A Scalable IoT–Cloud Architecture with Deep Q-Learning for Air Quality Monitoring and Alerting

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ABSTRACT
Air pollution poses a growing threat to public health in rapidly urbanizing cities, particularly in Sub-Saharan Africa, where real-time monitoring infrastructure is limited. This paper presents the design and implementation of a scalable IoT and cloud-based architecture for air quality monitoring and intelligent alerting in Accra, Ghana. The system integrates low-cost ESP32-based sensor nodes with a Deep Q-Network (DQN) to classify pollution severity and issue adaptive, context-aware alerts. Eight key environmental parameters, including PM1.0, PM2.5, PM10, VOCs, CO, LPG, temperature, and humidity, are continuously monitored and analyzed using cloud-based processing. Real-time data is visualized through a web dashboard, while critical alerts are disseminated via SMS to ensure user accessibility. The DQN agent supports decision transparency through Q-values, feature importance, and temporal trend analysis. Experimental results demonstrate a training accuracy of 89% and a field test classification accuracy of 82.9%, confirming the system's effectiveness for scalable, real-time, and interpretable environmental health monitoring in resource-constrained settings.

General Terms
Artificial Intelligence, Internet of Things, Environmental Monitoring, Real-Time Systems, Cloud Computing, Reinforcement Learning.

Keywords
Air Quality Monitoring, Deep Q-Network, ESP32, IoT, Reinforcement Learning, Cloud Infrastructure, Environmental Sensing, Smart Cities.

1. INTRODUCTION
Air pollution is a pressing challenge in rapidly urbanizing cities, particularly in developing regions like Accra, Ghana. Common pollutants such as particulate matter (PM1.0, PM2.5, PM10), carbon monoxide (CO), volatile organic compounds (VOCs), and liquefied petroleum gas (LPG) often exceed recommended limits, contributing to a wide range of health issues, including asthma, cardiovascular diseases, and premature mortality [1], [2]. Despite the severity of this public health risk, most cities in Sub-Saharan Africa lack adequate real-time air quality monitoring infrastructure [3]. Existing solutions are typically static, centralized, and offer limited spatial and temporal coverage, making it difficult to respond effectively to localized pollution events or inform the public promptly.

The motivation for this research stems from the urgent need to empower individuals and communities with real-time, reliable, and actionable information on air quality. Traditional systems that rely on predefined pollutant thresholds are limited in their ability to adapt to changing environmental patterns. They also fail to capture complex interactions between pollutants and ambient conditions, such as temperature and humidity, which can influence pollutant dispersion and health risk. Recent advancements in low-cost IoT sensors, cloud computing platforms, and machine learning, particularly reinforcement learning, offer a compelling opportunity to move beyond static monitoring systems toward intelligent, adaptive, and user-oriented solutions.

This paper proposes the design and implementation of an intelligent, reinforcement learning enhanced air quality monitoring and alert system tailored for deployment in urban environments. The system integrates ESP32-based sensor nodes equipped with multiple environmental sensors to capture real-time data on key pollutants and weather conditions. This data is transmitted to a cloud-based platform, where a Deep Q-Network (DQN) agent is trained to classify pollution severity and generate appropriate alerts. The alerts are delivered through a responsive web dashboard and SMS messaging, supported by interpretable decision outputs including Q-values, feature importance, and short-term pollution trends. The goal is to create an end-to-end framework that enables real-time monitoring, intelligent alerting, and actionable feedback, ultimately supporting healthier urban living through informed decision-making.

2. RELATED WORKS
Many existing air quality monitoring systems rely on static, rule-based threshold mechanisms to trigger alerts. These systems typically use fixed pollutant concentration cutoffs, often based on WHO or national air quality standards, to classify air quality levels. For instance, Saleh et al. [4] developed an Arduino-based indoor monitoring system that triggered LED alerts when gas concentrations exceeded preset thresholds. While simple and cost-effective, this approach lacked adaptability to fluctuating environmental conditions or individual exposure contexts. Similarly, Marche et al. [5] present a comprehensive IoT–Fog–Cloud architecture for real-time air quality monitoring that emphasizes modular design and edge computing for scalability and responsiveness. However, the system still relies on static threshold-based alerting, which limits its ability to adapt to dynamic environmental changes.

Kumar et al. [6] employed a Raspberry Pi-based system to monitor carbon monoxide and particulate matter; however, their approach relied on fixed threshold alerts and did not incorporate automated decision-making or advanced data analysis capabilities. Although threshold-based systems are easy to deploy, they are unable to capture nuanced pollution trends or respond to seasonal, temporal, or behavioral changes. These limitations have prompted a shift toward intelligent, data-driven approaches that can learn from environmental patterns.

