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IntelliGas: An Intelligent Hazardous Gas Monitoring System

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Abstract: - The rising rate of urbanization and industrialization has significantly increased the probability of unintended gas emissions. Those emissions can be highly dangerous to affect humans, work zone safety and even the environment. Traditional approaches of gas monitoring applications are limited to alarming users about the presence of hazardous gases in real-time with negligible scope for predicting the events beforehand. In this paper, we present an Edge AI-based hazardous gas detection and prediction monitoring framework that allows real-time monitoring along with predicting the chances of any hazardous event using Machine Learning algorithms. MH-Z19E and MQ-series gas sensors connected to Raspberry Pi edge-device are used to sense the real-time levels of carbon dioxide (CO_2), liquefied petroleum gas (LPG) and smoke. The data fetched from sensors will be locally analyzed by implementing edge-computing and MQTT-integrated pipeline stores the sensor data to MongoDB database for long-term historical data analysis and model training. Built Machine Learning algorithms based on Random Forest, XGBoost, and Long Short-Term Memory (LSTM) are used for predicting future levels of sensed gas as well as identifying abnormal environmental signatures. The integrated approach of predicting gas levels based on historical data along with providing real-time monitoring alerts for gas sensing provides a fool-proof solution for early warning systems, abnormality detection, and safety management use-cases. Designed framework can be utilized for various industries for commercial as well as environmental monitoring purposes.

Keywords: Hazardous Gas Emission, Environmental sustainability, Edge Artificial Intelligence, Machine Learning, Raspberry Pi, Predictive Monitoring, Internet of Things.

1. Introduction

The fast urbanization, industrialization, and energy consumption have increased the risk of hazardous gas emissions in residential, commercial, and industrial environments considerably. Leakage of gases like liquefied petroleum gas (LPG), carbon dioxide (CO2), methane and other toxic compounds can cause serious health hazards, environmental degradation, fire accidents and even loss of human life. Hence, continuous monitoring and early detection of hazardous gases have become an integral part of modern safety management systems. Conventional gas detection solutions mainly focus on real-time sensing and alarm generation when the gas concentration exceeds pre-defined thresholds. However, these systems are reactive, and there is limited time for preventive action before hazardous conditions become critical.

Recent developments in sensor technologies, artificial intelligence (AI), and the Internet of Things (IoT) have opened up new possibilities for the creation of intelligent gas monitoring systems with both detection and prediction capabilities. The efficacy of multimodal AI-based sensor fusion strategies for enhancing gas detection and identification accuracy was shown by Narkhede et al. [1]. Similar to this, Hubert and Padovese [2] demonstrated the possibility of predictive analytics in detecting gas leakage occurrences by using machine learning techniques for underwater gas leak detection. In order to improve operational safety and real-time decision-making, smart gas monitoring solutions that integrate AI and IoT technology have also been suggested for industrial settings [3].

Significant research efforts in intelligent sensing technologies have resulted from the increased interest in autonomous hazardous gas monitoring systems. The significance of autonomous gas detection systems that integrate cutting-edge sensors, artificial intelligence, and real-time analytics to enhance safety and dependability was highlighted in a thorough review by Chew et al. [4]. Additionally, Lalithadevi and Krishnaveni [5] demonstrated that machine learning models can successfully differentiate between various gas leakage scenarios while preserving decision-making transparency by introducing an interpretable machine learning framework for precise gas leakage detection and classification. In order to implement gas detection algorithms on devices with limited resources and enable low-power and low-latency operation at the network edge, Tiny Machine Learning (TinyML) techniques have also shown promise [6].

The use of machine learning approaches for air quality prediction and environmental monitoring has grown. In an IoT-based toxic gas monitoring system, Sakib et al. [7] examined many machine learning methods for Air Quality Index (AQI) prediction and found promising prediction accuracy. Aziz et al. [8] further illustrated the expanding relevance of artificial intelligence in sensing applications by creating an AI-driven electronic nose system that can monitor the environment and detect gas leaks in real-time. In order to detect gas risks in industrial settings, researchers have looked at sophisticated detection methods including RGB-thermal vision systems [9] and deep learning-based robotic inspection platforms [10].

