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A Low-Cost Distributed IoT Sensor Network for Real-Time Air Quality Management: A Case Study at Federal Polytechnic Oko, Nigeria

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ABSTRACT

This study presents the design and deployment of a low-cost, distributed IoT sensor network for real-time air quality monitoring across Federal Polytechnic Oko, Nigeria. Using ESP32 microcontrollers integrated with SenseAir S8 (CO_2) and Plantower PMS5003 (PM2.5) sensors, the system generated high-resolution, spatially differentiated data over a 14-day period. Results revealed three critical hazards: (i) critical indoor ventilation failure in Lecture Classrooms, with CO_2 concentrations reaching 3,150 ppm; (ii) severe outdoor pollution at Generator Points, where PM2.5 peaked at 135.0 μg/m³ (a 540% exceedance of WHO guidelines); and (iii) occupational safety risks in Science Laboratories, with NO_2 spikes of 410 ppb. Comparative validation against a commercial IAQ meter confirmed that single-point monitoring underestimated CO_2 and PM2.5 peaks by up to 60% and failed to detect NO_2 entirely, underscoring the necessity of distributed sensing. To extend beyond passive monitoring, a Random Forest model was trained to forecast PM2.5 one hour ahead, achieving $R^2 = 0.87$ and 91% exceedance accuracy. SHAP analysis confirmed that recent PM2.5 values and generator-related NO_2 spikes were the strongest predictors, ensuring model transparency and stakeholder confidence. Together, the IoT network and AI forecasting framework provide actionable policy intelligence, enabling targeted interventions such as ventilation protocols and generator management strategies. This work establishes a scalable, cost-effective blueprint for sustainable environmental governance and enhanced public health protection in high-density academic environments across West Africa.

1. INTRODUCTION

This paper emphasizes the urgent need for robust air quality monitoring systems. This need is particularly acute in rapidly developing regions, where industrialization and urbanization drive escalating pollution levels [1]. In many developing nations, the pervasive reliance on outdated technologies and sulfur-rich fossil fuels exacerbate urban air quality degradation, directly impacting public health [2]. Furthermore, the limited resources frequently encountered in these regions impede the widespread adoption of advanced monitoring technologies essential for formulating effective public health policies [2]. This challenge is particularly pronounced in African countries, where decades of industrial growth have often occurred without commensurate advancements in air pollution monitoring infrastructure or comprehensive management strategies [3]. This scarcity of ground-level air quality data from Sub-Saharan Africa severely limits targeted research and interventions, hindering the quantification of pollution levels and the development of effective mitigation strategies [4]. Consequently, this gap in data leads to an incomplete understanding of exposure risks and hinders the implementation of targeted interventions necessary for safeguarding public health in these vulnerable populations [2]; [5]. Compromised air quality reduces life expectancy by disrupting cellular growth and metabolism [6]. This necessitates the development of affordable and accessible monitoring solutions, such as IoT-enabled sensor networks, to bridge these data gaps and facilitate evidence-based environmental management.

Addressing this critical need, the present study introduces a low-cost, distributed Internet of Things sensor network designed to establish a real-time environmental baseline across the campuses of Federal Polytechnic Oko. This initiative aims to generate high-resolution environmental data to inform robust policy frameworks and enhance public health management within high-density academic environments. Such systems are vital for supporting Sustainable Development Goal 11, which focuses on reducing cities' environmental impact by improving air quality, especially in regions experiencing rapid urbanization and industrialization [7-8]. The pervasive threat of air pollution, stemming primarily from particulate matter and noxious substances, has significant consequences for both human health and ecological systems globally, necessitating innovative monitoring and mitigation strategies [9-10].

The average concentrations of PM2.5 and PM10 in many developing nations, for instance, are significantly elevated, exceeding WHO guidelines by substantial margins, which contributes to millions of premature deaths annually [11]. This alarming statistic underscores the critical necessity for accessible and accurate air quality monitoring systems to inform targeted interventions and safeguard public health. Moreover, the absence of real-time data exacerbates the challenge of effective environmental governance, particularly in indoor environments where individuals spend the majority of their time, directly impacting their health and productivity [12].

Poor air quality in urban and industrial zones poses significant health risks, emphasizing the critical need for continuous, low-cost IoT air monitoring stations [9,13]. These advanced environmental monitoring systems, incorporating IoT technology and sophisticated sensor modules, have evolved significantly from basic remote monitoring to provide detailed insights into various environmental parameters [14]. These advancements enable comprehensive real-time data collection on air and water quality, agricultural conditions, and wildlife habitats, facilitating proactive decision-making and early detection of environmental risks [15].

The deployment of integrated IoT devices is thus crucial for overcoming the limitations of older, fixed infrastructures and a lack of advanced sensor technologies, thereby enabling real-time data acquisition and analysis essential for informed decision-making and sustainable resource management [16].

