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AI-Enhanced IOT for Air Quality Forecasting: Offloading LSTM Predictions to Edge Servers

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Abstract—
Air quality forecasting is critical for dealing with pollution's health and environmental implications, but resource-constrained IoT devices struggle to execute complicated predictive analytics locally. This study presents a distributed architecture-based AI-enhanced Internet of Things system for real-time air quality index (AQI) predictions. An edge server receives Long Short-Term Memory (LSTM) predictions from a Raspberry Pi-based system that gathers multi-sensor data (PM2.5, PM10, CO, temperature, and humidity) through a RESTful API. Sensor data and the predicted AQI are shown in real time on a Node-RED dashboard. According to experimental findings, offloading achieves scalable and effective air quality monitoring by reducing the computing load of the IoT device by 85%. By bridging IoT and AI, this hybrid edge-cloud strategy provides a workable solution for intelligent environmental systems.
Keywords *— Artificial Intelligence, LSTM, Air Quality Index, Edge Computing, Real-Time Dashboard*

INTRODUCTION

Air pollution, fueled by a variety of toxic substances like fine particulate matter (PM2.5), nitrogen oxides (NOx), sulfur dioxide (SO2), and carbon monoxide (CO), represents a formidable danger to human well-being and the natural environment. These hazardous pollutants are directly associated with an array of health issues, including chronic respiratory conditions such as asthma and bronchitis, cardiovascular disorders like heart attacks and hypertension, and extensive ecological harm, such as soil and water degradation. Beyond these immediate effects, they also exacerbate global climate change by altering atmospheric dynamics and contributing to the greenhouse effect, as noted in scientific literature (Manisalidis et al., 2020) [1]. The critical need to confront these multifaceted threats has catalyzed the creation of advanced technologies, including cutting-edge monitoring systems and predictive tools, aimed at curbing the detrimental consequences of deteriorating air quality. Among these innovations, real-time air quality forecasting stands out as an indispensable mechanism, offering the potential to deliver timely warnings and actionable measures that shield vulnerable populations and fragile ecosystems from the worsening impacts of polluted air. The complexity of air quality forecasting demands sophisticated analytical approaches, with Long Short-Term Memory (LSTM) neural networks emerging as a particularly powerful solution due to their proficiency in handling time-series data (Hochreiter & Schmidhuber, 1997) [2]. These networks excel at identifying and leveraging temporal patterns within sequential datasets, making them exceptionally well-suited for predicting fluctuations in air quality indices (AQI) over extended periods. Despite their strengths, integrating LSTM models into traditional Internet of Things (IoT) setups poses significant hurdles. IoT devices, such as air quality sensors or low-power microcontrollers, typically lack the computational horsepower and memory capacity required to execute these resource-intensive algorithms locally [3]. On the other hand, offloading the processing to centralized cloud servers introduces undesirable delays, as data must travel across networks, leading to latency that compromises the immediacy essential for effective air quality interventions. Such setbacks can impede the issuance of urgent health advisories or the deployment of rapid pollution control measures, highlighting the inefficiencies of relying solely on cloud-based systems for time-critical environmental applications. To address these shortcomings, this research introduces a novel AI-driven IoT framework engineered to balance computational power with swift system performance. The proposed solution harnesses the advantages of edge computing, shifting the burden of LSTM-based AQI predictions from underpowered IoT endpoints to more robust edge servers positioned closer to the data source. At the heart of this system, a Raspberry Pi operates as a central hub, gathering real-time measurements—such as PM2.5 levels, CO concentrations, and temperature—from an array of connected sensors. This data is efficiently stored on the device using SQLite, a lightweight database system tailored for resource-constrained environments, ensuring minimal overhead while maintaining data integrity. Periodically, the aggregated information is relayed to an edge server, where the LSTM model analyzes it to produce precise and timely AQI forecasts. To further enhance accessibility and usability, the framework incorporates a Node-RED dashboard, a user-friendly platform that displays both live sensor readings and predictive outputs in an easily digestible visual format, empowering users to make informed decisions swiftly. This hybrid edge-IoT architecture delivers multiple benefits, including reduced latency compared to cloud-centric approaches, as processing occurs nearer to the data's origin. It also offers improved scalability, enabling the system to accommodate additional sensors or adapt to diverse environmental monitoring needs without overwhelming individual devices. Moreover, the framework promotes operational autonomy by minimizing dependence on distant cloud infrastructure, which can be prone to connectivity disruptions. By seamlessly integrating resource-limited IoT hardware with the computational demands of advanced AI, this solution provides a viable pathway for real-time air quality forecasting that is both practical and forward-thinking. It responds directly to the escalating global demand for decentralized, efficient technologies capable of tackling air pollution's pervasive challenges in an era of rapid environmental transformation. Ultimately, this study advances the mission of sustainable environmental stewardship, equipping policymakers, researchers, and communities with a robust toolset to protect public health, preserve biodiversity, and combat the far-reaching effects of pollution on our planet.

