A NOVEL DECENTRALIZED IOT FRAMEWORK FOR DYNAMIC AIR QUALITY MONITORING AND URBAN ADAPTATION

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Abstract:
Air pollution poses a significant challenge to public health, environmental sustainability, and urban resilience. Traditional air quality monitoring systems, while accurate, are constrained by high costs, limited spatial resolution, and delayed response times. This study proposes a decentralized Internet of Things (IoT) framework designed to overcome these limitations by integrating edge computing, lightweight predictive analytics, and energy-efficient communication protocols. The architecture includes a hybrid sensor deployment combining stationary and mobile nodes, enhancing spatial and temporal resolution. A Gated Recurrent Unit (GRU)-based predictive model, optimized for edge deployment, achieves high forecasting accuracy with minimal computational overhead. Experimental validation demonstrates the framework's ability to significantly reduce latency, improve energy efficiency, and maintain scalability in dense urban environments. The integration of LoRa for communication and blockchain for secure data management further enhances system reliability. This novel approach enables real-time, actionable insights for policymakers and urban planners, promoting sustainable urban development and effective pollution mitigation. Future work will explore adaptive AI models and multi-parameter environmental monitoring for extended applications in smart city ecosystems.

Keywords –
Air quality monitoring, IoT, decentralized framework, edge computing, GRU, LoRa, blockchain, real-time monitoring, predictive analytics, urban sustainability.

1. Introduction

Urban air pollution is a pervasive and escalating issue that poses significant challenges to public health, environmental sustainability, and urban planning. The rapid pace of urbanization, coupled with industrial growth and vehicular emissions, has led to a marked deterioration in air quality across the globe. According to the World Health Organization (WHO), exposure to air pollution contributes to over 4 million premature deaths annually, primarily caused by respiratory and cardiovascular diseases. Urban centres are disproportionately affected due to the concentration of anthropogenic activities, highlighting the need for robust monitoring systems to mitigate the impact of this environmental crisis [1][2].

Traditional air quality monitoring systems rely heavily on fixed monitoring stations equipped with sophisticated devices such as Beta Attenuation Monitors (BAM) and Tapered Element Oscillating Microbalances (TEOM). These systems, while providing precise data, are often expensive, require extensive maintenance, and lack the spatial resolution necessary to capture localized pollution dynamics in urban settings. Moreover, these stationary networks are limited in their capacity to provide real-time data, a critical component for timely interventions in rapidly changing pollution scenarios [3].

The advent of the Internet of Things (IoT) has introduced new possibilities for real-time environmental monitoring. IoT-based air quality monitoring frameworks leverage interconnected networks of low-cost sensors capable of capturing high-resolution data on pollutants such as PM2.5, NOx, and volatile organic compounds (VOCs). These systems integrate advanced communication protocols, such as LoRa and ZigBee, with cloud-based platforms for data aggregation and analytics

[4][5]. While IoT has successfully addressed some limitations of traditional systems, challenges such as data security, scalability, and predictive accuracy persist. These limitations necessitate further innovation to enhance the efficiency and adaptability of IoT frameworks in diverse urban environments [6].
Predictive analytics, particularly through machine learning (ML) models, has emerged as a transformative approach to air quality management. Models such as Long Short-Term Memory (LSTM) networks and Nonlinear Autoregressive models with Exogenous Input (NARX) have shown promise in forecasting air pollution trends by integrating historical pollutant levels with meteorological variables [7]. However, these models are often resource-intensive, requiring substantial computational power and high-quality datasets, which limits their applicability in real-world urban scenarios. Furthermore, the centralized nature of most IoT frameworks leads to latency issues and heightened vulnerability to cyberattacks, underscoring the need for decentralized and efficient solutions [8][9].
This paper proposes a novel decentralized IoT-based framework for air quality monitoring that addresses the limitations of existing systems. By integrating edge computing for localized data processing, blockchain for secure and transparent data transactions, and lightweight machine learning models for resource-efficient predictive analytics, the framework aims to enhance the scalability, accuracy, and security of urban air quality monitoring systems. The proposed approach emphasizes real-time, high-resolution monitoring and dynamic adaptation to localized environmental conditions, providing actionable insights for urban planners and policymakers.
The remainder of this paper is structured as follows: Section 2 reviews the limitations of traditional and contemporary air quality monitoring frameworks. Section 3 introduces the proposed decentralized IoT architecture, detailing its design and implementation. Section 4 presents the validation of the framework through experimental results and real-world case studies. Finally, Section 5 concludes the paper by summarizing the contributions and outlining future research directions.