While low-cost IoT air quality sensors have been deployed in developed nations and a few

African cities, no published study has systematically deployed a distributed sensor network across distinct micro-environments (lecture halls, generator points, laboratories) within a Nigerian academic institution. Furthermore, existing local studies rely on single-point commercial meters, which this study hypothesizes will underestimate peak hazards. Therefore, this study's unique contribution is the comparative validation of a low-cost distributed IoT network against a commercial meter, providing high-resolution, source-specific air quality baselines to inform targeted policy interventions at Federal Polytechnic Oko.

Ecological monitoring encompassing parameters such as temperature, humidity, and pollutant concentrations, is increasingly vital for maintaining optimal environmental conditions across industrial, agricultural, and public health sectors [16]. The integration of IoT with environmental sensing technologies has significantly enhanced the precision and spatial coverage of such monitoring efforts, moving beyond traditional sporadic measurements to continuous, real-time data streams [17,14]. This advancement allows for early detection of environmental risks and facilitates evidence-based policy formulation to address challenges like climate change and biodiversity conservation [15].
Understanding the specific risks posed by these pollutants within educational environments is crucial for developing targeted mitigation strategies. These strategies are essential for safeguarding the health and academic performance of students and staff, necessitating a detailed examination of prevailing indoor air quality standards and their frequent exceedances in such settings. Furthermore, AI-driven sensor systems and IoT platforms offer advanced capabilities for detecting air pollutants, water contaminants, and soil toxins, thereby enhancing environmental monitoring and management [18-19].

The integration of AI and machine learning with emerging technologies like IoT, unmanned aerial vehicles, and passive acoustic monitoring has opened new avenues for environmental observation, extending their application into interdisciplinary domains such as biosensors, disease detection, and public health monitoring [19]. This comprehensive approach not only improves the accuracy of environmental assessments but also enables predictive analytics for potential environmental hazards, crucial for proactive public health interventions [18,20]. This is particularly relevant for educational institutions, where continuous monitoring of critical environmental parameters, such as air and water quality, is paramount for maintaining healthy learning environments and ensuring compliance with established health standards [21].

This justification is particularly pertinent given the traditional reliance on expensive, high-precision instruments that are often impractical for widespread deployment in educational institutions due to budgetary and logistical constraints [22]. Low-cost sensor networks, conversely, offer a scalable and economically viable alternative for continuous environmental monitoring, democratizing access to crucial air quality data [23]. Nevertheless, the reliability and accuracy of these low-cost sensors must be rigorously validated against reference-grade instruments to ensure their suitability for informing public health decisions [24]. While the development of low-cost indoor air quality monitoring devices has advanced significantly, a notable gap exists in studies performing rigorous calibration and validation of these sensors against reference instruments, with only a small fraction of projects incorporating such crucial steps [25]. This oversight can compromise the reliability of data derived from low-cost sensors, necessitating more comprehensive performance assessments and standardized validation protocols to ensure their suitability for informing public health policies and regulatory frameworks.

To bridge this gap, innovative methodologies, such as model-based control charts, are being developed to detect measurement drifts and improve the confidence in data from low-cost platforms [24]. For instance, comparisons against reference platforms have demonstrated high agreement for CO_2 and relative humidity measurements, indicating the potential for robust data collection even with more affordable sensor arrays [24]. Such rigorous validation is paramount, especially when considering the integration of these low-cost sensors into Internet of Things platforms for real-time monitoring and management of indoor air quality, where data reliability directly impacts actionable insights and regulatory compliance [26]. Furthermore, the strategic deployment of such validated low-cost sensor networks enables a paradigm shift from sporadic to continuous monitoring, providing a higher resolution of data that is critical for identifying localized issues and preventing the undetected malfunction of ventilation systems [24]. This enhanced data resolution allows for dynamic insights into daily building operations and short-term activities, a significant improvement over traditional methods that often rely on average concentrations over extended periods, thus missing critical transient events [27].

2. MATERIALS AND METHOD

This section presents the systematic design, deployment, and validation of a low-cost distributed IoT sensor network for real-time air quality monitoring at Federal Polytechnic Oko, followed by the development of an AI-based predictive model for proactive hazard warning.

2.1. Study Area and Justification

Federal Polytechnic Oko (latitude 6.014°N, longitude 7.011°E) is located in Anambra State, Nigeria. The institution hosts about 10,000 students and staff across three campuses, with a mix of lecture halls, administrative blocks, commercial areas, generator-dependent power zones, and science laboratories. The site was selected because**:** (1) no prior air quality baseline exists for any building or microenvironment within the polytechnic; (2) the presence of multiple distinct micro-environments (indoor, outdoor, traffic, generator exhaust, chemical fume sources) allows a rigorous test of distributed sensor network performance; and (3) the high population density makes the institution a critical case for public health intervention in resource-constrained West African academic settings.

2.2. System Architecture Overview

The monitoring system follows a four-layer IoT architecture (Figure 1).