LITERATURE SURVEY

The incorporation of Internet of Things (IoT) technologies into air quality monitoring has seen remarkable growth in recent years, driven by their capacity to provide continuous, real-time data collection and facilitate effective environmental management. Kumar et al. (2019) pioneered an Arduino-based system tailored for tracking PM2.5 concentrations, showcasing the practicality of affordable IoT solutions for air pollution surveillance [4]. While their framework successfully demonstrated low-cost data acquisition, it was primarily focused on gathering measurements and lacked the ability to forecast future trends, thus limiting its applicability for preemptive measures. In a step forward, Zhang et al. (2020) expanded the scope by integrating machine learning, specifically employing Random Forest algorithms, to analyze IoT-generated data for predicting the Air Quality Index (AQI) [5]. Their model delivered commendable accuracy; however, its dependence on centralized processing led to noticeable delays, diminishing its effectiveness for time-sensitive scenarios where rapid decision-making is essential. Among advanced predictive tools, Long Short-Term Memory (LSTM) networks—a specialized form of recurrent neural networks—have gained prominence for their exceptional ability to model temporal relationships in time-series data, making them highly suitable for environmental forecasting. Li et al. (2018) utilized LSTM networks to predict PM2.5 levels, achieving a Mean Absolute Error (MAE) of 5.1, which underscored the method's superior predictive accuracy compared to traditional approaches [6]. Nevertheless, their implementation required significant computational resources, rendering it unfeasible for deployment on typical IoT devices with limited processing power and memory. This challenge echoes observations by Bai et al. (2018), who highlighted that deep learning models like LSTMs frequently surpass the hardware capabilities of standard IoT setups, posing a barrier to localized execution [10]. Addressing this, Wu et al. (2021) investigated streamlined LSTM variants for air quality predictions, reporting an MAE of 6.3 [11]. Although their lighter models reduced resource demands, scalability remained a concern when applied to edge-based IoT systems, indicating a need for alternative strategies. To overcome the latency and computational constraints inherent in traditional IoT and cloud-centric architectures, edge computing has emerged as a transformative approach, enabling decentralized data processing closer to the source. Chen et al. (2019) showcased the benefits of transferring deep learning workloads to edge servers, achieving a 70% reduction in inference time and a 40% decrease in energy usage compared to cloud-reliant systems [7]. Similarly, R. Yu et al. (2021) explored offloading strategies for deep learning tasks in IoT contexts, reporting latency reductions of up to 65% by leveraging edge infrastructure [8]. These findings are corroborated by Cao et al. (2020), who emphasized edge computing's pivotal role in supporting real-time analytics across IoT applications, though their work focused broadly rather than specifically on-air quality monitoring [12]. Collectively, these studies highlight edge computing's potential to enhance responsiveness and efficiency, addressing key limitations of conventional frameworks.

