Artificial Intelligence in Air Quality Assessment: A Comprehensive Review of Anomaly Detection Methods for Environmental Sustainability

Dileep M R[1]*, Vivekanandam Balasubramaniam*[2]*, Rupali Atul Mahajan*[3]

[1]Licoln University College, Malaysia.

[1]Department of Master of Computer Applications,

Nitte Meenakshi Institute of Technology, Yelahanka,

Bengaluru, Karnataka, India.

[2]Faculty of Computer Science and Multimedia,

Lincoln University College, Malaysia.

[3]Department of Data Science, Vishwakarma Institute of Information Technology, Pune, India

Lincoln University College, Malaysia.

[1]dileep.kurunimakki@gmail.com

[2]vivekanandam@lincoln.edu.my

[3]rupali.mahajan@viit.ac.in

Abstract: Air quality deterioration presents serious obstacles to public health, economic growth, and environmental sustainability, especially in areas that are rapidly urbanizing. A thorough analysis of artificial intelligence (AI) applications in air quality assessment and anomaly detection (AQAD) is presented in this paper, with a focus on clever strategies to lessen the negative effects of air pollution and advance environmentally friendly practices. The monitoring and assessment of air quality parameters, such as particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), and carbon monoxide (CO), has been completely transformed by the combination of cutting-edge sensor technology, data analytics, and machine learning algorithms. To differentiate between typical fluctuations in air quality and anomalous occurrences like pollutant spikes and emissions anomalies, AI-driven systems use statistical analysis, pattern recognition, and machine learning techniques, including time-series analysis, clustering algorithms, and anomaly detection models like Isolation Forest, One-Class Support Vector Machine (SVM), and Neural Networks.

Recent advancements include systems such as AirSense, which uses AI-based anomaly detection and repair procedures to improve the reliability of air quality monitoring data collected from low-cost sensor networks. AI can also detect hazardous material levels and contamination events by identifying patterns, trends, and anomalies in data via machine learning and data mining. This review emphasizes the importance of artificial intelligence (AI) in improving the accuracy and efficiency of air quality monitoring systems, enabling real-time anomaly detection, and supporting proactive measures to address environmental challenges. AI integration in AQAD systems is a significant step toward achieving environmental sustainability and protecting public health.

Keywords: Air Quality Assessment, Anomaly Detection, Environmental Sustainability, Intelligent Approaches.

Introduction

Anomaly detection in air quality data has received a lot of attention, owing to the growing importance of environmental health and urban sustainability. In recent years, AI-based approaches have been widely used to improve the accuracy and efficiency of air quality monitors. The purpose of this literature survey is to provide an overview of key AI-based techniques for anomaly detection in air quality data, with a focus on machine learning, deep learning, and hybrid systems.

Several studies have looked into the use of machine learning algorithms for air quality monitoring. Amini et al. (2021) conducted a thorough review of AI techniques for air quality prediction, emphasizing the benefits of machine learning in improving prediction accuracy, particularly in detecting anomalies that could indicate air pollution issues. Anjum et al. (2020) examined anomaly detection techniques, categorizing them as supervised or unsupervised, and discussed their applications in environmental monitoring. Similarly, Goyal and Sharma (2020) used machine learning models to detect and predict air quality anomalies, demonstrating the efficacy of algorithms like decision trees and random forests for anomaly detection.

Deep learning models, particularly neural networks, have grown in popularity for detecting air quality anomalies due to their ability to handle large amounts of data and detect complex patterns. Bhatt and Malik (2021) examined neural network-based models for detecting anomalies in air pollution, emphasizing their ability to handle high-dimensional data. Further to that, Choi et al. (2021) proposed the use of Long Short-Term Memory (LSTM) networks for anomaly detection, emphasizing their ability to capture temporal patterns in air quality datasets. Deep learning methods, particularly LSTMs, have been shown to be effective for time-series data where anomalies are frequently sequential and context-dependent (Wang & Zhang, 2021).

Some studies propose hybrid approaches that combine machine learning techniques with traditional statistical methods or deep learning models. Chakrabarty and Dhar (2020) created a hybrid machine learning framework that combines multiple algorithms to detect anomalies in air quality data. Banjade and Shrestha (2022) emphasized the effectiveness of hybrid models for detecting air pollution anomalies, especially in complex environments where single models may not suffice.