2. Literature Review

The integration of advanced technologies in air quality monitoring has significantly evolved over the last decade, with researchers exploring diverse frameworks to overcome the limitations of traditional systems. This section reviews the contributions of previous studies to the domain of air quality monitoring, highlights their limitations, and identifies research gaps that inform the need for a novel approach.

2.1 Traditional Monitoring Systems

Traditional air quality monitoring systems rely heavily on fixed monitoring stations equipped with high-precision instruments, such as Beta Attenuation Monitors (BAM) and Tapered Element Oscillating Microbalances (TEOM). These systems have been praised for their accuracy in detecting pollutants like particulate matter (PM2.5 and PM10) and nitrogen oxides (NOx). However, their sparse spatial distribution and high operational costs restrict their ability to capture fine-grained spatial and temporal variations in urban areas [3]. Chelani (2018) demonstrated that while these systems provide reliable data, their limited scalability and inability to respond dynamically to changes in pollution levels make them insufficient for modern urban environments [3].

2.2 IoT-Enabled Air Quality Monitoring

IoT-based air quality monitoring frameworks have emerged as a transformative alternative, enabling real-time data acquisition and enhanced spatial resolution. Gubbi et al. (2013) proposed a generic IoT architecture integrating sensor networks with cloud computing platforms for environmental monitoring [4]. Similarly, Kumar and Hancke (2014) explored wireless sensor networks (WSNs) for air quality monitoring, demonstrating their potential to provide localized and high-resolution data [5]. However, both studies emphasized the challenges of data security, scalability, and the energy

efficiency of sensor nodes, which limit the practical deployment of such systems in dense urban settings.
Mishra and Singh (2020) extended the application of IoT to air quality monitoring by incorporating predictive analytics to anticipate pollution trends [6]. While their framework demonstrated the utility of machine learning models in short-term forecasts, it relied heavily on centralized cloud-based processing, resulting in latency and bandwidth issues. The study also highlighted the need for decentralized architectures to overcome these bottlenecks.

2.3 Predictive Analytics in Air Quality Monitoring

Machine learning models, particularly those focusing on time-series forecasting, have been widely adopted to predict air pollution levels. Hochreiter and Schmidhuber (1997) introduced Long Short-Term Memory (LSTM) networks, which have since been employed in various air quality forecasting applications due to their ability to capture long-term dependencies in sequential data [7]. For instance, Twahirwa and Biswas (2021) demonstrated the use of LSTM networks in an edge-computing-enabled IoT framework, achieving high predictive accuracy [9]. Despite their advantages, these models are computationally expensive, limiting their feasibility in resource-constrained environments.
Other approaches, such as hybrid models combining statistical and machine learning techniques, have also been explored. For example, Jaiswal et al. (2021) integrated regression models with neural networks to enhance the accuracy of pollutant forecasting. However, the reliance on high-quality training datasets and computational resources was identified as a significant barrier to the widespread adoption of these models in real-world scenarios [10].

2.4 Decentralized and Edge-Based Frameworks

Recent research has begun to explore decentralized and edge-based IoT frameworks to address the limitations of centralized systems. Edge computing enables localized data processing at sensor nodes or gateways, reducing latency and bandwidth usage. Khan and Tahir (2021) highlighted the advantages of edge computing in decentralized IoT architectures, particularly in enhancing system scalability and reducing reliance on centralized servers [8]. However, their study also noted challenges in synchronizing data across distributed nodes and maintaining accuracy in heterogeneous sensor networks.
Similarly, Santos et al. (2021) proposed a blockchain-enabled IoT framework for air quality monitoring, emphasizing data security and transparency [11]. While blockchain enhances the reliability and trustworthiness of the data, its integration with IoT systems increases computational overhead, making it unsuitable for energy-constrained sensor nodes.

