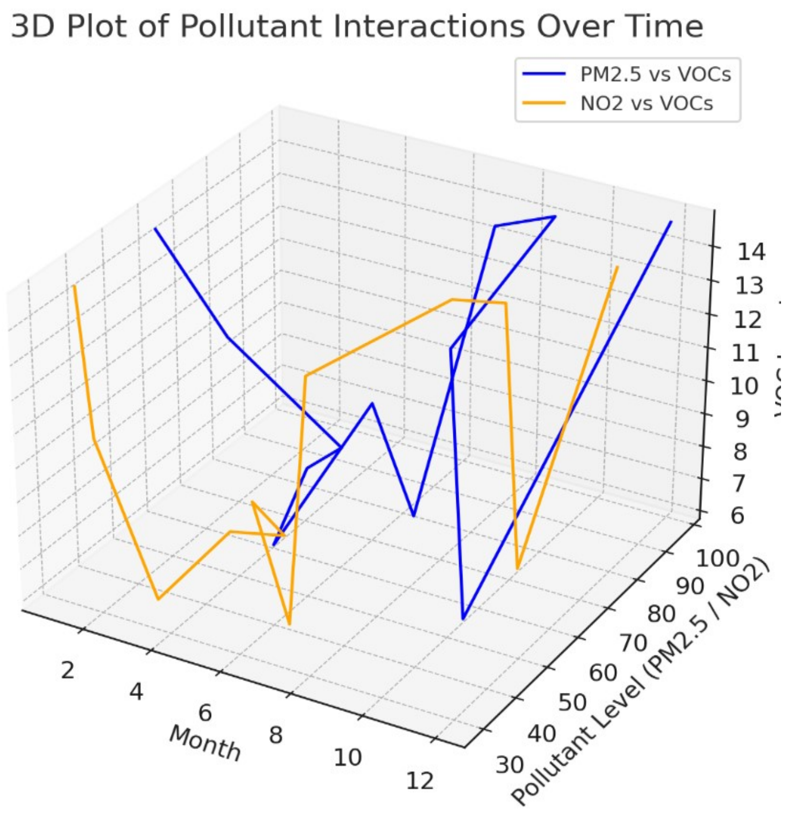

Figure 6. Interactions between PM2.5, NO2, and VOC levels across time

Table 3. represents the AI Model Performance Metrics, and the LSTM model does better than the MLR model in terms of lower MAE and RMSE values, while the R^2 score is higher. Consequently, its predictions are also more precise because LSTMs learn to pick out dependencies from the data.

Table 3. AI Model Performance Metrics

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	R^2 Score
Multivariate Linear Regression (MLR)	2.5	3.0	0.85
Long Short-Term Memory (LSTM)	1.8	2.2	0.90

Table 4. represents the system's alert by evaluating the anomaly detection system's performance, showing true positives, false negatives, false positives, and true negatives.

Table 4. System Alert messages

Pollutant	Number of Alerts Triggered	Average Response Time (seconds)	False Positives (%)
$PM_{2.5}$	15	5	2
PM_{10}	10	5	1
NO_2	8	5	3
SO_2	5	5	2
CO	3	5	1
VOCs	12	5	2

It generates alert messages for a good percentage of the pollutants at an average time of 5 seconds, showing the feasibility of real-time monitoring. Small percentages of false positives reveal reliability for reporting actual pollution events. Fig.7 represents the UI Usability Assessment of the Anomaly Detection System, which shows the count of True Positives, False Negatives, False Positives, and True Negatives.