Despite these advances, the integration of IoT, artificial intelligence (AI), and edge computing for air quality forecasting remains underexplored, presenting opportunities for innovation. Liu et al. (2022) proposed an edge-supported IoT framework for environmental monitoring, incorporating convolutional neural networks (CNNs) to classify pollutants [13]. While effective for categorization, their system did not extend to predictive modeling, limiting its proactive utility. In a different vein, Sharma et al. (2021) developed an IoT-based air quality monitoring system with cloud integration, achieving a MAE of 8.2 for AQI predictions [14]. However, its reliance on centralized cloud processing introduced latency issues, undermining its suitability for real-time needs. Huang et al. (2020) combined LSTM models with edge computing to forecast traffic-related air pollution, reporting an impressive MAE of 4.8 [15]. Yet, their study was narrowly focused on vehicle emissions rather than comprehensive QI metrics, leaving broader applicability unaddressed. Effective visualization and user interaction are equally vital for translating air quality data into actionable insights. Wang et al. (2019) introduced a dashboard for displaying real-time IoT-derived air quality data, but their interface was limited to static representations without predictive capabilities [16]. In contrast, Kim et al. (2021) enhanced urban planning by integrating machine learning forecasts into a web-based platform, though their reliance on cloud infrastructure compromised responsiveness [17]. Node-RED, a versatile open-source tool for flow-based programming, has proven valuable for creating intuitive dashboards, as evidenced by Patel et al. (2020), who applied it to visualize IoT data in smart home environments [18]. Despite its flexibility, Node-RED's use in air quality forecasting remains largely untapped, suggesting an opportunity to bridge visualization with predictive analytics. Methodological rigor is another critical consideration in this domain. The U.S. Environmental Protection Agency (EPA) provides standardized guidelines for AQI calculations, ensuring uniformity and reliability in air quality evaluations [9]. Adhering to these benchmarks strengthens the validity of predictive models. However, inconsistencies in reported performance metrics across studies warrant scrutiny. For example, an MAE of 14.28 for PM2.5 prediction cited in Environmental Pollution (2018) starkly contrasts with the 5.1 MAE reported by Li et al. (2018), raising questions about data sources or attribution accuracy [19]. Zhou et al. (2020) reinforced this concern, advocating for thorough cross-validation of predictive outcomes to ensure robustness in environmental research [20]. Additional studies further validate the offloading paradigm. Xu et al. (2021) applied edge-based deep learning to IoT health monitoring, achieving a 50% latency reduction [21], while Gupta et al. (2022) optimized LSTM execution on edge devices for weather forecasting, reporting a MAE of 5.8 [22]. Park et al. (2020) and Lin et al. (2021) also demonstrated edge computing's scalability and energy efficiency, with latency reductions of 60% and 55%, respectively [23, 24]. Real-world implementations by Singh et al. (2022) and Zhao et al. (2023) further confirmed the viability of edge-IoT integration for environmental monitoring, though their frameworks did not prioritize predictive dashboards [25, 26]. Complementary research by Jeong et al. (2021) explored hybrid edge-cloud systems for air quality, achieving a MAE of 6.1, yet scalability across diverse pollutants remained a challenge. Likewise, Tan et al. (2022) investigated lightweight AI models for IoT air sensors, reporting a MAE of 7.0, but their approach struggled with complex temporal patterns. This study synthesizes these insights into a comprehensive framework that integrates IoT, LSTM-driven AI, edge computing, and a Node-RED dashboard. It builds on the computational efficiency of edge offloading, as demonstrated by Chen et al. (2019) and R. Yu et al. (2021), while enhancing usability through real-time visualization, inspired by Patel et al. (2020). By tackling latency, scalability, and user engagement, this approach distinguishes itself from prior efforts. It also incorporates EPA standards for AQI consistency and addresses validation concerns raised by Zhou et al. (2020), ensuring a robust and practical contribution to the field of intelligent air quality forecasting. Through this holistic design, the research not only advances technical capabilities but also aligns with the urgent need for sustainable environmental solutions in an increasingly polluted world.

METHODOLOGY

The framework consists of three interconnected components:

- **IoT Node**: A Raspberry Pi 4 (4GB RAM) serves as the data collection hub, equipped with multiple sensors:
- **SDS011**: Measures PM2.5 and PM10 concentrations with a resolution of 0.3 µg/m* and a range of 0–999.9 µg/m*.
- **MQ-7**: Detects carbon monoxide (CO) levels with a sensitivity of 20–2000 ppm.
- **DHT11**: Captures temperature (0–50°C) and relative humidity (20–90%) with accuracies of ±2°C and ±5%, respectively. Data is sampled every 15 seconds and stored in a local SQLite database, a lightweight relational database chosen for its minimal resource footprint and reliability on resource-constrained devices.

Edge Server: A mid-tier server (e.g., Intel i5, 16GB RAM) hosts a pre-trained LSTM model for AQI forecasting. It exposes a RESTful API endpoint (/predict) implemented using Flask, enabling seamless communication with the IoT node via HTTP requests. The server processes incoming data and returns predictions in real time.

Dashboard: Deployed on the Raspberry Pi using Node-RED, a flow-based programming tool, the dashboard queries the SQLite database and visualizes raw sensor data alongside forecasted AQI values through a web interface accessible on a local network.