Simultaneously, the development of Edge AI has revolutionized the design and implementation of intelligent monitoring systems. Edge AI lowers latency, bandwidth usage, and reliance on cloud infrastructure by enabling machine learning inference and data processing directly on local devices. Because Edge AI can facilitate autonomous decision-making and real-time analytics, Gill et al. [11] highlighted it as a critical technology for future intelligent systems. In a similar vein, Wardana [12] highlighted the usefulness of edge-based machine learning models for environmental monitoring applications by demonstrating their efficacy for air quality prediction. In order to increase monitoring effectiveness and system scalability, recent research has also investigated the integration of edge computing with IoT-based gas detection systems, utilizing high-speed communication technologies and sensor fusion techniques [13,14].

Despite these developments, a lot of current gas monitoring systems are still restricted to real-time detection and alert systems; they lack predictive capabilities that may offer early warnings before hazardous gas concentrations are reached. Furthermore, there is ongoing research into anomaly detection techniques for spotting subtle leakage patterns, especially for small-scale leaks that traditional threshold-based systems might miss [15]. To provide proactive hazard management, intelligent gas safety systems that integrate edge computing, predictive analytics, and real-time monitoring are therefore required.

2. Objectives

The primary objective of this research is to develop an intelligent hazardous gas monitoring system that combines edge computing and machine learning techniques to enable proactive safety management through real-time detection and predictive analysis.

The specific objectives are as follows:

1. To design and develop a low-cost hazardous gas monitoring system capable of continuously measuring environmental parameters such as carbon dioxide (CO_2), liquefied petroleum gas (LPG), smoke concentration, and air quality using MH-Z19E and MQ-series gas sensors.

2. To implement an edge computing architecture using Raspberry Pi for local data acquisition, processing, and analysis in order to reduce communication latency and improve real-time responsiveness.

3. To establish a reliable data communication framework using the MQTT protocol and MongoDB database for efficient storage, transmission, and management of sensor data.

4. To develop and evaluate machine learning models, including Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks, for predicting future gas concentration levels and environmental conditions.

5. To implement anomaly detection mechanisms that can identify abnormal gas patterns and potential leakage events before they reach hazardous levels.

6. To generate intelligent alerts and early warning notifications based on both real-time measurements and predictive outcomes to support proactive decision-making.

7. To develop a web-based monitoring dashboard for visualizing real-time sensor readings, historical trends, prediction results, and safety alerts.

8. To assess the performance of the proposed system in terms of detection accuracy, prediction accuracy, response time, reliability, and suitability for deployment in industrial, commercial, and environmental monitoring applications.

3. Methods

The proposed IntelliGas: An Intelligent Hazardous Gas Monitoring System was developed to provide real-time hazardous gas monitoring and future gas concentration prediction while minimizing cloud dependency. The system integrates IoT sensors, edge computing, machine learning, MQTT communication, and a web-based dashboard for continuous environmental monitoring.