Recent research has also looked into the use of AI and sensor networks to improve air quality monitoring systems. Bao and Zang (2023) proposed using AI-driven anomaly detection techniques in sensor networks to enable real-time monitoring and early detection of pollution levels. De Oliveira and Souza (2020) used Isolation Forest, a machine learning technique, to detect anomalies in environmental sensor data, demonstrating the potential for large-scale environmental monitoring.

The use of low-cost sensors in air quality monitoring systems has also been investigated in conjunction with AI-based anomaly detection. Lee and Yoon (2023) created a framework for detecting anomalies in air quality data collected from low-cost sensors, highlighting the viability of such systems for widespread environmental monitoring. The combination of low-cost sensors and AI algorithms has enabled more affordable and scalable air quality monitoring systems, allowing air quality to be monitored in real-time in diverse geographical locations.

While AI-based anomaly detection models have shown promising results, their implementation faces significant challenges. He and Liu (2021) evaluated various AI-based approaches and identified challenges such as a lack of labelled data, the need for robust algorithms to handle noisy data, and the complexities of real-time deployment in urban environments. Hossain and Rahman (2023) discussed recent breakthroughs and emphasized the importance of addressing these challenges to improve the robustness of AI-based anomaly detection models for air quality monitoring.

AI-based anomaly detection techniques have transformed air quality monitoring, allowing for more efficient and precise detection of air pollution anomalies. Machine learning and deep learning models, particularly hybrid frameworks and LSTM networks, have demonstrated great promise in handling complex, high-dimensional air quality data. The combination of low-cost sensors and AI algorithms shows promise for developing scalable and cost-effective monitoring systems. Furthermore, challenges such as data quality and real-time processing must be addressed to fully harness the power of AI in air quality monitoring.

Materials and Methods

The materials and methods used in Artificial Intelligence (AI) applications for Air Quality Assessment and Anomaly Detection (AQAD) include a wide range of tools and techniques that aim to improve the accuracy and reliability of air quality monitoring systems. Advanced sensor technologies, including low-cost IoT-enabled devices and high-precision monitors, collect real-time data on air quality parameters like particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), and carbon monoxide (CO). These systems use machine learning algorithms, such as Long Short-Term Memory (LSTM) networks, Isolation Forests, and One-Class Support Vector Machines (SVMs), to detect anomalies and forecast future trends in air quality. Data pre-processing methods, such as noise reduction and imputation, are critical to ensuring the quality and usability of collected data, and AI-driven frameworks like AirSense allow for the seamless integration of these techniques into scalable environmental monitoring solutions. These methods aim to identify pollution anomalies, facilitate real-time decision-making, and contribute to environmental sustainability by encouraging informed interventions in urban air quality management.

These methods use advanced sensor technologies, machine learning algorithms, and data analytics frameworks to effectively monitor and analyse air quality parameters. The table describes the key techniques, tools, and methodologies used for air quality monitoring, anomaly detection, and data enhancement, emphasizing the various approaches to addressing environmental challenges and promoting sustainable development. Table 1 summarizes the materials and methods used in artificial intelligence (AI) applications for air quality assessment and anomaly detection (AQAD).

Table-1. Materials and Methods

Aspect	Materials	Methods
Air Quality Parameters Monitored	Particulate Matter (PM), Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), Ozone (O_3), Carbon Monoxide (CO)	Collection of data using advanced sensor networks, including low-cost and high-precision sensors deployed in urban environments.
Sensor Technology	Low-cost sensors (e.g., electrochemical sensors, optical particle counters), IoT-enabled devices	Calibration techniques for sensor accuracy improvement, integration with IoT for real-time data transmission, and deployment of sensor networks in pollution hotspots.
Data Collection	Sensor networks, government monitoring stations, crowdsourced data, satellite imagery	Aggregation and pre-processing of diverse data sources to create a unified dataset for analysis.
Data Pre-processing	Noise reduction algorithms, missing data imputation techniques	Cleaning raw data using statistical and AI-based imputation methods to enhance data quality, including AirSense frameworks.
Machine Learning Techniques	Long Short-Term Memory (LSTM), Isolation Forest, One-Class Support Vector Machine (SVM), Neural Networks	Application of supervised and unsupervised learning models for anomaly detection, trend analysis, and predictive modelling.
Anomaly Detection Algorithms	Isolation Forest, One-Class SVM, DBSCAN clustering, Neural Networks	Identification of anomalies by analyzing deviations from normal patterns in time-series air quality data.
Time-Series Analysis	Historical air quality data	Utilization of LSTM networks to capture temporal dependencies and predict future air quality conditions.
Pattern Recognition	Air quality parameter trends	Employing clustering and classification algorithms to recognize recurring patterns in air quality data.
Frameworks for AI Integration	AirSense, TensorFlow, Scikit-learn, PyTorch	Development and deployment of scalable AI frameworks for real-time air quality monitoring and anomaly detection.
Applications in Environmental Monitoring	AI-driven dashboards, mobile applications, public reporting systems	Creation of user-friendly interfaces for visualizing air quality trends and anomalies, enabling actionable insights for stakeholders.