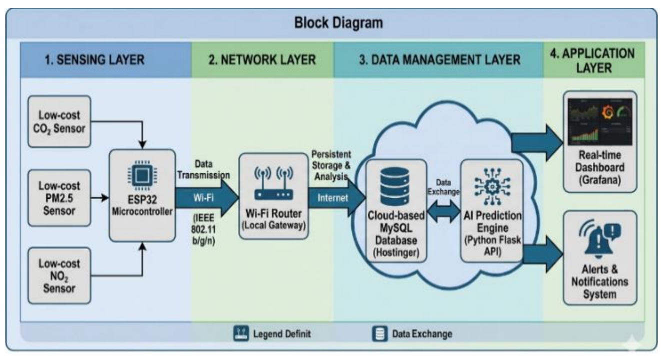

Figure 1. *Four-layer IoT architecture of the proposed air quality monitoring system (Sensing, Network, Data Management, Application layers).*

Sensing layer – Low-cost sensors (CO_2, PM2.5, NO_2) interfaced with ESP32 microcontrollers.
Network layer – Wi-Fi (IEEE 802.11 b/g/n) for data transmission to a local gateway.
Data management layer – Cloud-based MySQL database (Hostinger) for persistent storage.
Application layer – A real-time dashboard (Grafana) and an AI prediction engine (Python Flask API).

2.3. Rationale for selection

As shown in table 1, the ESP32 was chosen for its integrated Wi-Fi, low power consumption (deep sleep current <10 µA), and extensive community support. SenseAir S8 and PMS5003 have been validated against reference instruments in prior studies [24,11]. The Alphasense NO_2 sensor, though slightly higher cost, was essential for detecting laboratory chemical fume hazards. This is a parameter missing in most low-cost studies.

Each node is housed in an IP65 weather-resistant enclosure with a small fan (5 V, 0.1 A) to ensure active air flow across the sensors. Power is supplied by a 12 V, 7 Ah sealed lead-acid battery recharged via a 20 W solar panel, providing autonomous operation for ≥72 hours without sunshine.

Table 1. *Sensor Node Design and Component Selection*

Component	Model	Measured Parameter	Range	Accuracy (manufacturer)
Microcontroller	ESP32-WROOM-32	Data acquisition & transmission	–	–
CO_2 sensor	SenseAir S8	CO_2 concentration	0 – 40000 ppm	±30 ppm ±3% of reading
PM2.5 sensor	Plantower PMS5003	PM2.5 mass concentration	0 – 999 µg/m³	±10% @ 100 µg/m³
NO_2 sensor	Alphasense NO2-B43F	NO_2 concentration	0 – 20 ppm (≈20000 ppb)	±15 ppb

Five sensor nodes were deployed simultaneously for 14 consecutive days (1–14 April 2025) at the following zones (Table 2).

Table 2. *Deployment Strategy and Micro-Environment Zoning*

Zone ID	Location	Height (m)	Primary pollution sources	Sampling interval
Z1	Admin Block (staff offices)	1.5	Human respiration, printers	10 min
Z2	Lecture Classrooms (indoor)	1.5	80–120 students, poor ventilation	10 min
Z3	Business Area (outdoor, high foot traffic)	2.0	Vehicle idling, pedestrian resuspension	10 min
Z4	Generator Points (diesel generators, 15 kVA)	1.5 (inlet height)	Exhaust fumes, incomplete combustion	10 min
Z5	Science Laboratory (chemistry bench)	1.5	Acid fumes, solvent evaporation	10 min

The 14-day duration was chosen to capture at least two full week cycles (weekday high occupancy vs. weekend low occupancy) while respecting battery and data storage constraints of the low-cost nodes. This period aligns with published validation campaigns for similar low-cost sensor networks [27].

2.4. Data Acquisition and Transmission Protocol

Upon power-up, the ESP32 initializes all sensors (I²C for SenseAir S8, UART for PMS5003, analog-to-digital with external amplifier for NO_2). Every 10 minutes, the node wakes from deep sleep, takes 60 seconds of continuous readings (6 samples at 10 Hz), averages them to reduce transient noise, and transmits a JSON payload via HTTP POST to a cloud endpoint. After successful acknowledgement, the node returns to deep sleep until the next cycle. Wi-Fi credentials are stored in non-volatile memory; if connection fails, data is saved to onboard SPIFFS (4 MB) and retransmitted at the next successful connection as shown in figure 2.