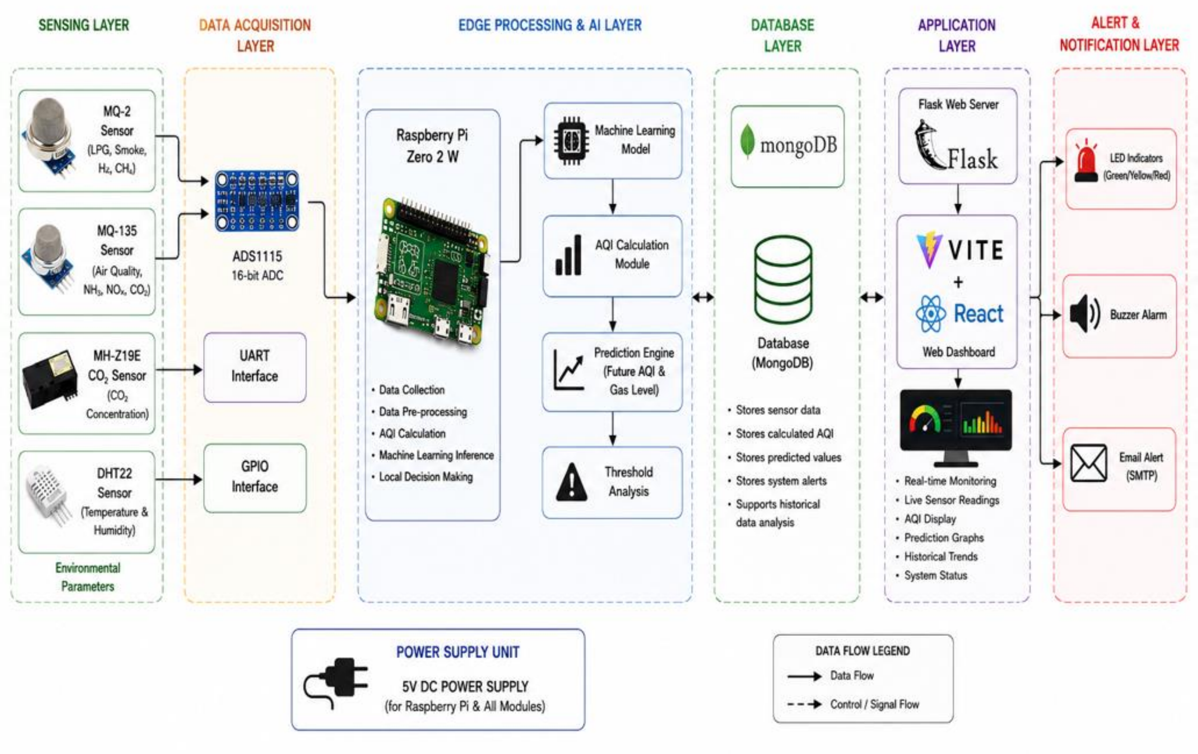

Figure 1: Proposed System Architecture

The proposed architecture integrates multimodal gas sensing, edge computing, machine learning-based prediction, AQI estimation, and real-time alert generation on a Raspberry Pi Zero 2 W platform, enabling proactive hazardous gas monitoring and environmental safety management [1], [2].

The architecture consists of six major layers: Sensing Layer, Data Acquisition Layer, Edge Processing & AI Layer, Database Layer, Application Layer, and Alert & Notification Layer.

1. Sensing Layer

The sensing layer is responsible for collecting environmental parameters from the surrounding atmosphere.

• MQ-2 Gas Sensor: Detects combustible gases and smoke; sensitive to LPG, methane (CH_4), hydrogen (H_2), and smoke particles; produces analog voltage proportional to gas concentration.

• MQ-135 Gas Sensor: Detects air quality-related pollutants, is sensitive to NH_3, NOx, CO_2, benzene, and other harmful gases, and is used for estimating indoor air quality.

• MH-Z19E CO_2 Sensor: NDIR-based sensor, provides accurate CO_2 concentration measurements in ppm, and communicates digitally through a UART interface.

• DHT22 Sensor: Measures ambient temperature and humidity, providing environmental conditions that influence gas sensor performance.

2. Data Acquisition Layer:

This layer converts and transfers sensor outputs to the Raspberry Pi.

• ADS1115 ADC Module: 16-bit Analog-to-Digital Converter, converts analog outputs from MQ-2 and MQ-135 into digital values, communicates with Raspberry Pi through the I^2C protocol, and provides higher resolution than conventional ADC modules.

• UART Interface: Used to receive digital CO_2 measurements from MH-Z19E.

• GPIO Interface: Used to collect temperature and humidity data from the DHT22.

3. Edge Processing & AI Layer:

The Raspberry Pi Zero 2 W acts as the edge computing device where all processing and decision-making occur locally.

• Raspberry Pi Zero 2 W Performs: Data collection, Data preprocessing, feature extraction, AQI calculation, machine learning inference, and local decision-making.

• Machine Learning Module: The trained ML models analyze historical and current sensor readings to predict future gas concentrations. Predictions include: MQ-2 gas level, MQ-135 gas level, CO_2 concentration, and the AQI value.

Forecast horizons: 2 minutes, 5 minutes, 10 minutes

• AQI Calculation Module: Calculates Air Quality Index using sensor readings and predefined AQI formulas. AQI categories: Safe, warning, and critical.

• Prediction Engine: Uses trained machine learning models to estimate future environmental conditions before hazardous levels occur.

• Threshold Analysis: Compares current readings with thresholds and predicted readings with thresholds. This enables early warning generation and preventive actions before hazardous conditions arise.

4. Database Layer:

Provides reliable storage for monitoring, reporting, and machine learning analysis.

• MongoDB Database: Stores real-time sensor readings, calculated AQI values, predicted gas concentrations, historical records, and alert logs.

Main Collections:

LiveData: Stores the latest sensor values and predictions.

Analytics History: Stores periodic historical records for trend analysis.

Alerts: Stores generated war ning and critical alerts.

5. Application Layer:

The application layer provides user interaction and visualization.

Flask Web Server: Acts as a backend API server, Retrieves data from MongoDB, Sends real-time information to dashboard.