Machine learning techniques, particularly hybrid deep learning models, have demonstrated strong performance in forecasting air quality indices (AQI). For example, architectures combining ARIMA, CNN, and LSTM have been used to capture both spatial and temporal pollution dynamics across multiple cities [7]. Zhang and Li [8] applied CNN–LSTM networks for urban AQI forecasting, achieving high accuracy but without translating forecasts into actionable public alerts. Other studies have incorporated attention mechanisms, ARIMA, LSTM, and XGBoost into unified models, significantly improving forecasting performance in terms of RMSE and MAE [9], [10]. However, while these methods enhance prediction capabilities, most lack real-time alert delivery and interpretability for non-technical end users.

Several IoT-based platforms have integrated machine learning to enable continuous air quality monitoring and alerting. For example, Bandara et al. [11] introduced AirSPEC, a system built on ESP8266, Node-RED, and machine learning techniques to process sensor data and issue email-based alerts through a mobile dashboard. GASDUINO and similar open-source projects stream MQ sensor data to online dashboards and generate alerts when fixed thresholds are exceeded [12]. While these systems demonstrate the feasibility of combining IoT with real-time feedback, they often rely on static rule sets and lack adaptive intelligence or reinforcement learning models to personalize or optimize alerts based on context.

The reviewed literature demonstrates considerable progress in integrating IoT, machine learning, and reinforcement learning for air quality monitoring. Threshold-based systems offer simplicity but lack adaptability and responsiveness. Machine learning models, particularly deep hybrid architectures, demonstrate strong predictive capabilities but often fall short of delivering real-time, user-centered alerts. Similarly, many IoT platforms offer real-time monitoring but rely on static rules or lack transparency in decision-making.

These limitations highlight a clear research gap: the absence of an end-to-end, real-time air quality monitoring and alert system that combines low-cost IoT deployment, adaptive reinforcement learning-based decision-making, cloud integration, and interpretable alert delivery for urban environments. This paper addresses this gap by proposing a scalable, DQN-powered system that not only learns from real-world air quality data but also generates actionable, transparent alerts through web and SMS interfaces, thereby supporting public health responsiveness in data-scarce regions.

3. MATERIALS AND METHODS USED

This section outlines the hardware components, software frameworks, and experimental methodologies employed in developing and testing the intelligent cloud-based air quality monitoring system. The implementation involved a systematic approach combining IoT sensor deployment, cloud infrastructure configuration, machine learning model development, and comparative field testing. The materials selected and methods applied were chosen to ensure system reliability, scalability, and accuracy in real-world deployment scenarios.

3.1 Materials Used

3.1.1 ESP32 Microcontroller

The ESP32 development board shown in Figure 1 was selected as the primary microcontroller due to its dual-core processing architecture and integrated Wi-Fi connectivity. It functioned as the central control unit for each sensor node, coordinating data acquisition, local processing, and cloud communication tasks. The microcontroller was programmed to interface with the multi-sensor array, including MQ-5, MQ-135, MQ-9, PMS5003, and DHT22 sensors. It collected environmental data from these sensors, performed real-time validation and preprocessing, and then transmitted the processed data to Google Cloud Platform via secure HTTPS protocols. The ESP32 also managed alert generation through in-app notifications and SMS messaging via Twilio API integration.

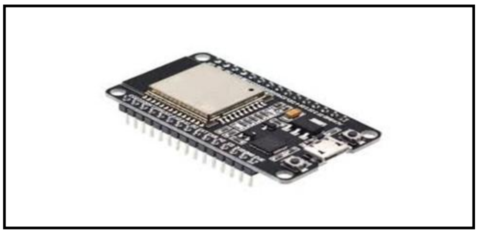

Figure 1: ESP32 Development Board

3.1.2 MQ-5 Gas Sensor

The MQ-5 gas sensor was used to detect concentrations of LPG and methane in the ambient air. This semiconductor-based sensor employs a tin dioxide (SnO_2) sensing element that shows changes in conductivity when exposed to target gases. The sensor's main purpose was to monitor potential gas leaks and combustible gas accumulations that could pose safety risks in residential and industrial settings. It operated within a detection range of 200 - 10,000 ppm for both LPG and methane, providing an analog output voltage that correlates to gas concentration. The MQ-5 was connected to the ESP32's 12-bit ADC via analog pins, allowing for continuous monitoring and real-time data transmission to the cloud platform for reinforcement learning analysis and intelligent decision-making regarding air quality patterns and safety predictions.