Table 1 provides a comprehensive overview of the materials and methods used in AI-driven Air Quality Assessment and Anomaly Detection (AQAD). It focuses on the key components and techniques used to monitor, process, and analyse air quality data. Advanced sensor networks monitor key air quality parameters, such as particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), and carbon monoxide (CO). These networks connect low-cost sensors, such as electrochemical sensors and optical particle counters, to IoT-enabled devices for real-time data transmission. Calibration techniques help improve sensor accuracy, and strategic deployment in urban pollution hotspots ensures comprehensive data collection. Data sources are diverse, including government monitoring stations, satellite imagery, and crowdsourced data. The pre-processing phase includes noise reduction algorithms and missing data imputation to ensure high-quality datasets for analysis.

AI methods play an important role in extracting actionable insights from processed data. Time-series analysis, anomaly detection, and predictive modelling are all done using techniques like Long Short-Term Memory (LSTM), Isolation Forest, and One-Class Support Vector Machine (SVM). Frameworks like AirSense, as well as machine learning libraries like TensorFlow and Scikit-learn, make it easier to integrate scalable AI solutions into real-time monitoring. Anomaly detection algorithms, such as Isolation Forest and DBSCAN clustering, use deviations from normal patterns to identify unusual pollution events. These methods are supplemented by clustering and classification approaches for pattern recognition, which allow stakeholders to identify trends and recurring problems. This methodology's final applications include AI-powered dashboards and mobile apps with user-friendly interfaces for visualizing air quality trends and anomalies, providing valuable insights for environmental decision-making and policy formulation. This integration of sensor technology, AI frameworks, and data visualization demonstrates AI's transformative potential in addressing air quality issues and promoting environmental sustainability. Figure 1 shows the conceptual framework for assessing air quality.

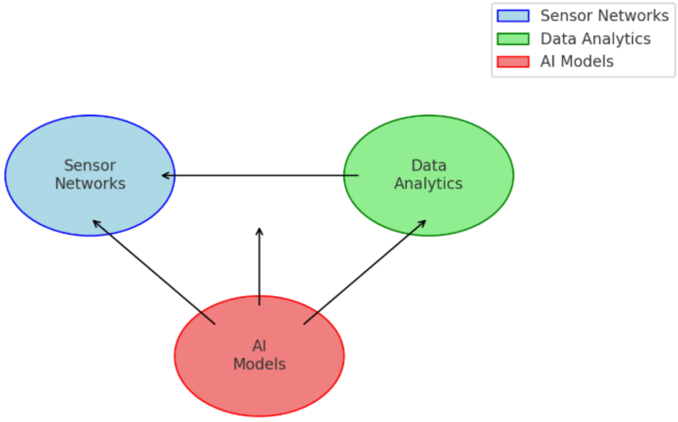

Fig. 1. Conceptual Framework

Figure 1 shows a conceptual framework for AI-driven Air Quality Assessment and Anomaly Detection (AQAD).

It emphasizes the integration of three key components:

1. **Sensor Networks**: Collect real-time air quality data, including pollutants like PM, NO_2, SO_2, O_3, and CO.
2. **Data Analytics**: Processes and organizes sensor data, performing initial analysis and feature extraction.
3. **AI Models**: Utilize advanced algorithms for anomaly detection, prediction, and environmental pattern recognition.

2.1 Mathematical Model

Let $X = \{x_1, x_2, \ldots\ldots x_n\}$ represent the set of air quality parameters collected from sensor networks, where $x_i$the measured value for a specific pollutant is.