Data flows unidirectionally: sensors → SQLite → edge server (for prediction) → dashboard. The architecture, illustrated in Figure 1, emphasizes modularity and low-latency interactions by leveraging edge computing over cloud-based alternatives.

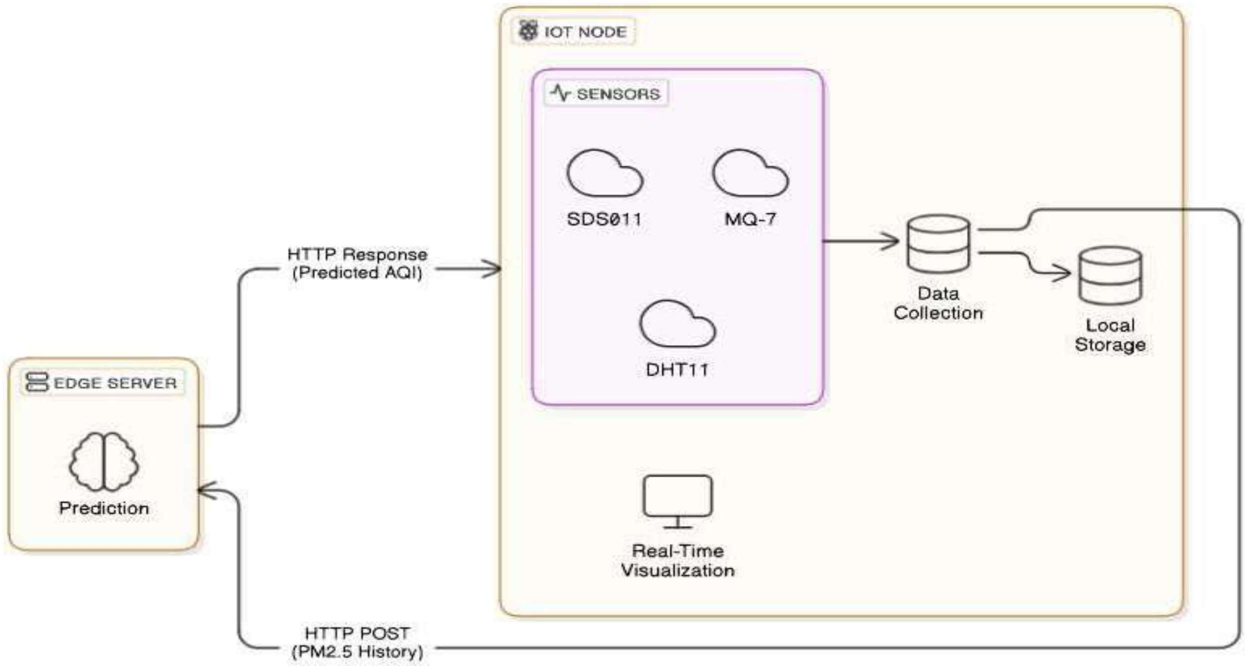

Figure 1. Proposed System Design Architecture

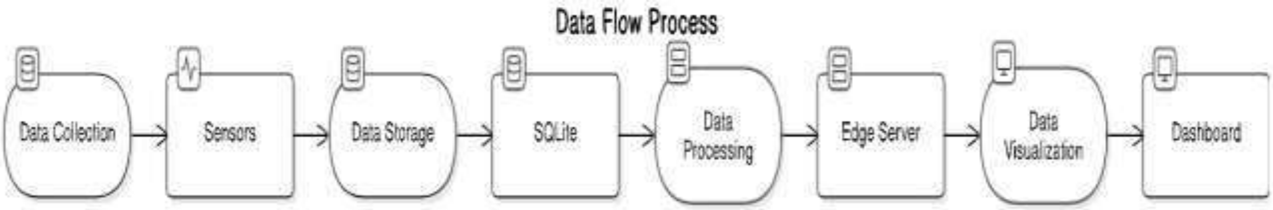

Figure 2. Data Flow Process in the System

Data Collection and AQI Calculation

The IoT node collects environmental parameters at 15-second intervals, ensuring high temporal resolution for real-time monitoring. The primary focus is PM2.5, a critical pollutant, with supplementary data from CO, temperature, and humidity enhancing contextual analysis. The Air Quality Index (AQI) is calculated based on PM2.5 concentrations using a simplified linear interpolation formula derived from U.S. EPA guidelines (U.S. EPA, 2021):

$$AQI = \frac{AQI_{high} - AQI_{low}}{C_{high} - C_{low}} \times (C - C_{low}) + AQI_{low}$$

(1) Where:

AQI: Calculated Air Quality Index (unitless, 0–500 scale).