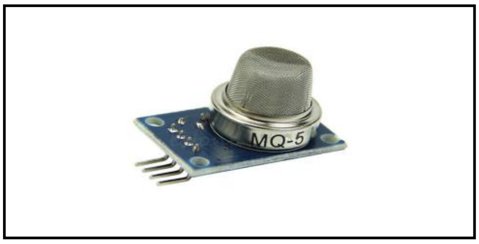

Figure 2: MQ-5 Gas Sensor

3.1.3 MQ-135 Air Quality Sensor

The MQ-135 air quality sensor was used to detect VOCs and provide a general air quality assessment. This semiconductor gas sensor features a tin dioxide (SnO_2) sensitive layer that changes resistance when exposed to various air pollutants, including ammonia, nitrogen oxides, alcohol, benzene, smoke, and carbon dioxide. Operating within a detection range of 10 - 300 ppm for ammonia and 10 - 1000 ppm for other target gases, the MQ-135 produced analog voltage signals corresponding to pollutant concentrations.

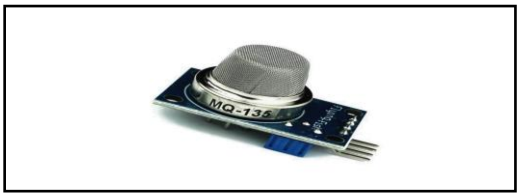

Figure 3: MQ-135 Air Quality Sensor

3.1.4 MQ-9 Carbon Monoxide Sensor

The MQ-9 gas sensor was implemented specifically to detect and monitor carbon monoxide (CO) levels in the ambient environment. The sensor's primary role is to detect dangerous CO concentrations that pose significant health risks, particularly in enclosed spaces where combustion processes occur. Operating within a detection range of 10 - 1000 ppm for carbon monoxide, the MQ-9 provides an analog voltage output that is directly proportional to CO concentration levels.

Figure 4: MQ-9 Carbon Monoxide Sensor

3.1.5 DHT22 Temperature and Humidity Sensor

The DHT22 sensor was employed for measuring ambient temperature and relative humidity parameters essential for comprehensive air quality assessment. This digital sensor utilizes a capacitive humidity sensing element and a thermistor for temperature measurement, providing calibrated digital output signals. Operating within a temperature range of -40°C to 80°C (±0.5°C accuracy) and a humidity range of 0 - 100% (±2 - 5% accuracy), the DHT22 transmits data via a single-wire digital communication protocol.

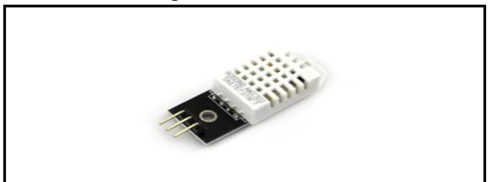

Figure 5: DHT22 Temperature and Humidity Sensor

3.1.6 PMS5003 Particulate Matter Sensor

The PMS5003 sensor was utilized for detecting and quantifying particulate matter concentrations in three size categories: PM1.0, PM2.5, and PM10. This laser-based optical sensor employs light scattering principles to measure airborne particles, providing precise measurements of fine and coarse particulate matter that significantly impact human respiratory health. Operating with a measurement range of 0 - 500 μg/m³ for all particle sizes and providing real-time concentration data via UART serial communication, the PMS5003 delivered digital output with ±10% accuracy.

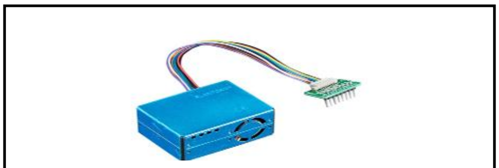

Figure 7: PMS5003 Sensor

3.1.7 Google Cloud Infrastructure

The project utilized Google Cloud Platform as the backbone infrastructure to provide scalable, reliable, and high-performance cloud computing services for the reinforcement learning-based air quality monitoring system.

3.1.7.1 Data Storage

InfluxDB was deployed on Google Compute Engine instances to serve as the primary time-series database, optimized for handling continuous sensor data streams with high write throughput and efficient temporal queries. This specialized database architecture enabled rapid ingestion of real-time environmental measurements while supporting complex time-based analytics required by the reinforcement learning algorithms.

3.1.7.2 API Services

Flask-based RESTful APIs were containerized and deployed on Google Kubernetes Engine (GKE) clusters to provide scalable backend services for data ingestion and processing. The Kubernetes orchestration enabled automatic scaling, load balancing, and fault tolerance, ensuring consistent API performance under varying data loads from multiple sensor nodes feeding the reinforcement learning models.

3.1.7.3 Machine Learning

Google Cloud Vertex AI was employed for the complete reinforcement learning lifecycle, including agent training, policy optimization, and model deployment. This managed AI platform facilitated the development of reinforcement learning algorithms that continuously learned from sensor data patterns to make intelligent decisions regarding air quality predictions and adaptive alert generation.