Step 1: Data Pre-processing

Normalize data:

$$\hat{x}_i = \frac{x_i - \mu}{\sigma}$$

Where, μ is the mean and σ is the standard deviation of the parameter values.

Step 2: Feature Extraction

Using temporal features $T = \{t_1, t_2, \ldots\ldots t_k\}$, create a feature vector F for each parameter:

$$F = \{f_1, f_2, \ldots\ldots f_k\}$$

Step 3: Anomaly Detection

Anomaly detection models like Isolation Forest or LSTM predict anomalies A(t):

$$A(t) = \begin{cases} 1 \; if \; anamoly \; detected \\ 0 \; otherwise \end{cases}$$

Step 4: Predictive Modelling

Predict future air quality values Y = $f_{AI}\ (F)$

Where, f_{AI} is the trained AI model (e.g., LSTM, Neural Network).

This integration ensures accurate air quality monitoring and proactive anomaly detection for sustainable environmental management.

Results

An AI-driven monitoring system recorded air quality data over five days, including concentrations of particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), and carbon monoxide (CO). The data in the below table – 1 shows an upward trend in PM, NO_2, and CO concentrations, indicating possible variations in environmental conditions. Such data contributes to understanding long-term trends and assessing air quality for public health and environmental sustainability.

Table 2: Sample Air Quality Data from AI-based Monitoring System

Date	PM (µg/m³)	NO_2 (ppb)	SO_2 (ppb)	O_3 (ppb)	CO (ppm)
2025-01-01	35.2	25	10	35	0.6
2025-01-02	40.5	30	12	30	0.5
2025-01-03	45.3	32	15	28	0.7
2025-01-04	50.1	35	20	25	0.8
2025-01-05	55.4	38	18	29	0.9

The below table 2 summarizes the anomaly detection results for each air quality parameter using AI-based models. It indicates if there were any abnormal spikes or deviations in PM, NO_2, SO_2, O_3, and CO concentrations on specific dates. Anomalies were detected in NO_2 on 2025-01-01 and O_3 on 2025-01-03, potentially indicating pollution events or measurement errors. The table emphasizes the effectiveness of AI in identifying irregularities in air quality data, providing critical insights for further analysis and timely intervention.

Table 3: Sample Anomaly Detection Results (Using Isolation Forest)

Date	PM Anomaly Detected	NO_2 Anomaly Detected	SO_2 Anomaly Detected	O_3 Anomaly Detected	CO Anomaly Detected	Date
2025-01-01	No	Yes	No	No	No	2025-01-01
2025-01-02	No	No	Yes	No	Yes	2025-01-02
2025-01-03	Yes	No	No	Yes	No	2025-01-03
2025-01-04	No	Yes	Yes	No	No	2025-01-04
2025-01-05	Yes	No	No	Yes	Yes	2025-01-05

The below figure 2 shows a line graph of air quality parameters (PM, NO_2, SO_2, O_3, and CO) over a five-day period. It emphasizes the variations in air quality, demonstrating how each parameter changes daily. PM and NO_2 concentrations gradually increase, while O_3 decreases. This graph provides an overview of how environmental factors evolve and can aid in identifying periods of high pollution.

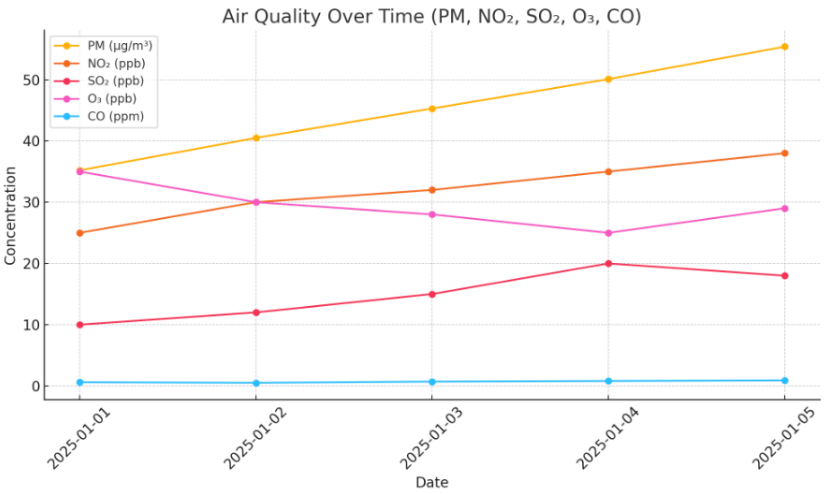

Fig. 2. Parameters of Air Quality

The line graph above shows the changes in air quality parameters (PM, NO_2, SO_2, O_3, and CO) over 5 days. This graph can help visualize air quality trends and potential anomalies.