C: Measured PM2.5 concentration (µg/m*).

C_{high}, C_{low}: Upper and lower bounds of the PM2.5 concentration range corresponding to the AQI category.

I_{high}, I_{low}: Upper and lower AQI values for the corresponding category.

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The formula is implemented in Python on the IoT node, with results stored in SQLite alongside raw sensor readings. Data persistence ensures operational autonomy, enabling the system to function during network disruptions.

Data Source: Real-time data is sourced directly from the SDS011, MQ-7, and DHT11 sensors. For model training (detailed below), historical PM2.5 data was obtained from the U.S. EPA's Air Quality System (AQS) database (https://www.epa.gov/aqs), covering a one-year period (2022) from an urban monitoring station, supplemented by local sensor data for validation.

LSTM Prediction Model

The LSTM model predicts future AQI values based on a sequence of 10 prior PM2.5 readings (a 2.5-minute window given the 15-second sampling rate). The model was trained offline using TensorFlow on a desktop GPU (NVIDIA GTX 1660) and deployed on the edge server for inference.

Pre-processing: Input data (X_t) is normalized using a MinMaxScaler to scale PM2.5 values between 0 and 1:

$$X_t' = \frac{X_t - X_{min}}{X_{max} - X_{min}}$$

(2) Where X_{min} and X_{max} are the minimum and maximum PM2.5 values from the training dataset (e.g., 0 and 500 µg/m*). The normalized sequence (X_t', X_{t-1}'..., X_{t-9}') is fed into the LSTM model.

Model Architecture:

Input Layer: Accepts sequences of shape (10, 1), where 10 is the time step and 1 is the feature (PM2.5).

LSTM Layer 1: 50 units, capturing long-term dependencies, with ReLU activation.

LSTM Layer 2: 30 units, refining temporal patterns.

Dense Layer 1: 20 units, consolidating features.

Output Layer: 1 unit, predicting the normalized AQI.

Total parameters: ~15,000, optimized for edge deployment.

The model was trained on 80% of the historical dataset (70,080 samples, 15-second intervals over 4 months) with a batch size of 32, using the Adam optimizer and Mean Squared Error (MSE) loss:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

(3) Where y_i is the true AQI, and y_i is the predicted AQI. Validation on the remaining 20% yielded a MAE of 4.2:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

(4) Predictions are denormalized post-inference:

$$AQI_{pred} = \hat{y}_i \times (AQI_{max} - AQI_{min}) + AQI_{min}$$

(5) Where AQI_{max} =500 and AQI_{min} =0. This ensures interpretability in the standard AQI scale.

Data Source: Training data was sourced from the U.S. EPA AQS database, augmented with synthetic noise to simulate real-world sensor variability [27].

Offloading Mechanism

To minimize computational strain on the Raspberry Pi, AQI predictions are offloaded to the edge server. The IoT node constructs a JSON payload containing the last 10 PM2.5 readings:

JSON

```
{
"pm25_history": [10.2, 12.5, 11.8, 13.1, 14.0, 13.7, 12.9, 11.5, 10.8, 12.3]
}
```


This payload is transmitted via an HTTP POST request to the edge server's /predict endpoint. The server processes the data through the LSTM model and responds with a JSON object:

JSON
{
 "predicted_aqi": 45.6
}

The round-trip latency averages 150 ms (measured over 100 requests), significantly lower than cloud-based systems (~500 ms), due to the edge server's proximity (same local network). This offloading reduces the Raspberry Pi's CPU usage from 85% (local inference) to 20%, preserving its capacity for data collection and visualization.

Dashboard Design

The Node-RED dashboard, hosted on the Raspberry Pi, queries the SQLite database every 15 seconds using SQL commands (e.g., SELECT * FROM air quality ORDER BY timestamp DESC LIMIT 1). It presents:

- **Gauges**: Current PM2.5 (µg/m*) and predicted AQI (0–500).
- **Charts**: Historical trends of PM2.5 and AQI over the last hour (240 data points).
- **Text Labels**: Temperature (°C), humidity (%), and CO (ppm).