3.1.7.4 Real-Time Processing

Google Cloud Pub/Sub served as the messaging middleware for asynchronous data streaming, while Google Cloud Dataflow provided stream processing capabilities for real-time data transformation and preparation before feeding into the reinforcement learning training pipeline.

3.1.7.5 Communication

WebSocket services were implemented to enable persistent, low-latency bidirectional communication between the cloud infrastructure and web dashboard, while Twilio API integration provided SMS messaging capabilities for critical air quality alerts and notifications to users' mobile devices.

3.2 Methods Used

3.2.1 Data Collection Methodology

A distributed network of ESP32-based sensor nodes was deployed across three distinct environmental zones: high-pollution areas near dusty roads and clean residential settings. This arrangement ensured spatial diversity in air quality measurements. Each sensor node was equipped to monitor gas concentrations, particulate matter, and ambient environmental conditions. Data acquisition was carried out over a continuous six-week period during May and June 2025, with sampling conducted at 15-minute intervals. All sensor nodes were synchronized using Network Time Protocol (NTP) servers to maintain consistent timestamping. Real-time calibration routines and automated outlier detection were implemented to enhance the accuracy and reliability of the measurements.

Cross-validation among co-located sensors, along with benchmarking against certified reference instruments, confirmed a measurement accuracy within ± 5%. The system achieved a data completeness rate of 99.7% over the monitoring period. In total, approximately 30,000 validated records were collected, capturing eight environmental parameters: LPG, VOCs, CO, PM1.0, PM2.5, PM10, temperature, and humidity. This dataset forms a robust foundation for subsequent modeling and evaluation of air quality dynamics.

Table 1. Statistical Summary of the Parameters

Parameter	Mean	Std Dev	Min	Max
LPG (ppm)	1126.87	613.78	230.10	2043.30
VOC (ppm)	163.07	87.62	30.10	281.50
CO (ppm)	42.87	23.11	7.30	75.70
PM1.0 (μg/m³)	85.87	49.20	11.70	161.80
PM2.5 (μg/m³)	148.89	86.56	18.70	307.40
PM10 (μg/m³)	230.81	135.01	26.40	518.60
Temperature (°C)	41.12	7.88	22.50	53.80
Humidity (%)	54.19	7.83	37.40	75.60

3.2.2 Machine Learning Model Development

The core of the intelligent alert system is a Deep Q-Network (DQN), which employs a neural network to approximate the optimal action-value function (Q-function). This network takes the current environmental state as input and outputs Q-values for each possible action. The action with the highest Q-value is then selected as the recommended alert level. The architecture of the Deep Q-Network utilized in this system is illustrated in Figure 8.

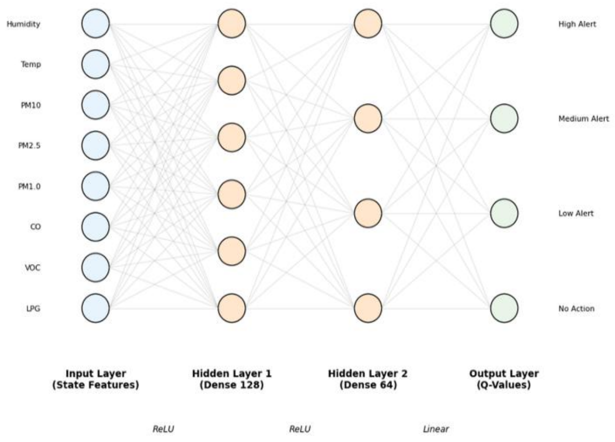

Figure 8: Deep Q-Network Architecture

The Deep Q-Network (DQN) receives eight input features: humidity, temperature, PM10, PM2.5, PM1.0, CO, VOCs, and LPG, which together represent real-time air quality conditions. The architecture consists of two hidden layers with 128 and 64 neurons, respectively. Both layers use Rectified Linear Unit (ReLU) activation functions to capture non-linear relationships in the data. The output layer contains four nodes with a linear activation function, corresponding to the possible actions: High Alert, Medium Alert, Low Alert, and No Action. These nodes output Q-values that guide decision-making.

4. SYSTEM DESIGN, ANALYSIS AND IMPLEMENTATION

4.1 System Design and Analysis

This section presents the architectural framework and analytical approach employed in developing the intelligent air quality monitoring system. The design methodology encompassed hardware integration, cloud infrastructure configuration, reinforcement learning model architecture, and user interface development, with subsequent analysis of system performance and operational efficiency.