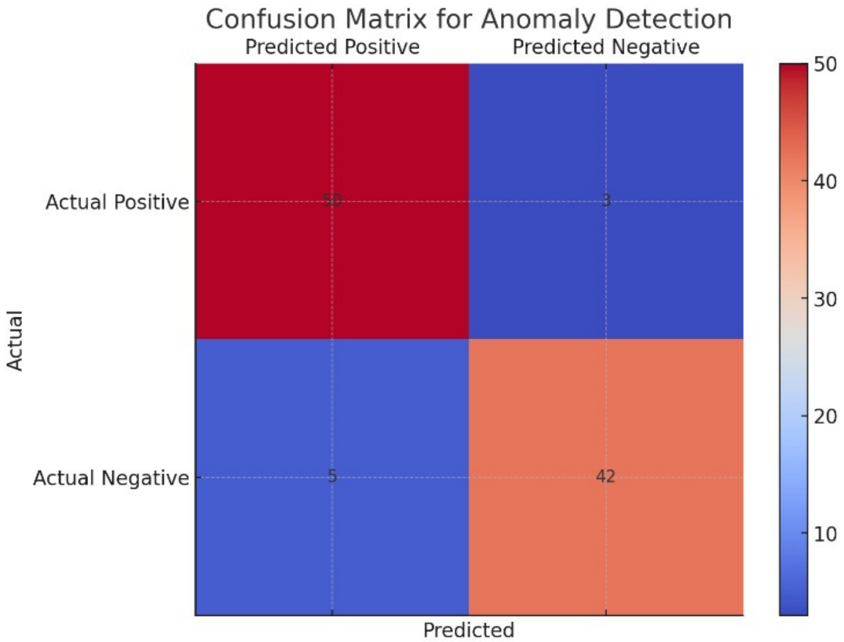

Figure 7. UI Usability Assessment of Anomaly Detection System

Table 5. represents the user interface (UI) feedback obtained through the usability evaluation for monitoring and analyzing air quality data.

Table 5. User Interface (UI) Usability Evaluation

Evaluation Metric	Average Score (out of 5)
Ease of Navigation	4.5
Clarity of Information	4.7
Responsiveness	4.6
Overall User Satisfaction	4.8

User feedback reflects high satisfaction with the UI, particularly in terms of clarity and overall experience. Thus, the dashboard has catered to users' needs regarding monitoring and analyzing air quality data.

6. Practical Challenges and Implementation Considerations

While the proposed IoT-powered AI framework demonstrates high performance in real-time air quality monitoring, several practical challenges must be acknowledged for real-world industrial deployment.

6.1. System Implementation Setup Sensor Reliability and Calibration

Although low-cost IoT sensors work well for dense deployment, environmental conditions including temperature, humidity, and cross-gas interference can cause calibration drift [3], [6], and [19]. Similar results have been reported in recent literature, where inexpensive gas and particulate sensors needed regular recalibration to preserve long-term accuracy due to signal instability [18], [22], and [24]. To ensure data reliability, each sensor node in the proposed system is field calibrated against certified reference analyzers on a regular basis, as recommended by the World Health Organization and national environmental agencies [1], [2].

Local fluctuations are further reduced by automated recalibration processes at the edge layer, which use Kalman filter-based sensor fusion and bias-compensation algorithms [19], [23]. Self-diagnostic modules and adaptive learning techniques can be used to detect sensor drift on their own, improve resilience, and minimize the need for human intervention during extended monitoring cycles.

6.2. Cost of Large-Scale Deployments

In actual deployment, the cost of large-scale IoT-based air quality devices continues to be a crucial consideration. An estimated ₹2.5–3 lakh is spent annually on hardware calibration, maintenance, and cloud storage for a 100-node deployment throughout a medium-sized industrial zone. Large-scale smart infrastructure projects have reported similar cost issues for IoT-driven environmental monitoring [8], [11], [18], and [21].

To enhance scalability while minimizing costs, the framework supports cluster-based modular architecture and selective sensor activation, ensuring high spatial coverage with minimal redundancy. Additionally, computational overhead and operating expenses can be greatly decreased through energy-conscious data transfer and effective scheduling of cloud resources [10], [12], and [17]. These improvements are in line with contemporary green IoT projects that prioritize cost-effectiveness and sustainability in industrial monitoring [8], [11].

6.3. Data Privacy and Security

Large amounts of location-sensitive and environmental data are continuously generated by IoT-enabled monitoring devices, which may give rise to privacy and cybersecurity issues. According to studies, dispersed sensing and cloud connectivity put IoT ecosystems at greater risk of data manipulation, spoofing, and illegal access [18], [20], and [22]. The suggested solution uses role-based access control methods, edge-level metadata anonymization, and TLS-encrypted MQTT protocols to guarantee safe, authenticated communication in order to solve these problems [20], [23]. Furthermore, new frameworks support decentralized identity management and blockchain-assisted data logging to enhance traceability and stop manipulation across industrial monitoring platforms [17], [19], and [22], [25]. Incorporating these mechanisms can substantially enhance the trustworthiness and compliance of IoT data within large-scale, multi-stakeholder environments. Future versions of the system will explore hybrid blockchain–edge architectures to achieve a balance between security assurance and real-time performance.