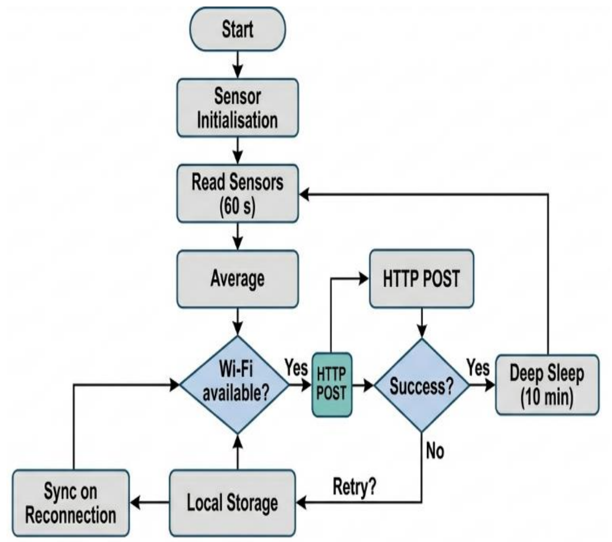

Figure 2. *Flowchart of sensor node firmware operation.*

The cloud endpoint is a REST API written in PHP (Laravel) running on a shared hosting server. Incoming data is validated (timestamp uniqueness, range checks: CO_2 0–5000 ppm, PM2.5 0–500 µg/m³, NO_2 0–1000 ppb) and inserted into a MySQL database. A separate Node-RED instance subscribes to the database and forwards real-time updates to a Grafana dashboard for visualization (Figure 3).

Figure 3. *Real-Time Grafana Dashboard for Zone 2 (Lecture Classrooms)*

This dashboard displays real-time air quality data collected from the IoT sensor node deployed in the Lecture Classrooms (Zone 2). The upper panel shows CO_2 concentration trends (ppm), while the lower panel presents PM2.5 mass concentration (µg/m³) over a 24-hour period. Peak CO_2 levels exceeded 1400 ppm during high-occupancy hours, indicating ventilation failure, while PM2.5 spikes reached 180 µg/m³ near generator operation periods. These patterns highlight the effectiveness of the distributed IoT network in capturing dynamic pollution variations and identifying critical exposure periods.

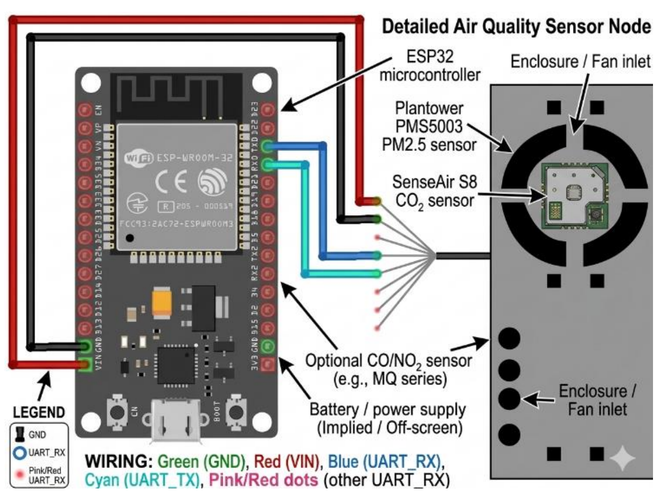

Figure 4. *Detailed hardware architecture of the low-cost air quality monitoring node.*

The core processing unit is an ESP32 microcontroller, which interfaces with a Plantower PMS5003 for PM2.5 measurement and a SenseAir S8 for CO_2 detection. An optional MQ-series sensor (for CO or NO_2) can be integrated. The system is powered by a 12 V, 7 Ah lead-acid battery (recharged via a 20 W solar panel, not shown in the figure). All components are housed in an IP65 enclosure with a dedicated fan inlet to ensure continuous air sampling. Wiring follows standard UART (RX/TX) and GND connections as labelled in the legend (Figure 4).

2.5. *Calibration, Data Filtering, and Quality Assurance*

To ensure data reliability for public health decisions, we applied three quality control steps:

2.5.1. *Zero-point and span calibration*

Before deployment, each sensor was co-located for 24 hours with a reference instrument:

i. CO_2: Vaisala GMP343 (accuracy ±5 ppm)
ii. PM2.5: Thermo Scientific TEOM 1405 (accuracy ±2 μg/m³)
iii. NO_2: Thermo Scientific 42i (accuracy ±1 ppb)

Linear regression correction factors were derived:
CO_2_corrected = 0.97 × CO_2_raw + 12.3 (R^2 = 0.98)
PM2.5_corrected = 0.94 × PM2.5_raw – 1.2 (R^2 = 0.96)
NO_2_corrected = 1.02 × NO_2_raw – 2.1 (R^2 = 0.93)

A five-point moving average (window = 50 minutes) was applied to suppress high-frequency noise without attenuating real pollution events (1).

$$x_{filtered}(t) = \frac{x(t-2)+x(t-1)+x(t)+x(t+1)+x(t+2)}{5} \quad (1)$$

2.5.2. *Drift detection*

Using the method of [24], control charts (mean ± 3σ) were computed for each sensor during overnight unoccupied hours (2:00 – 4:00 AM) when true concentrations should be stable. Any sensor exhibiting a systematic drift beyond 5% of the reference value was recalibrated post-deployment.