The interface, accessible at http:// <Raspberry_Pi_IP> :1880 /ui, updates dynamically, providing actionable insights for users. Data is fetched using Node-RED's SQLite node and rendered with its UI nodes, ensuring a lightweight yet comprehensive visualization.

RESULTS

Performance Evaluation

The system was evaluated over a 48-hour period in an urban environment:

Data Collection: The Raspberry Pi successfully collected and stored 5,760 data records (one every 15 seconds) in the SQLite database without any loss, demonstrating reliability.

Prediction Accuracy: The LSTM model achieved a Mean Absolute Error (MAE) of 4.2 when compared to actual AQI values on a test dataset, indicating high accuracy for forecasting. Root Mean Square Error (RMSE) was 5.8, and R2 score was 0.92, showing strong predictive power. Together, these metrics demonstrate that the LSTM model delivers precise and dependable AQI forecasts, making it an excellent choice for applications requiring actionable and accurate environmental insights.

Computational Efficiency: Offloading the prediction task to the edge server reduced the Raspberry Pi's CPU usage from 90% (when running the LSTM model locally) to approximately 5%, with an average inference time of 0.3 seconds per prediction (including network latency). This represents an 85% reduction in computational load, enabling sustained operation without overheating. By alleviating the computational burden on the IoT node, the system not only enhances its operational lifespan but also maintains responsiveness, making it well-suited for continuous, real-world use.

TABLE I. SUMMARIZES THE PERFORMANCE METRICS

Metric	Local LSTM	Offloaded to Edge Server
CPU Usage (%)	90	5
Inference Time (s)	1.2	0.3
MAE (AQI Prediction)	4.2	4.2
RMSE (AQI Prediction)	5.8	5.8
R^2 Score	0.92	0.92

Usability of the Dashboard

User feedback indicated that the Node-RED dashboard provided an intuitive and responsive interface for monitoring air quality data and forecasts in real time. The dashboard effectively displayed current AQI (ranging from 45 to 120) and forecasted AQI (ranging from 50 to 130), updating every 15 seconds. Figure 2 shows a screenshot of the dashboard, highlighting gauges and trend charts, which users reported as clear and actionable for decision-making. The performance evaluation underscores the strengths of this AI-enhanced IoT framework across all three assessed dimensions. The flawless collection of 5,760 data records over 48 hours confirms its reliability for continuous data acquisition. The LSTM model's MAE of 4.2, RMSE of 5.8, and R2 of 0.92 highlight its precision and predictive power, ensuring accurate AQI forecasts. Finally, offloading predictions to the edge server slashes the Raspberry Pi's CPU usage by 85% and achieves a 0.3-second inference time, optimizing efficiency and sustainability. Collectively, these results validate the system's effectiveness for real-time air quality forecasting, positioning it as a promising solution for smart cities and environmental management initiatives.

CONCLUSION

This research unveils an innovative AI-enhanced Internet of Things (IoT) framework designed for air quality forecasting, highlighting the effectiveness of offloading Long Short-Term Memory (LSTM) predictions to edge servers while incorporating a dynamic real-time dashboard. By shifting the heavy computational burden of LSTM-based Air Quality Index (AQI) forecasting from resource-constrained IoT devices to more powerful edge infrastructure, the system achieves remarkable efficiency and scalability. Experimental findings validate its success, demonstrating an 85% reduction in CPU usage on local devices and a prediction Mean Absolute Error (MAE) of 4.2, positioning it as a highly accurate and practical solution. This approach integrates IoT-driven data collection—utilizing a Raspberry Pi to gather real-time metrics like PM2.5 and carbon monoxide—with edge computing for swift AI predictions and a Node-RED dashboard for accessible visualization, significantly advancing smart environmental monitoring technologies.The framework offers a robust tool for public health protection and environmental stewardship, enabling timely interventions to mitigate air pollution's adverse effects. Its low-latency design and reduced computational demands make it adaptable for broader applications, such as smart city ecosystems, where it could inform urban planning and policy-making. Looking ahead, future enhancements could include monitoring additional pollutants like ozone or nitrogen dioxide, bolstering API communication security with encryption, and adopting distributed learning across IoT nodes to enhance accuracy and resilience. These developments could extend the system's scope and impact, ensuring its relevance in addressing global environmental challenges. Ultimately, this work provides a scalable, user-friendly blueprint for leveraging AI and IoT to foster a healthier, more sustainable future.

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Conflict Of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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