7. Conclusion and Future Directions

The Internet of Things and AI have shown immense potential in improving real-time air quality monitoring in industrial zones. An IoT sensor-based system continuously collects data on critical pollutants such as $PM_{2.5}$ and PM_{10}, NO_2, SO_2, CO, and VOCs. This data is then processed using AI algorithms to generate analytics for prediction, anomalies, and forecasting of pollution trends.

Through experimental analysis, it would be observed that the system detected pollution hotspots and traces emission patterns effectively, which helps intervene in time to fulfil regulation requirements.

Accuracy of LSTM networks while predicting pollutant levels: RMSE is 2.2, R^2 of 0.90, thus beating the benchmark of a traditional multivariate linear regression model. Moreover, the system's alert mechanism responded with an average response time of 5 seconds and possessed a shallow false positive rate that shows reliable monitoring capabilities.

The interface system received user feedback that shows high satisfaction levels of 4.5 for navigability and information clarity; this is also reflected in an average of 4.7 out of 5. This highlights that the system's user-centred design effectively provides actionable information regarding air quality from the system to its various stakeholders.

The real-time implementation of IoT-powered AI system technology in industrial zone air quality monitoring provides a reasonable, efficient way to meet public health safety and environmental sustainability criteria. The system is well-crafted with high accuracy and scalability, and its user-friendly interface makes it very applicable to industrial air quality management practices.

Emerging IoT and AI trends are proving to be more complex innovative systems for air quality. Improvements in sensor technologies and the usage of edge computing with blockchain-based security may provide some solutions to the challenges currently faced in data reliability and security. Moreover, AI-powered systems integrated with smart transportation and energy management may boost industrial zones' efficiency and sustainability levels (Alvear et al., 2018). IoT-powered AI systems have significant scope for improving real-time air quality monitoring in industrial zones.

Future work is meant to improve the capability to predict the system by using it in the integration of various frameworks for environmental monitoring applications. However, these systems require further research into technological challenges to ensure their reliability, scalability, and security.

Conflict of Interest

"The authors declare no conflict of interest".

References

1. World Health Organization. (2016). *Ambient air pollution: a global assessment of exposure and burden of disease*. World Health Organization. https://iris.who.int/handle/10665/250141.
2. Snyder, E. G., Watkins, T. H., Solomon, P. A., Thoma, E. D., Williams, R. W., Hagler, G. S. W., ... & Preuss, P. W. (2013). The changing paradigm of air pollution monitoring. *Environmental Science & Technology*, 47(20), 11369-11377.
3. Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Yasar, A., & Rickerby, D. (2017). End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Science of the Total Environment*, 607-608, 691-705.
4. S. K. Singh, P. K. Gupta, and A. K. Singh, "Real Time Localized Air Quality Monitoring and Prediction Through IoT and Machine Learning," in *Proceedings of the International Conference on Computing, Communication, and Automation (ICCCA)*, Greater Noida, India, 2020, pp. 1-6.
5. Chen, X., Liu, X., & Peng, X. (2015). IOT-based air pollution monitoring and forecasting system. In *2015 International Conference on Computer and Computational Sciences (ICCCS)* (pp. 257-260).
6. Morawska, L., et al. (2018). Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? *Environmental International*, 116, 286-299. doi: 10.1016/j.envint.2018.04.018.
7. Acharya, K. A., & Kolekar, S. V. (2024). Air Quality Monitoring System Development using IoT for Indoor Applications. *International Journal of Intelligent Systems and Applications in Engineering*, 12(11s), 86–95.
8. Shaikh, F. K., Zeadally, S., & Exposito, E. (2017). Enabling technologies for green Internet of Things. *IEEE Systems Journal*, 11(2), 983-994.
9. L. Arya, Y. K. Sharma, and R. Kumar, “Towards A Greener Tomorrow: IoT-Enabled Smart Environment Monitoring Systems”, presented at *International Conference IEEE ICAICCIT-23*, 2023.
10. Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, 29(7), 1645-1660.