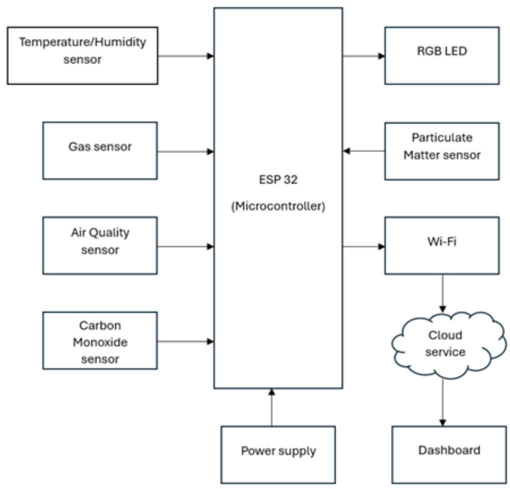

Figure 9: Block Diagram of Proposed System

Figure 10 below gives the workflow of the proposed system.

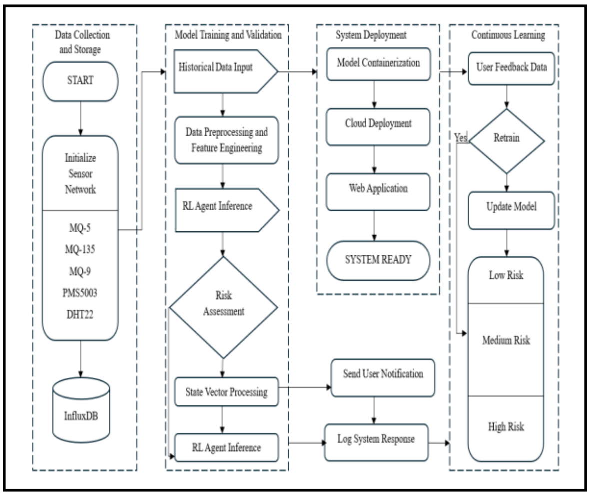

Figure 10: Proposed System Workflow

Figure 11 depicts the complete circuit schematic and hardware integration layout for the intelligent air quality monitoring system's sensor node architecture. The circuit design was systematically configured to accommodate the multi-sensor requirements essential for comprehensive environmental monitoring in dust-prone areas targeted by this research study.

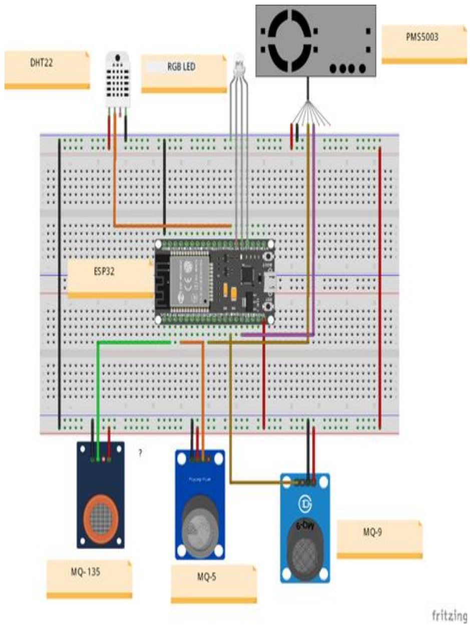

Figure 11: Circuit Diagram of the IoT-based Air Quality Monitoring System

4.2 System Implementation

The intelligent air quality monitoring system was developed, assembled, and deployed in a robust enclosure to ensure protection from environmental conditions. The complete system was field-tested for 6 weeks in both highly polluted areas adjacent to dusty roads and clean air environments to validate performance under varying pollution conditions. All sensor components and the ESP32 microcontroller were integrated into a single monitoring unit with optimized power management for extended operation. The system utilized Wi-Fi connectivity to transmit real-time data to the Google Cloud Platform infrastructure, enabling continuous monitoring without requiring local internet infrastructure. The web-based dashboard was accessible remotely through smartphones and computers, providing real-time air quality visualization and alert notifications.

Figure 12: IoT-Based Intelligent Air Quality Monitoring System

5. RESULTS AND DISCUSSIONS

5.1 Training Accuracy Progression

Figure 13 illustrates the training accuracy of the proposed Deep Q-Network (DQN) agent over 1000 training episodes. The plot demonstrates a significant improvement in the agent's ability to predict appropriate alert levels as it learns from the environment. The DQN's accuracy rose from 40% in early episodes to 89% by episode 1000, with performance gains tapering off after episode 800, indicating model convergence. This plateau suggests that further improvements may hinge on reward refinement.