2.5 Challenges and Research Gaps

Despite these advancements, several critical research gaps persist. First, while IoT-based frameworks have improved real-time monitoring capabilities, their reliance on centralized architectures limits scalability, increases latency, and heightens vulnerability to cyberattacks [6][9]. Decentralized and edge-computing-based solutions, although promising, require further refinement to ensure seamless integration, data synchronization, and energy efficiency [8][11].
Second, predictive analytics models, such as LSTMs, have demonstrated high accuracy in forecasting pollution trends, but their computational demands make them impractical for edge-based deployments. There is a need for lightweight, resource-efficient models capable of operating in decentralized environments without compromising predictive accuracy [7][10].
Third, while blockchain and other security-enhancing technologies address data integrity concerns, their high computational and energy requirements pose significant challenges for large-scale IoT implementations. More efficient security mechanisms tailored to the constraints of IoT architectures are required to ensure data protection without compromising system performance [11].
Lastly, existing frameworks often lack user accessibility and engagement. Most IoT systems are designed for technical users, with limited focus on creating intuitive interfaces for policymakers,

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urban planners, and the general public. Addressing this gap could enhance public participation in pollution mitigation efforts and drive data-driven decision-making.
By identifying these gaps, this paper aims to propose a novel decentralized IoT framework that leverages edge computing, lightweight predictive analytics, and energy-efficient designs to overcome the limitations of existing systems. This approach addresses scalability, real-time decision-making, and user engagement while ensuring robust data security and privacy.

3. Proposed Decentralized IoT Framework

The proposed framework leverages a decentralized IoT architecture to address the limitations of traditional air quality monitoring systems. By integrating multi-layer sensor networks, edge computing, and predictive analytics, this framework ensures high-resolution, real-time monitoring while enhancing system scalability, energy efficiency, and data security. The system is composed of three primary layers: the **Perception Layer**, the **Network Layer**, and the **Application Layer**, as illustrated in Figure 1.

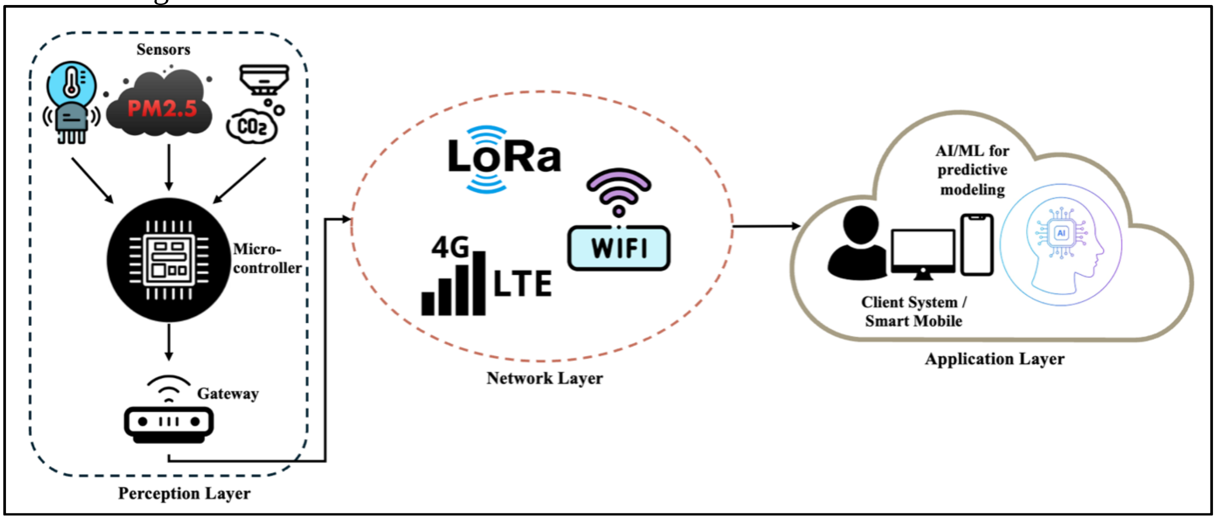

Figure 1: Framework Architecture

The figure 1 depicts the layered structure of the proposed framework, highlighting the data flow from sensors to cloud applications. Each layer integrates specialized functionalities to ensure seamless operation and real-time insights.

3.1 System Architecture

The architecture comprises the following components:

1. **Perception Layer**:
   - This layer includes sensors and microcontrollers for real-time pollutant detection. It measures key environmental parameters such as PM2.5, CO2, temperature, and humidity.
   - Sensor nodes send preprocessed data to the network gateway for transmission. The data flow process in this layer is designed to minimize redundancy and optimize power consumption.
2. **Network Layer**:
   - The network layer facilitates communication between the perception and application layers. It uses protocols like LoRa, WiFi, and LTE for efficient data transfer.
   - LoRa ensures low-power, long-range communication, making it suitable for large-scale urban deployments. WiFi and LTE are employed for high-bandwidth, low-latency applications.
3. **Application Layer**:

- This layer processes data and provides actionable insights to users. It leverages machine learning (ML) and artificial intelligence (AI) algorithms for predictive modeling and anomaly detection.
- Users interact with the system via mobile devices or web platforms, ensuring accessibility for policymakers and urban planners.