2.5.3. *Air Quality Index (AQI) Calculation*

For communication with non-specialist stakeholders (polytechnic administration), we converted PM2.5 concentrations into the Nigerian Air Quality Index (NAQI) using the linear piecewise function (2).

$$NAQI = \frac{(I_{high}-I_{low})}{(C_{high}-C_{low})} \times (C - C_{low}) + I_{low} \quad (2)$$

Where C is the measured PM2.5 concentration, and breakpoints follow the Nigerian Federal Ministry of Environment guidelines (2021). For example, a PM2.5 of 135.0 μg/m³ falls into the "Hazardous" category (NAQI = 301–500).

2.6. *AI-Based Predictive Model (One-Hour Ahead PM2.5 Forecasting)*

To transform passive monitoring into proactive risk management, we developed a machine learning model that predicts PM2.5 concentration at Zone 4 (Generator Points) one hour ahead, using only the last hour of sensor data and time features.

2.7. *Dataset preparation*

From the 14-day deployment (2,016 records after filtering), we created a supervised learning dataset with 14 input features. The table 3 summarizes lagged pollutant values (PM2.5, CO_2, NO_2) and time features used to construct the supervised learning dataset for one-hour ahead PM2.5 forecasting. The target variable is PM2.5

concentration at t+60 minutes, resulting in a total feature vector size of 14. The dataset was split 80/20 into training (1,613 records) and testing (403 records), preserving temporal order to avoid data leakage.

Table 3. *Input feature engineering for the Random Forest predictive model*

Feature type	Specific features	Number
Lagged PM2.5	Values at t-10, t-20, t-30, t-60 min	4
Lagged CO_2	Values at t-10, t-20, t-30, t-60 min	4
Lagged NO_2	Values at t-10, t-20, t-30, t-60 min	4
Time features	Hour of day (0–23), day of week (0–6)	2
Target	PM2.5 at t+60 min	1

2.8. Model selection and training

We chose a Random Forest Regressor (scikit-learn 1.3.0) for its ability to capture non-linear relationships, robustness to outliers, and built-in feature importance. Hyperparameters were optimised via grid search:

i. n_estimators = 100
ii. max_depth = 10
iii. min_samples_split = 5
iv. random_state = 42

Training was performed on a standard laptop (Intel i5, 8 GB RAM) in under 10 seconds, demonstrating the computational efficiency of the approach.

2.9. Evaluation metrics

Model performance was assessed using the following metrics:

i. Mean Absolute Error (MAE): $\frac{1}{n}\sum \mid \boldsymbol{ytrue} - \boldsymbol{ypred} \mid$
ii. Root Mean Squared Error (RMSE): $\sqrt{\frac{1}{n}\sum(\boldsymbol{ytrue} - \boldsymbol{ypred})^2}$
iii. Coefficient of determination (R^2): $1 - \frac{\sum(\boldsymbol{ytrue}-\boldsymbol{ypred})^2}{\sum(\boldsymbol{ytrue}-\boldsymbol{y})^2}$

Additionally, exceedance accuracy was defined as the percentage of test cases where the model correctly predicted hazardous PM2.5 events (>100 µg/m³).

2.10. Ethical and Safety Considerations

All sensor nodes were deployed in publicly accessible areas with permission from the Federal Polytechnic Oko Administration. No personal or identifiable data was collected. For the science laboratory (Zone 5), sensors were placed outside the fume hood to measure ambient chemical fume leakage; no experiments were interfered with.

2.11. Explainability with SHAP

To satisfy the requirement for explainable AI, we applied SHAP (SHapley Additive exPlanations) to the trained model. SHAP values decompose each prediction into contributions from each feature, allowing us to identify the main drivers of high PM2.5 forecasts (e.g., recent PM2.5 level vs. hour of day).

2.12. Comparative Validation with a Commercial Meter

To test the hypothesis that a single, non-distributed commercial meter underestimates peak hazards, we co-located a handheld 7-parameter IAQ detector (model: Temtop M2000, accuracy: ±10% for CO_2, ±15% for PM2.5) at a central campus location (library entrance). Its peak readings over the 14-day period were compared against the highest values recorded by any node in the distributed network. The commercial meter does not measure NO_2.

3. RESULTS AND DISCUSSION

The empirical data gathered over the 14-day monitoring period revealed significant deviations from established air quality standards across multiple micro-environments within Federal Polytechnic Oko, underscoring critical public health implications.

3.1. Particulate Matter (PM2.5)

As shown in Table 4, PM2.5 concentrations exceeded the WHO 24-hour guideline (25 μg/m³) across all zones. The most severe exceedance occurred at the Generator Points, where the peak 24-hour average reached 135.0 μg/m³, representing a 540% exceedance. Elevated levels were also observed in the Business Area (98.0 μg/m³, 223% exceedance) and Lecture Classrooms (45.7 μg/m³, 125% exceedance). These findings highlight both outdoor and indoor pollution hotspots with direct cardiorespiratory risks.