React + Vite Dashboard: Provides real-time monitoring and displays MQ-2 concentration, MQ-135 concentration, CO_2 concentration, temperature, humidity, and AQI.

Prediction Visualization: Shows predicted gas levels, predicted AQI values, and future environmental trends.

Historical Analytics: Displays historical charts, trend analysis, and alert history

System Status: Displays sensor status, hardware status, MQTT communication status, and Raspberry Pi status

6. Alert & Notification Layer:

This layer provides immediate warnings whenever Hazardous conditions are detected.

LED Indicators

- Green LED → Safe condition
- Orange LED → Warning condition
- Red LED → Critical condition

Buzzer Alarm: Activated when gas concentration exceeds safety thresholds, provides instant local notification.

Email Alert (SMTP): Sends warning messages to authorized users.

7. Dashboard Visualization:

A React.js dashboard provides real-time visualization of the monitoring system.

The dashboard includes:

- Live sensor gauges
- AQI indicator
- Prediction graphs
- Historical analytics
- Active alerts
- System health monitoring
- Hardware status
- MQTT connection status

The dashboard automatically refreshes as new MQTT messages arrive.

8. Overall Workflow:

The complete operational workflow of the proposed system is summarized as follows:

1. Environmental sensors collect gas and environmental parameters.
2. The ADS1115 digitizes analog sensor outputs.
3. Raspberry Pi acquires all sensor readings.
4. Edge AI models predict future gas concentrations and AQI.
5. Hazard levels are determined based on current and predicted values.
6. Local LEDs and buzzer are activated if hazardous conditions are detected.
7. Sensor data and predictions are published through MQTT.
8. The backend stores the data in MongoDB.

9. The React dashboard displays live monitoring, predictions, analytics, and alerts.

This methodology enables accurate, low-latency, and reliable hazardous gas monitoring by combining edge computing, machine learning, IoT sensing, and real-time visualization into an integrated predictive monitoring system.

4. Results

The proposed system was successfully implemented using Raspberry Pi Zero 2W, MQ-2, MQ-135, MH-Z19E, and DHT22 sensors.