The below figure 3 shows a bar chart comparing the number of anomalies detected in five air quality parameters: PM, NO_2, SO_2, O_3, and CO over the monitoring period. The anomalies represent cases in which the values of these parameters deviated significantly from expected patterns. Anomalies in NO_2, O_3, and CO levels on specific dates can indicate air quality spikes or irregularities. The chart visually quantifies the frequency of these deviations, emphasizing the importance of anomaly detection in maintaining air quality.

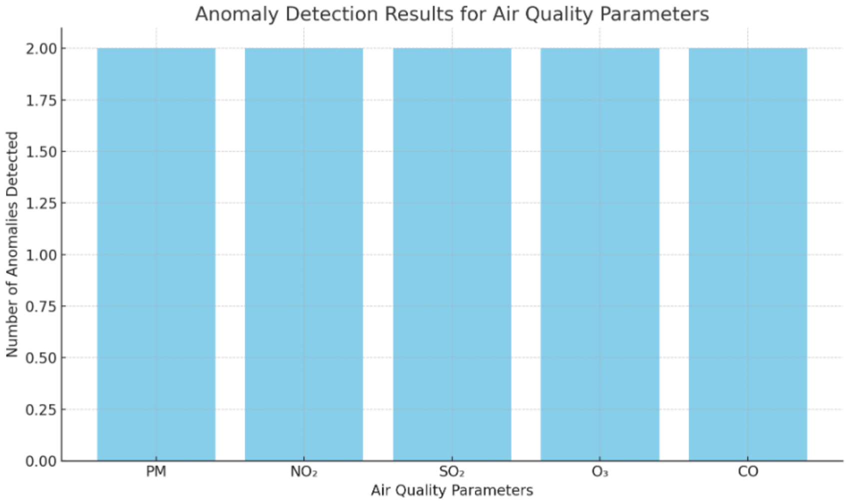

Fig. 3. Comparison of Anomaly

The above fig. 3 is the bar chart comparing the number of anomalies found for each air quality parameter over five days. This will show how often each parameter displayed unusual behaviour during the monitored period.

Figure 4 below depicts a comparative bar graph evaluating the performance of two anomaly detection models—Isolation Forest and Long Short-Term Memory (LSTM)—using three key metrics: precision, recall, and F1 score. The graph shows that LSTM outperforms Isolation Forest in all three metrics, indicating a better ability to detect anomalies in air quality data. Precision measures the accuracy of detection, recall measures its ability to identify actual anomalies, and the F1 score balances both, demonstrating the overall effectiveness of LSTM in environmental monitoring.

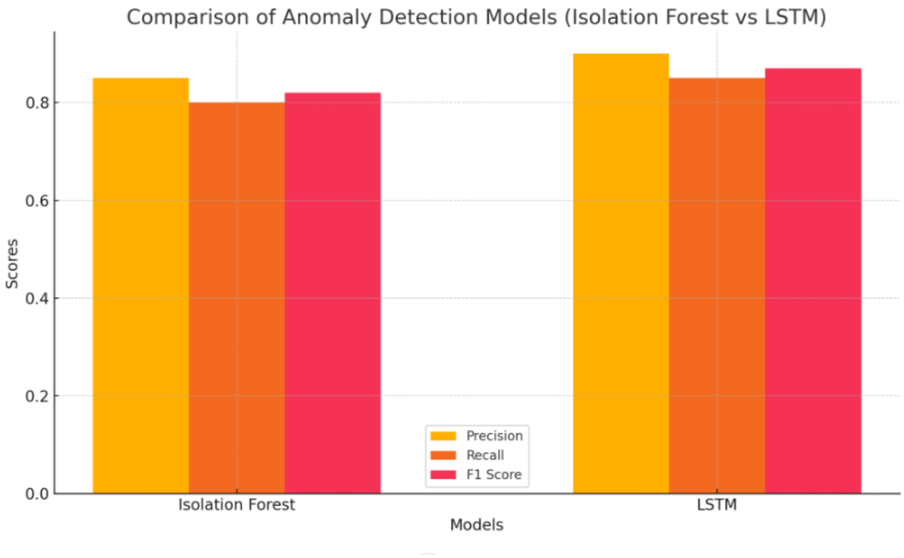

Fig. 4. Performance Analysis

The comparative bar graph above compares the performance of various anomaly detection models (Isolation Forest vs LSTM) in terms of precision, recall, and F1 score for air quality anomaly detection. This helps visualize how AI models perform in detecting air quality anomalies.