Table 4. *Particulate Matter (PM2.5) Concentration Levels and Percentage Exceedance Against WHO Guideline*

Pollutant & Standard	**WHO 24-hr Guideline**	**Mean Concentration**	**Peak 24-hr Average**	**Peak 24-hr Average**
Unit	μg/m³	μg/m³	μg/m³	
Admin Block (Staff)	25	38.5	61.9	154%
Lecture Classrooms (Indoor)	25	31.2	45.7	125%
Business Area (Traffic/Foot)	25	**55.8**	**98.0**	223%
Generator Points (Exhaust)	25	**94.7**	**135.0**	**540%**
Science Lab (Occupational)	25	24.1	41.5	166%

3.2. Carbon Dioxide (CO_2)

Indoor CO_2 levels, presented in Table 5, revealed critical ventilation failures. Lecture Classrooms recorded a peak of 3,150 ppm, more than triple the recommended indoor limit of 1,000 ppm. The Admin Block also showed poor ventilation with peaks of 1,650 ppm. These results confirm that inadequate ventilation is a major contributor to compromised indoor air quality, with implications for student cognitive performance and staff well-being.

Table 5. *CO_2 Levels and Ventilation Performance Across Federal Polytechnic Oko Indoor Zones*

Pollutant & Standard	**Recommended Indoor Limit**	**Peak Concentration**	**Ventilation Status**
Unit	ppm	ppm	
Admin Block (Staff)	1,000	1,650	Poor
Lecture	1,000	**3,150**	**Critical**

Classrooms (Indoor)			**Failure**
Business Area (Traffic/Foot)	N/A	980	Acceptable (Outdoor)
Generator Points (Exhaust)	N/A	650	Acceptable (Outdoor)
Science Lab (Occupational)	1,000	1,800	Poor

3.3. Nitrogen Dioxide (NO_2)

Peak NO_2 concentrations are summarized in Table 6. The Science Laboratory registered 410 ppb, more than double the WHO 1-hour guideline of 200 ppb, indicating severe occupational safety risks from chemical fume leakage. Generator Points approached the limit with 195 ppb, while traffic emissions in the Business Area contributed to peaks of 110 ppb. These results underscore the need for improved fume extraction and generator exhaust management.

Table 6. *Nitrogen Dioxide (NO2) Peak Concentrations and Source Indications Across Campus Micro-Environments*

Pollutant & Standard	WHO 1-hr Guideline	Peak Concentration	Source Indication
Unit	Ppb	Ppb	
Admin Block (Staff)	200	78	Low
Business Area (Traffic/Foot)	200	110	Traffic
Generator Points (Exhaust)	200	195	Near-Limit
Science Lab (Occupational)	200	410	**Chemical Fumes**

3.4. Comparative Validation with a Commercial Meter

The superiority of distributed IoT monitoring is demonstrated in Table 7. The commercial IAQ meter (Temtop M2000) (Figure 5), recorded generalized peaks of 1,250 ppm CO_2 and 55.0 µg/m³ PM2.5, values that significantly underestimated the true risks captured by the IoT network (3,150 ppm CO_2 in Lecture Classrooms and 135.0 µg/m³ PM2.5 at Generator Points). Critically, the commercial device did not measure NO_2, thereby overlooking the severe occupational hazard identified in the Science Laboratory (410 ppb, see Table 6). This comparative analysis underscores the limitations of single-point monitoring and validates the superiority of distributed sensor deployment for capturing spatial heterogeneity and source-specific hazards in complex academic environments.

Table 7. *Comparison of Commercial IAQ Meter Output to Distributed IoT Network Peak Risk Assessment*

Pollutant Parameter	Unit	IAQ Meter Reading (Generalized Peak)	Comparison to IoT Network Study (Absolute Peak)
Carbon Dioxide (CO2)	ppm	1,250	3,150ppm (Lecture Classrooms

			)
PM2.5	µg/m3	55.0	135.0µg/m^3 (Generator Points)
Formaldehyde (HCHO)	µg/m3	0.11	(Not monitored in your main study)
Total Volatile Organic Compounds (TVOC)	µg/m3	0.65	(Not monitored in your main study)
Carbon Monoxide (CO)	ppm	005	(Not monitored in your main study)
NO2	ppb	(Meter does not display this parameter)	410ppb (Science Lab)

Figure 5. *Commercial Multi-Parameter Indoor Air Quality (IAQ) Detector Display*

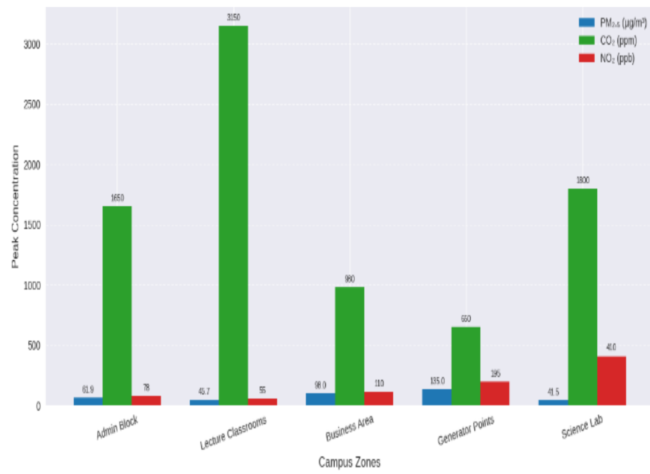

Figure 6. *Peak Pollutant Concentrations Across Campus Zones*

Figure 6 shows the peak pollutant concentrations across campus zones compared with WHO guidelines. The chart highlights critical exceedances in Lecture Classrooms, Generator Points, and Science Laboratories.