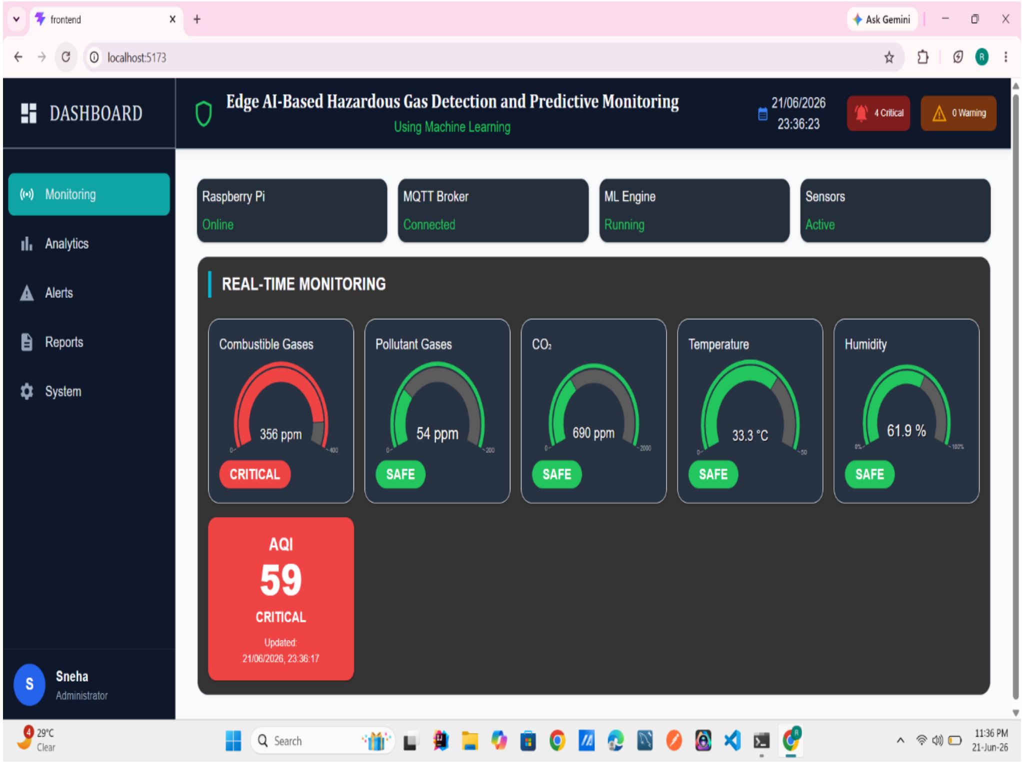

Figure 2: Real-Time Monitoring Performance

The Real-Time Monitoring dashboard displays live measurements of combustible gases, pollutant gases, CO_2 concentration, temperature, humidity, and AQI. During testing, the MQ-2 sensor detected a combustible gas concentration of 356 ppm, which exceeded the critical threshold and triggered a Critical Alert. Other environmental parameters remained within safe limits. The dashboard successfully provided continuous visualization of sensor readings and system status, demonstrating the capability of the proposed system for real-time hazardous gas monitoring.

The experimental results demonstrate that the proposed system successfully performed real-time environmental monitoring and hazardous gas detection. The MQ2 sensor detected a critical combustible gas concentration of **356 ppm**, triggering a critical alert, while the MQ135 sensor (**54 ppm**) and CO_2 sensor (**690 ppm**) remained within safe limits. The recorded temperature (**33.3 °C**) and humidity (**61.9%**) indicated normal environmental conditions. An AQI of **59** exceeded the prototype's critical threshold, resulting in a dashboard notification. Throughout the experiment, the Raspberry Pi, MQTT communication, machine learning engine, and sensor network operated reliably, providing continuous, low-latency monitoring and real-time visualization.

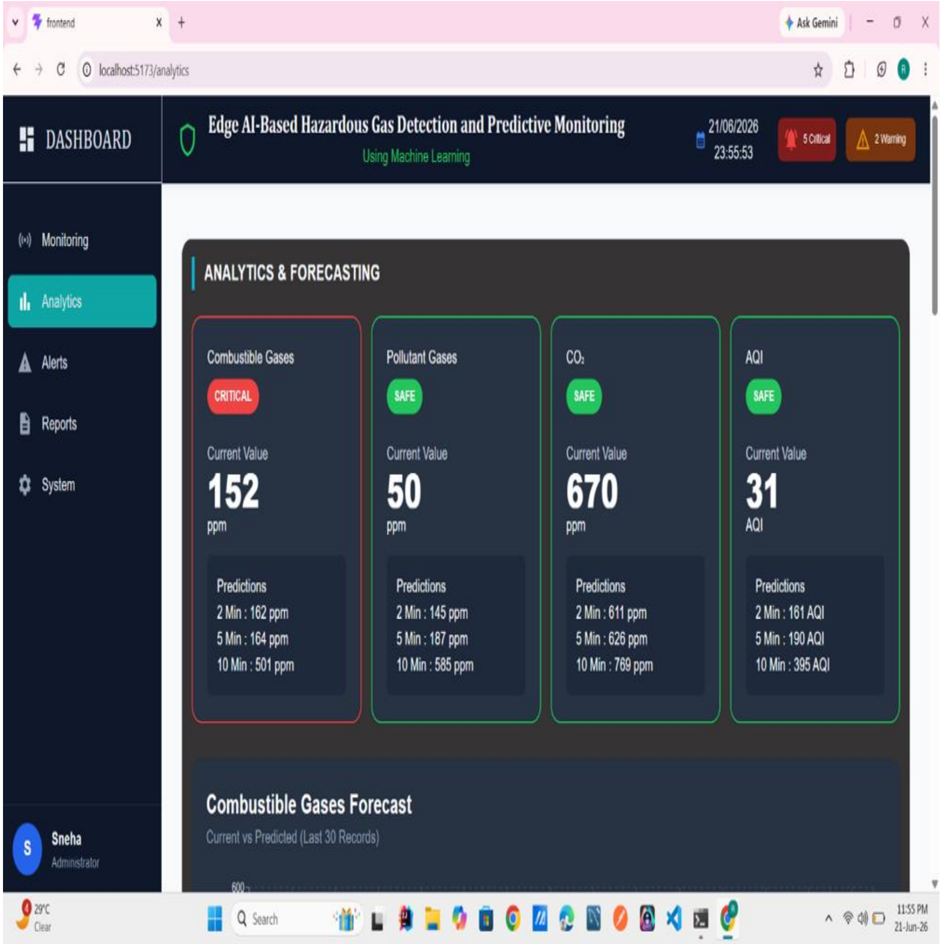

Figure 3: Analytics and Forecasting Perform

The Analytics and Forecasting module presents current sensor values along with machine learning-based predictions for 2-minute, 5-minute, and 10-minute horizons. Experimental results showed that the forecasting models successfully predicted future increases in gas concentration levels. For example, the combustible gas value increased from 152 ppm to a predicted 501 ppm after 10 minutes. The forecasting results confirm the effectiveness of the machine learning models in providing early warnings before hazardous conditions occur.