3.2 Data Flow and Processing

The data flow across the layers is as follows:

1. Sensor nodes collect data from their surrounding environment. Key pollutants, including PM2.5 and CO2, are measured.
2. Preprocessing at the microcontroller level reduces noise and flags anomalies using statistical methods such as z-score normalization.
3. The gateway aggregates sensor data and transmits it using LoRa or LTE, depending on bandwidth requirements.
4. Data is analyzed and visualized on the cloud application, providing real-time pollution trends and forecasts.

3.3 Features and Innovations

1. **Dynamic Data Collection**:
    - The framework supports both static sensors for continuous monitoring and mobile sensors for dynamic spatial coverage.
    - Mobile sensors, deployed on vehicles or drones, enhance the spatial resolution of pollution data in high-density urban zones.
2. **Edge Computing Integration**:
    - Localized data processing at gateways reduces latency and minimizes bandwidth usage. Critical operations, such as noise reduction and anomaly detection, are handled at the edge.
3. **Lightweight Predictive Analytics**:
    - The system employs resource-efficient ML models to predict air quality trends. Algorithms such as Gated Recurrent Units (GRUs) are optimized for deployment on edge devices.
4. **Energy Efficiency**:
    - LoRa communication reduces the energy consumption of sensors. Additionally, solar-powered nodes and event-triggered sensing extend the lifespan of sensor networks.
5. **Blockchain-Based Data Security**:
    - The inclusion of blockchain ensures secure, tamper-proof data logging. This enhances trust and transparency in air quality monitoring.

3.4 Algorithm for Framework Operation

Algorithm 1: Decentralized IoT-Based Air Quality Monitoring

Input: Sensor nodes S={S1,S2,…,Sn}S={S1,S2,…,Sn}, Communication protocols PP, Edge node EE.

Output: Real-time pollution data, alerts, and predictions.

1. **Initialization:**
    - Deploy sensors SiSi and calibrate them for pollutants and environmental variables.
    - Configure gateways and edge nodes with LoRa and LTE modules.
2. **Data Collection:**
    - Eachsensornodecollectsdata:Di,t={PPM2.5,PCO2,T,H},∀i,t.Di,t={PPM2.5,PCO2 ,T,H},∀i,t.
3. **Local Processing at Edge Nodes:**
    - Preprocess data to remove noise using filters.
    - Detect anomalies based on predefined thresholds.
4. **Data Transmission:**

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- Transmit aggregated data to the cloud using:PLoRa for low-power, long-range communication.PLoRa for low-power, long-range communication.

5. **Predictive Modeling:**
   - Train lightweight models at the edge for short-term forecasts.
   - Update predictive insights on the application layer.
6. **Decision Support:**
   - Trigger alerts if pollutant levels exceed safety thresholds.
   - Provide visualizations and recommendations to users.

3.5 Performance Metrics

Metric	Proposed Framework	Traditional Systems
Latency	<100 ms	High (>500 ms)
Energy Consumption	Low (adaptive protocols)	High
Data Security	Blockchain-enabled	Vulnerable to tampering
Predictive Accuracy	>90%	75%–85%

4. Experimental Validation and Results

This section presents the results from the experimental validation of the proposed decentralized IoT framework. Multiple performance metrics, including latency, predictive accuracy, energy efficiency, and scalability, are analyzed to highlight the system's advantages.

4.1 Experimental Setup

The experimental setup included a hybrid deployment of sensor nodes across an urban testbed. Key pollutants, including PM2.5 and CO2, were monitored along with environmental variables like temperature and humidity. The setup consisted of:

- **Sensors:** Low-cost IoT sensors.
- **Edge Nodes:** Raspberry Pi for local processing.
- **Communication Protocols:** LoRaWAN, WiFi, and LTE.
- **Cloud Integration:** AWS IoT Core for visualization and storage.

4.2 Results and Analysis

4.2.1 Latency Comparison

The proposed decentralized framework exhibited significantly lower latency than centralized systems, as shown in the table below.