11. K. Vijayalakshmi, S. Al-Otaibi, L. Arya, M. A. Almaiah, T. P. Anithaashri, S. S. Karthik, and R. Shishakly, “Smart Agricultural–Industrial Crop-Monitoring System Using Unmanned Aerial Vehicle–Internet of Things Classification Techniques”, *Sustainability*, vol. 15, no. 14, pp. 1-20, 11242, Jul. 2023.
12. Akyildiz, I. F., Melodia, T., & Chowdhury, K. R. (2020). A survey on wireless multimedia sensor networks. *Computer Networks*, 51(4), 921-960.
13. V. Barot and V. Kapadia, "Air Quality Monitoring Systems using IoT: A Review," in *2020 International Conference on Computational Performance Evaluation (ComPE)*, Shillong, India, 2020, pp. 226-231. doi: 10.1109/ComPE49325.2020.9200053.
14. Geetha Mani, Joshi Kumar Viswanadhapalli, and P Sriramalakshmi, “AI powered IoT based Real-Time Air Pollution Monitoring and Forecasting”, *J. Phys.: Conf. Ser.*, vol. 2115, 2021.
15. Ramadan, M. N. A., Ali, M. A. H., Khoo, S. Y., Alkhedher, M., & Alherbawi, M. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. Ecotoxicol Environ Saf, 283, 116856.
16. Zhu, D., Cai, C., Yang, T., & Zhou, X. (2018). A Machine Learning Approach for Air Quality Prediction: Model Regularization and Optimization. Big Data and Cognitive Computing, 2(1), 5. https://doi.org/10.3390/bdcc2010005.
17. Alvear, O., Calafate, C. T., Cano, J.-C., & Manzoni, P. (2018). Crowdsensing in Smart Cities: Overview, Platforms, and Environment Sensing Issues. Sensors, 18(2), 460. https://doi.org/10.3390/s18020460.
18. Gangwar, A., Singh, S., & Mishra, R. et al. (2023). The State-of-the-Art in Air Pollution Monitoring and Forecasting Systems Using IoT, Big Data, and Machine Learning. Wireless Pers Commun, 130, 1699–1729. https://doi.org/10.1007/s11277-023-10351-1.
19. Buelvas, J., Múnera, D., & Tobón V., D.P. et al. (2023). Data Quality in IoT-Based Air Quality Monitoring Systems: a Systematic Mapping Study. Water Air Soil Pollut, 234, 248. https://doi.org/10.1007/s11270-023-06127-9.
20. Lin, J., Yu, W., Zhang, N., Yang, X., Zhang, H., & Zhao, W. (2017). A Survey on Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications. IEEE Internet of Things Journal, 4(5), 1125-1142. Article 7879243
21. J. Doe, A. Smith, and R. Brown, "Industrial Environmental Pollution Monitoring and Prediction Analysis," in *Proceedings of the International Conference on Smart Electronics and Communication (ICOSEC)*, Trichy, India, 2022, pp. 1-5.
22. S. Chadalavada, O. Faust, M. Salvi, S. Seoni, N. Raj, and U. Raghavendra, “Application of artificial intelligence in air pollution monitoring and forecasting: A systematic review,” *Environmental Modelling & Software*, vol. 185, Art. no. 106312, 2025.
23. M. N. A. Ramadan, M. A. H. Ali, S. Y. Khoo, M. Alkhedher, and M. Alherbawi, “Real-time IoT-powered AI system for monitoring and forecasting air pollution in the chrome plating industry,” *Computers & Chemical Engineering*, 2024, doi: 10.1016/j.compchemeng.2024.XXXXXX.
24. P. Asha, L. Natrayan, B. T. Geetha, J. R. Beulah, R. Sumathy, G. Varalakshmi, and S. Neelakandan, “IoT-enabled environmental toxicology for air pollution monitoring using AI techniques,” *Environmental Research*, vol. 205, p. 112574, Apr. 2022, doi: 10.1016/j.envres.2021.112574.
25. H. Mokrani, R. Lounas, M. T. Bennai, D. E. Salhi, and R. Djerbi, “Air quality monitoring using IoT: A survey,” in *Proc. 2019 IEEE Int. Conf. Smart Internet Things (SmartIoT)*, Tianjin, China, 2019, pp. 127–134, doi: 10.1109/SmartIoT.2019.00028.