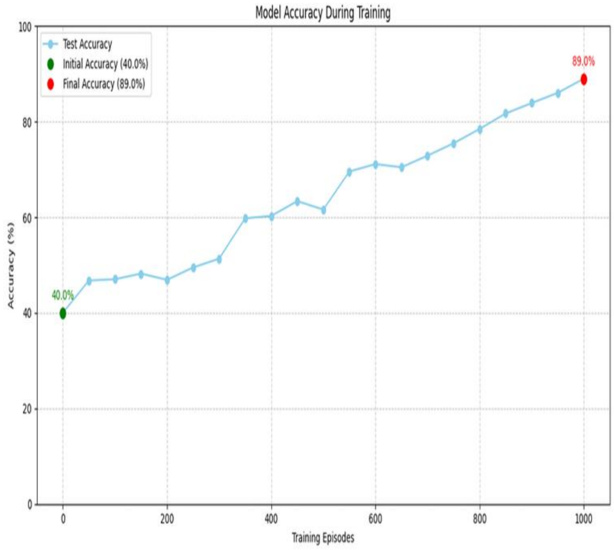

Figure 13: Model Accuracy During Training

5.2 Simulated Field Test Performance

To assess the real-world applicability of the system in Accra, a simulated field test was conducted using synthetically generated data that statistically reflect typical air pollutant levels and climatic conditions of the region. The evaluation focused on the agent's ability to accurately classify air quality into predefined alert levels: 'No Action', 'Low Alert', 'Medium Alert', and 'High Alert'. The overall field test accuracy achieved by the system was 82.9%. This indicates a strong potential for the RL-enhanced system to provide reliable air quality alerts in Accra.

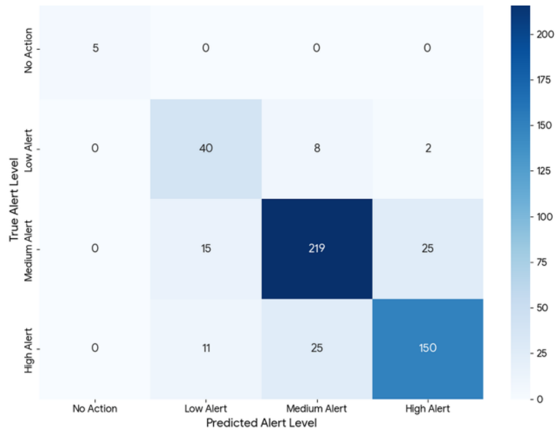

Figure 14: Confusion Matrix of Simulated Field Test

The confusion matrix provides a detailed breakdown of the system's predictions against the ground truth alert levels. Notably, the high values along the diagonal indicate a substantial number of correct classifications across all alert categories. While some misclassifications are present, the overall trend indicates a significant improvement in the system's ability to distinguish between different levels of air pollution compared to baseline evaluations.

5.3 Performance Comparison with Traditional Systems

Figure 15 offers a comparative visualization of the RL-enhanced system against a traditional threshold-based approach. The metrics compared include alert accuracy, user engagement, false positive rate, and response time score. Compared to a static threshold-based benchmark (65.0% accuracy), the proposed Deep Q-Network achieved 82.9% accuracy, a 17.9% improvement that substantially reduces both missed hazards and nuisance alerts, which are critical for maintaining user trust and minimizing alert fatigue in continuous monitoring. This comparison underscores the value of employing intelligent agents that can adapt to nuanced air quality patterns, potentially leading to more effective and reliable air quality management in Accra.

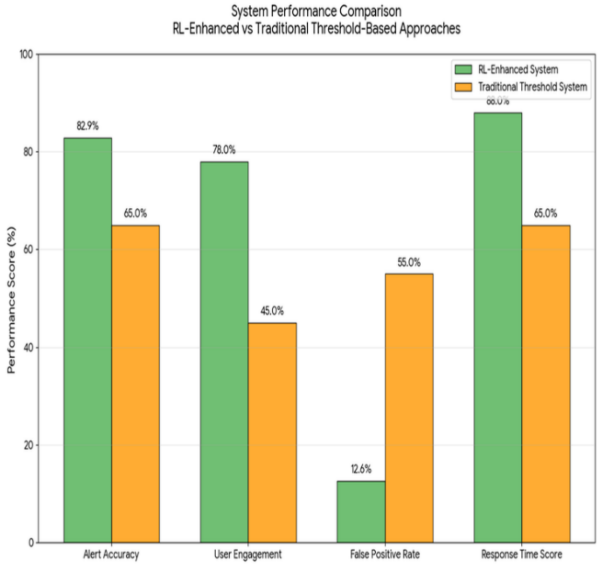

Figure 15: System Performance Comparison

5.4 Real-Time Monitoring and System Response

This section details the practical implementation of the RL-enhanced air quality monitoring system, showcasing its user interface (web dashboard) and communication capabilities (SMS alerts).