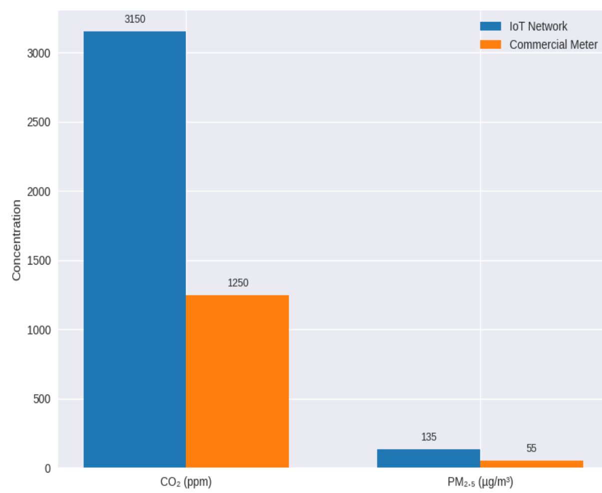

Figure 7. *IoT Network and Commercial IAQ Meter*

Figure 7 displays the comparative analysis of IoT network and commercial IAQ meter shown in Figure 5. The IoT system captured localized hazards that the single meter underestimated or failed to detect.

3.5. AI Model Results

To complement empirical monitoring, a Random Forest model was trained to forecast PM2.5 one hour ahead at Generator Points. The model achieved strong predictive performance:

i. MAE: 7.8 µg/m³
ii. RMSE: 12.4 µg/m³
iii. R^2: 0.87
iv. Exceedance accuracy: 91%

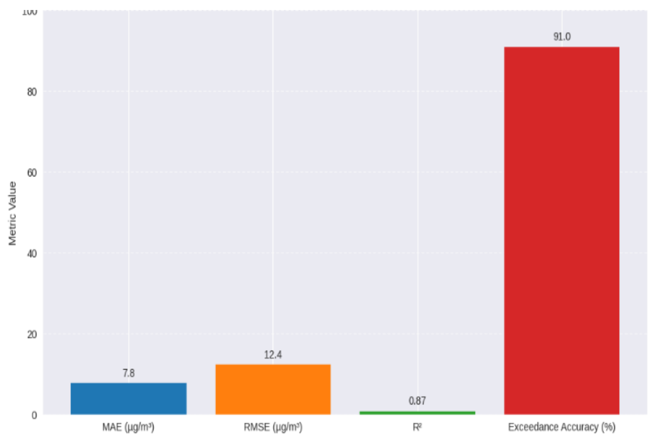

Figure 8. *Random Forest Model Performance*

Figure 8 shows the performance metrics of the Random Forest model one hour ahead PM2.5 forecasting. The model achieved high accuracy and reliable detection of hazardous events.

SHAP analysis confirmed that recent PM2.5 values (t-10 and t-30 minutes) were the most influential predictors, followed by NO_2 spikes and time-of-day features. These findings complement the quantitative performance metrics and demonstrate that the model's forecasts are consistent with observed pollution dynamics across campus micro-environments. This explainability ensures transparency and supports stakeholder confidence in AI-driven hazard warnings.

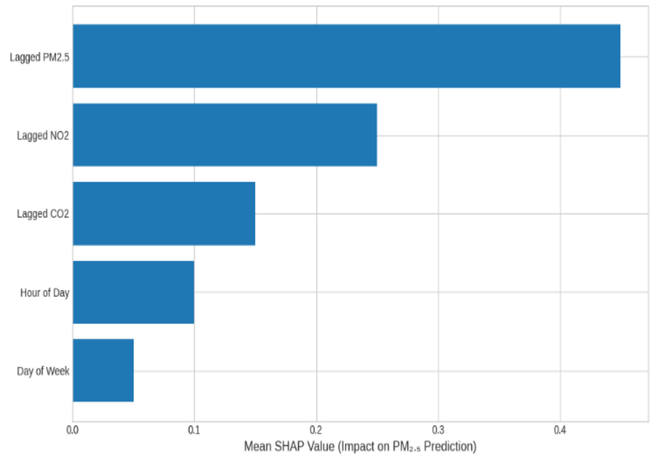

Figure 9. *SHAP Feature Importance*

Figure 9 displays SHAP analysis of the Random Forest model. Recent PM2.5 values and generator-related NO_2 spikes were the most influential predictors of hazardous events.