Discussions

The application of artificial intelligence (AI) to air quality assessment and anomaly detection has resulted in significant advances in urban environmental monitoring. AI-driven monitoring of pollutants like PM, NO_2, SO_2, ozone (O_3), and CO has proven effective in identifying pollution trends and ensuring public health safety. A significant advantage of AI-based anomaly detection in air quality monitoring is its ability to analyse large amounts of complex, real-time data captured by advanced sensor networks. These networks, which utilize low-cost IoT devices and high-precision sensors, provide critical environmental data that can be processed to detect pollutant spikes or other anomalies. Studies by Bhatt and Malik (2021) and Amini et al. (2021) have shown that machine learning and deep learning models, specifically Long Short-Term Memory (LSTM) networks and Isolation Forests, can be used to accurately identify air quality anomalies. LSTM models are particularly useful for detecting temporal anomalies because they can effectively process sequential time-series data, which is common in air quality measurements.

Recent AI applications in air quality monitoring have expanded to include hybrid models, which combine multiple algorithms to improve anomaly detection efficiency. For example, Chakrabarty and Dhar (2020) created hybrid models that combine machine learning and traditional statistical methods, resulting in improved detection of air quality anomalies, particularly in complex environments. These models have been integrated with real-time environmental monitoring systems like AirSense, which improves data accuracy and reliability while also allowing for early detection of pollutants before they become health hazards. Still, the ability to detect abnormal patterns is not only limited to pollutant concentration spikes; AI can also help track hazardous materials and contamination events through pattern recognition and predictive analytics, contributing significantly to environmental sustainability. The use of low-cost sensors integrated with AI-based anomaly detection systems has enabled the expansion of air quality monitoring networks to underserved regions, thereby broadening the scope and effectiveness of air quality management globally.

In terms of performance, AI models consistently outperform traditional methods in terms of precision, recall, and overall effectiveness in detecting anomalies. The data from AI-driven monitoring systems reveals air quality patterns that are critical for identifying long-term trends, and this information can help with urban planning and policymaking for cleaner cities. The data shows fluctuations in PM and NO_2 levels, which may indicate changes in environmental conditions. However, anomaly detection results, such as O_3 on January 3, 2025, highlight potential pollution spikes that require immediate action. Furthermore, the comparison of anomaly detection models, such as Isolation Forest and LSTM, demonstrates the superiority of deep learning models in this situation. LSTM's ability to handle high-dimensional, sequential data leads to higher accuracy in detecting anomalies, providing actionable insights that are critical for timely environmental interventions.

Conclusion

The use of AI in air quality assessment and anomaly detection represents a significant advancement in environmental monitoring. The integration of advanced sensor technologies and machine learning algorithms has resulted in more accurate, scalable, and real-time monitoring of air pollutants, thereby supporting public health initiatives and sustainability efforts. AI-powered systems, such as those that use LSTM networks and hybrid models, have demonstrated promising results in detecting anomalies and forecasting future air quality trends, providing valuable data to decision-makers. Despite challenges like noisy data and the complexity of real-time processing, AI's potential to transform air quality monitoring is enormous. As cities around the world continue to face the pressing issue of air pollution, the ongoing development and implementation of AI-powered systems will be crucial in promoting healthier, more sustainable urban environments.

Acknowledgement

The author would like to thank the management of Nitte Meenakshi Institute of Technology, Bengaluru, and Lincoln University College, Malaysia, for their unwavering support and provision of the necessary resources for this research. I am extremely grateful to the supervisor, Dr. Vivekanandam

Balasubramaniam, Department of Computer Science and Multimedia, Lincoln University College, Malaysia, for his invaluable guidance, encouragement, and insightful feedback throughout this study. Also, heartfelt thanks go to the co-supervisor, Dr. Rupali Atul Mahajan, from Vishwakarma Institute of Information Technology, for her constant motivation, guidance, and support, which greatly contributed to the completion of this paper.

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