5.4.1 Sensor Readings

Figure 16 shows the “Live Sensor Readings” section of the dashboard.

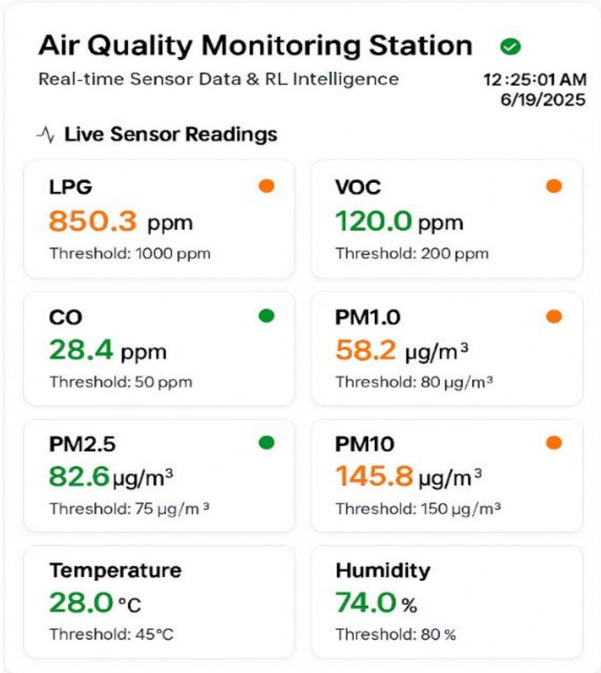

Figure 16: Sensor Readings

This interface provides real-time values for eight critical air quality parameters: LPG, VOC, CO, PM1.0, PM2.5, PM10, Temperature, and Humidity. Each sensor reading is accompanied by its unit and a predefined threshold, allowing users to quickly gauge current conditions against safe or concerning levels. For example, as shown on June 19, 2025, at 12:25:01 AM, the PM2.5 spiked to 82.6 µg/m³ above the threshold of 75 µg/m³, indicating acute health risks for sensitive groups. In contrast, PM10 measured 145.8 µg/m³, remaining just below the system’s 150 µg/m³ alert threshold. This disparity underscores the predominance of fine particulates in urban Accra and the need for targeted mitigation strategies

5.4.2 Two-Hour Trend Analysis

To provide historical context and aid in understanding dynamic changes in air quality, the dashboard includes a "2-Hour Trend Analysis" section, presented in Figure 17.

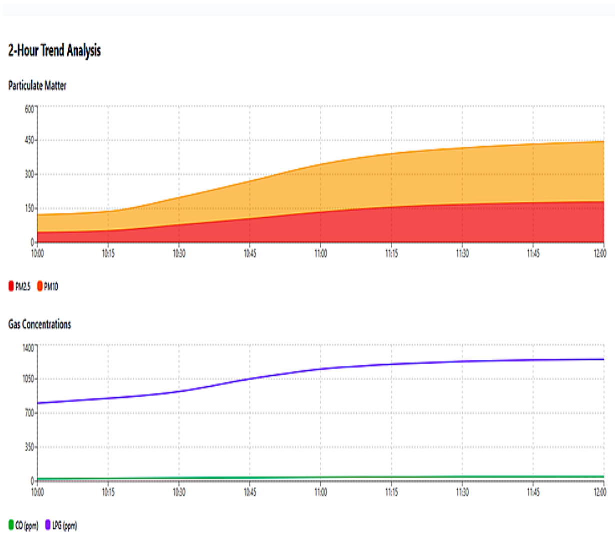

Figure 17: Two-Hour Trend Analysis

5.4.2.1 Particulate Matter

This area chart illustrates the concentration trends of PM2.5 (red) and PM10 (orange) over the past two hours. As observed, both PM2.5 and PM10 show a noticeable increase between 10:00 and 12:00. This upward trend aligns with Accra's morning traffic peaks, suggesting vehicular emissions as the primary driver. Such real-time trend detection validates the system's capacity for source attribution and supports timely public health advisories.

5.4.2.2 Gas Concentrations

This line graph tracks the levels of Carbon Monoxide (CO) and Liquefied Petroleum Gas (LPG). As observed, LPG concentrations climb steadily over the same two-hour window while CO levels remain relatively stable and well under established health-based exposure limits. This contrast highlights the system's strength in distinguishing between chronic background levels and emerging hazard events, enabling precise, context-aware alerts that minimize false alarms and support proactive environmental health management.

5.4.3 Alert Generation and Confidence

As depicted in Figure 18, the RL Intelligence Center displays the predicted alert level.