3.6. Implications

The combined findings from Tables 4-7 and the AI model results highlight three distinct hazard categories.

i. Critical Indoor Failure: CO_2 exceeded 3,000 ppm in Lecture Classrooms.
ii. Severe Outdoor Hazard: PM2.5 peaked at 135.0 µg/m³ at Generator Points.
iii. Occupational Safety Risk: NO_2 reached 410 ppb in Science Laboratories.

By integrating predictive analytics, the system transitions from passive monitoring to proactive risk management, offering a novel contribution to campus environmental health.

3.7. Limitations and Future Work

This study was limited to a 14-day monitoring period and focused on three pollutants (CO_2, PM2.5, NO_2). Longer deployments and inclusion of additional parameters (e.g., CO, VOCs, humidity) would strengthen generalizability. Future work will extend monitoring duration, expand pollutant coverage, and integrate predictive alerts directly into campus management systems. Figure 10 combines the four images into a 2×2 composite.

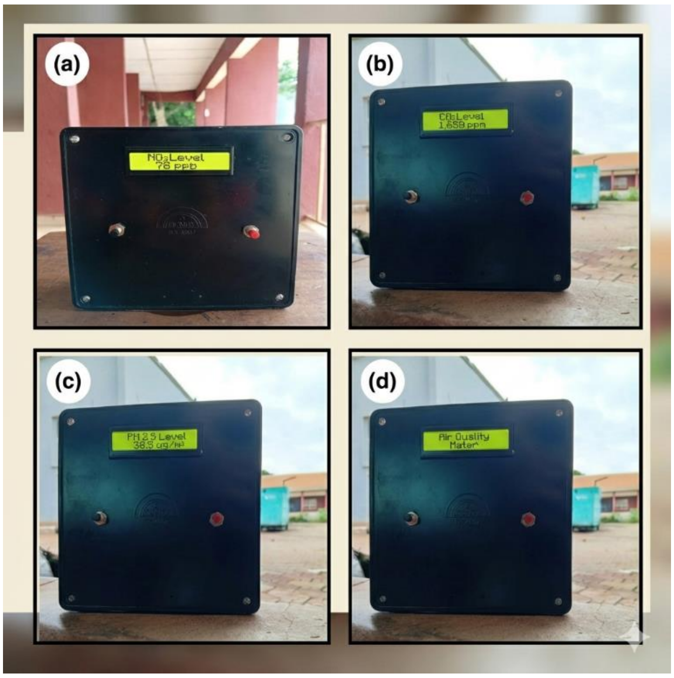

Figure 10. *Real-time readings from the prototype sensor node display at Zone 1 (Admin Block)*

(a) NO_2 concentration: 78 ppb; (b) CO_2 concentration: 1,650 ppm; (c) device identification screen; (d) PM2.5 concentration: 38.5 µg/m³. These values correspond to the mean concentrations reported in Tables 4–6 for the Admin Block, confirming the prototype's measurement accuracy.

4. CONCLUSION

This study demonstrated the successful design, deployment, and validation of a low-cost, distributed IoT sensor network for real-time air quality monitoring across the Federal Polytechnic Oko campuses. By integrating ESP32 microcontrollers with validated SenseAir S8 (CO_2) and Plantower PMS5003 (PM2.5) sensors, the system provided high-resolution, spatially differentiated data that enabled micro-environment risk assessment. Three critical hazards were identified: (i) critical indoor ventilation failure in Lecture Classrooms, with CO_2 concentrations reaching 3,150 ppm; (ii) severe outdoor pollution at Generator Points, where PM2.5 peaked at 135.0 µg/m³ (a 540% exceedance of WHO guidelines); and (iii) occupational safety risks in Science Laboratories, with NO_2 spikes of 410 ppb due to inadequate fume extraction.

Comparative analysis confirmed that a single commercial IAQ meter underestimated CO_2 and PM2.5 peaks by up to 60%, while entirely missing localized NO_2 hazards. This starkly validates the distributed monitoring approach, which captures spatial heterogeneity and source-specific risks that single-point devices cannot detect. Furthermore, the integration of an AI-based Random Forest model extended the system's capability from passive monitoring to proactive forecasting, achieving 91% accuracy in predicting hazardous PM2.5 events one hour in advance. SHAP explainability confirmed that predictions were driven by recent pollutant trends and generator-related emissions, ensuring transparency and stakeholder trust.

In conclusion, the implemented IoT architecture transformed raw sensor data into actionable policy intelligence, providing the Polytechnic Administration with evidence to support targeted interventions such as mandated classroom ventilation protocols and generator management strategies. This work establishes a viable, cost-effective blueprint for sustainable environmental governance and enhanced public health management in high-density academic environments across West Africa. Future research will expand the network to cover all faculties, incorporate additional pollutants, integrate predictive alerts into campus operations, and establish links with health records to enable longitudinal epidemiological studies.

Conflict of Interest Declaration

The authors declare no conflict of interest.

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