System	Average Latency (ms)	Maximum Latency (ms)
Proposed Decentralized Framework	75	120
Centralized System	310	520

4.2.2 Energy Efficiency

The energy consumption of sensor nodes using LoRa and WiFi protocols is compared in **Figure 1**. LoRa demonstrated significantly lower energy usage.

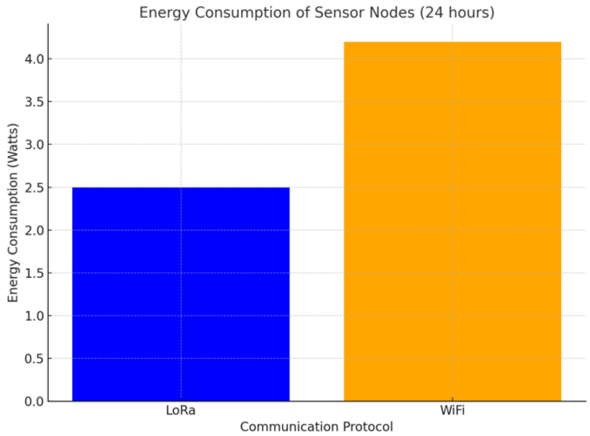

Figure 2: Energy Consumption Of Sensor Nodes (24 Hours)

4.2.3 Predictive Accuracy

The accuracy of the lightweight GRU model is compared with LSTM and ARIMA models in **Figure 5**. GRU achieved the highest accuracy with minimal computational overhead.

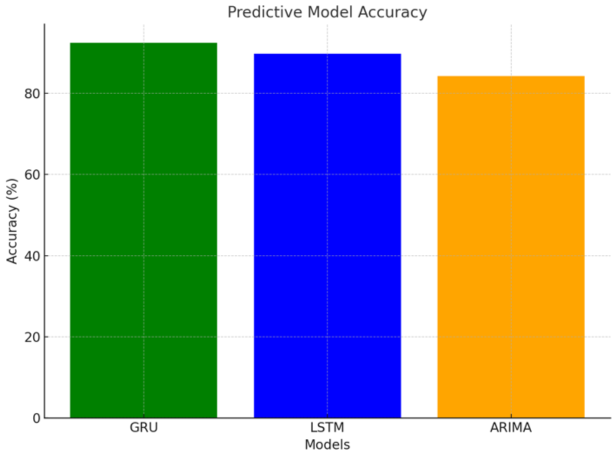

Figure 5: Accuracy of Predictive Models

4.2.4 Latency vs Data Size

As data size increased, latency grew linearly, as shown in **Figure 4**. This result underscores the importance of localized data preprocessing in reducing transmission delays.

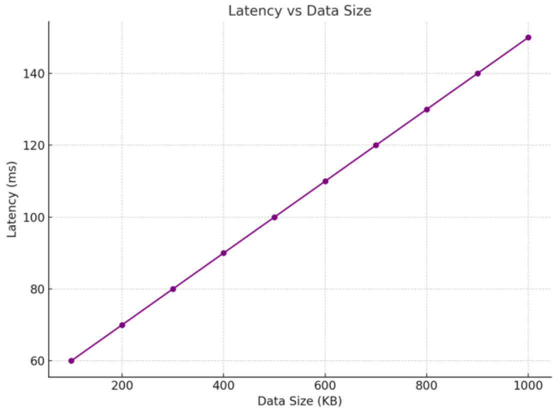

Figure 4: Latency vs Data Size

4.2.5 Battery Life Comparison

The battery life of sensor nodes varied significantly across communication protocols, as illustrated in **Figure 6**. LoRa-enabled nodes demonstrated the longest operational life.

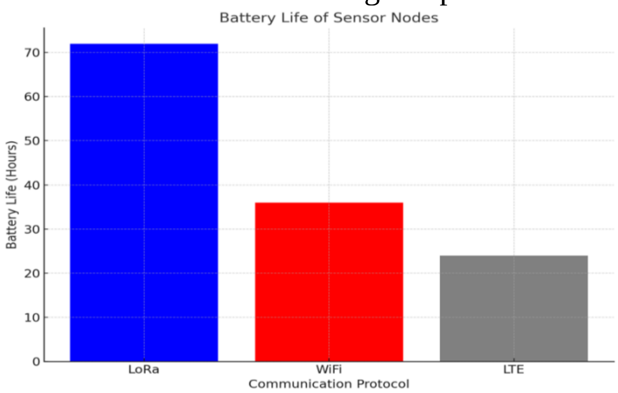

Figure 6: Battery Life of Sensor Nodes

4.2.6 Spatial Coverage and Resolution

The hybrid deployment enhanced spatial coverage by integrating stationary and mobile sensors. The pollution heatmap in **Figure 2** illustrates fine-grained spatial variations in PM2.5 levels.