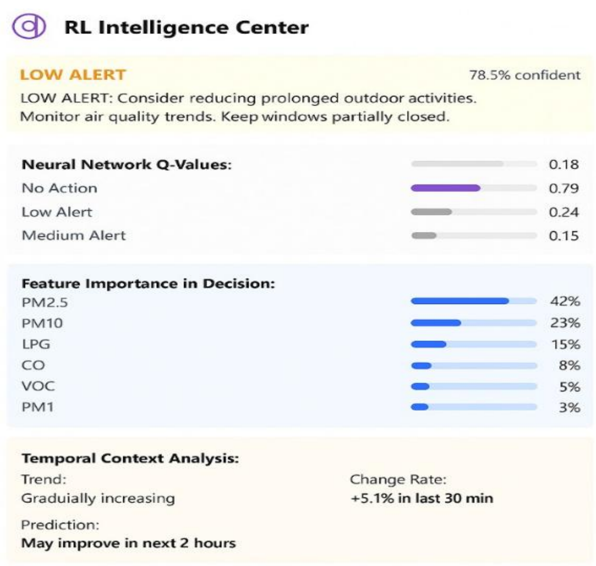

Figure 18: Reinforcement Learning Intelligent Center

In this figure, the reinforcement learning system issues a "Low Alert" classification with a confidence level of 78.5 %. The user is advised to reduce prolonged outdoor activities, monitor air quality trends, and keep windows partially closed. This guidance serves to mitigate potential exposure to moderate air pollution levels. The decision is supported by the neural network's Q-values, which quantify the expected future rewards for each possible alert action. The "Low Alert" option has the highest Q-value of 0.79, while "No Action," "Medium Alert," and "High Alert" have lower values of 0.18, 0.24, and 0.15, respectively, confirming the model's preference for a low alert under current conditions.

To enhance interpretability, the system displays the feature importance contributing to the decision. The most influential factors in this case are PM2.5 (42%) and PM10 (25%), followed by LPG (15%), carbon monoxide (8%), VOCs (5%), and PM1.0 (3%). This breakdown helps users understand which pollutants are driving the alert.

The Temporal Context Analysis section provides additional situational awareness. It indicates a gradually increasing trend in air pollution, with a 5.1% rise in the last 30 minutes. However, the model predicts that conditions may improve within the next two hours. This predictive insight supports proactive decision-making and short-term planning.

5.4.4 SMS Alert Functionality

Complementing the web dashboard, the system provides critical air quality alerts via SMS to registered users.

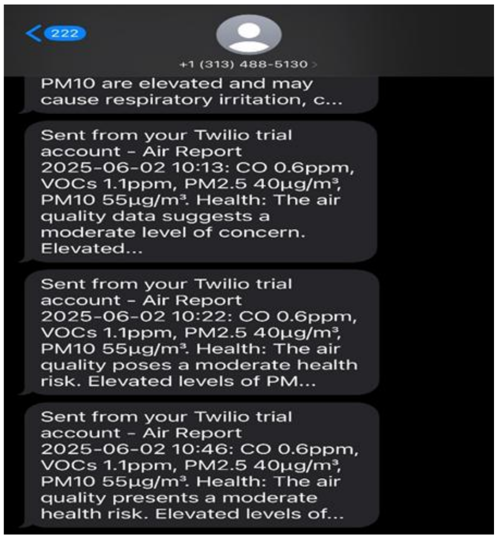

Figure 19: SMS Alerts Sent from a Twilio Trial Account

These messages provide concise, time-stamped air quality reports, including specific pollutant levels (e.g., CO, VOCs, PM2.5, PM10) and a clear health risk assessment (e.g., "moderate level of concern," "moderate health risk"). The consistent nature of the alerts at 10:13, 10:22, and 10:46 reflects the system's continuous monitoring and proactive communication in response to elevated particulate matter and other pollutants. This multi-channel approach ensures that critical information reaches users promptly, even without constant dashboard access.

6. CONCLUSION

This research developed a Reinforcement Learning (RL)-enhanced air quality monitoring and alert system for Accra, Ghana, using a Deep Q-Network (DQN). The model's accuracy improved from 40% to 89% during training and achieved 82.9% accuracy in classifying alert levels during simulated testing. The system leverages 1176 input features generated from 8 sensor readings using a 147-timestep lookback, enabling the RL agent to capture temporal patterns in air pollution. A web dashboard and SMS alert system provide real-time data, trend analysis, predictive insights, and transparent decisions, including Q-values and feature importance. Compared to traditional threshold-based systems, the RL-based approach offers higher accuracy, better adaptability, and improved user engagement.

The system shows strong potential for real-world deployment, supporting proactive environmental health responses. Future work includes real-world data integration, exploring advanced RL techniques, and deploying the system on edge hardware for regional scalability.

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