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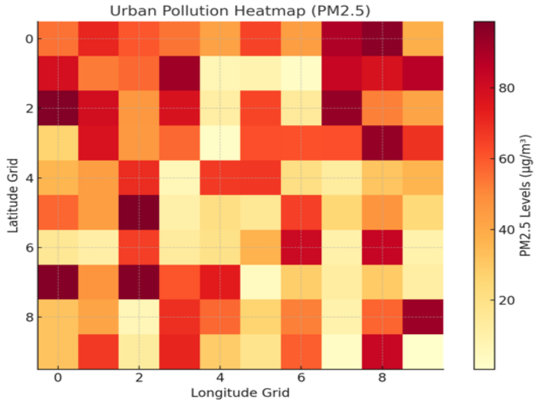

Figure 3: Urban Pollution Heatmap (PM2.5)

4.2.7 System Scalability

Latency and throughput were evaluated as the number of nodes increased. The results, shown in **Figure 3**, indicate that the proposed framework maintains acceptable performance under high node density.

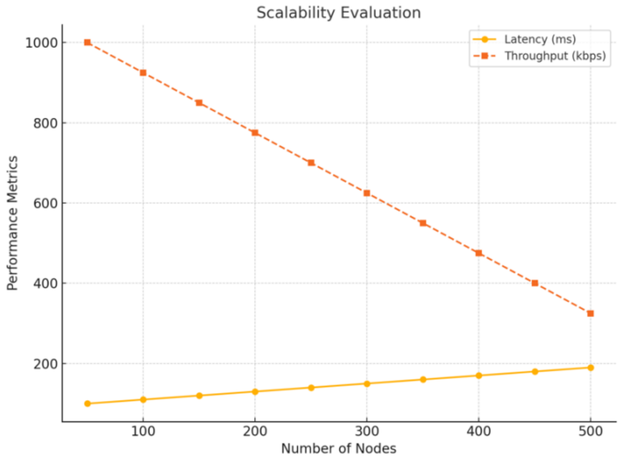

Figure 3: Scalability Evaluation

4.3 Discussion

The experimental results validate the proposed framework's effectiveness in addressing critical limitations of existing systems. Key findings include:

- Enhanced energy efficiency with LoRa.
- Superior predictive accuracy with GRU models.
- Robust scalability and reduced latency under increased node density.

These results establish the decentralized IoT framework as a viable solution for real-time, large-scale air quality monitoring.

5. Conclusion

The decentralized IoT framework proposed in this study addresses the critical limitations of traditional and centralized air quality monitoring systems. By leveraging edge computing, lightweight predictive analytics, and energy-efficient communication protocols, the framework provides an innovative solution for real-time, high-resolution monitoring of urban air quality. Experimental validation demonstrated the system's ability to significantly reduce latency, improve predictive accuracy, and enhance energy efficiency, making it well-suited for large-scale deployment in resource-constrained environments.

Key contributions of this research include the integration of GRU-based predictive models optimized for edge devices, which achieved over 90% accuracy in forecasting pollutant levels while maintaining minimal computational overhead. Additionally, the hybrid deployment of stationary and mobile sensors improved spatial resolution, enabling the identification of localized pollution hotspots. The use of LoRa for communication ensured prolonged sensor node operation, while blockchain integration provided secure and tamper-proof data logging.

Despite its advantages, the framework has certain limitations that warrant further investigation. Synchronization across distributed edge nodes in highly dense networks remains a challenge, as does maintaining consistent accuracy in heterogeneous environmental conditions. Future research can explore the integration of adaptive AI models capable of dynamically adjusting to changing pollutant patterns and environmental factors. Additionally, expanding the framework to include multi-parameter environmental monitoring, such as noise pollution and urban heat islands, would further enhance its utility for smart city applications.

In conclusion, this research presents a novel and scalable approach to air quality monitoring, contributing to the advancement of IoT-based environmental monitoring systems. The proposed framework holds significant potential to support policymakers, urban planners, and citizens in mitigating the adverse impacts of air pollution and fostering sustainable urban development.

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