Parameter	Current Value	2-Min Prediction	5-Min Prediction	10-Min Prediction
MQ2	152 ppm	162 ppm	164 ppm	501 ppm
MQ135	50 ppm	145 ppm	187 ppm	585 ppm
CO_2	670 ppm	611 ppm	626 ppm	769 ppm
AQI	31	161	190	395

Table 1: Forecast Results

The forecasting system successfully generated multi-horizon predictions. Short-term forecasts (2-minute and 5-minute) generally followed the current sensor trends. However, some 10-minute predictions exhibited larger variations, indicating the influence of sudden gas concentration changes within the dataset.

The predictive capability enables early warning generation before hazardous conditions occur, providing sufficient response time for preventive action.

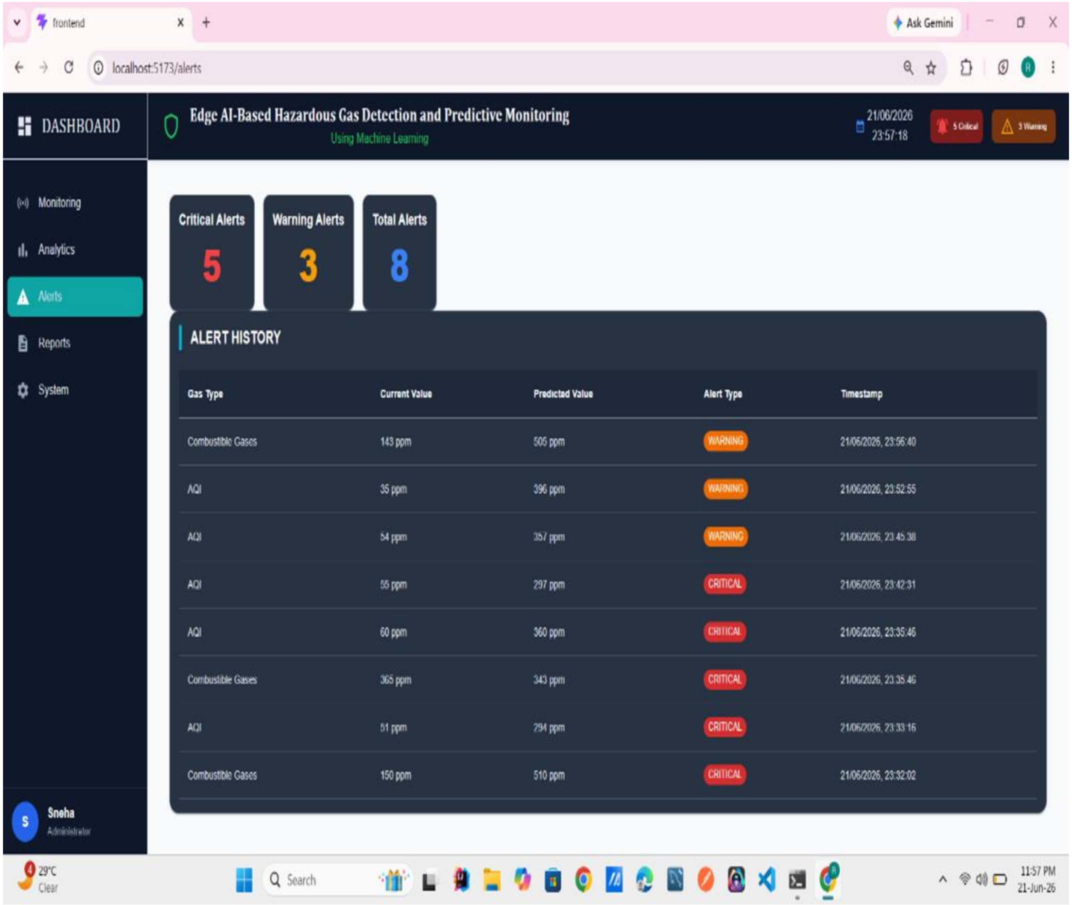

Figure 4: Alert Detection Performance

The Alerts dashboard records all warning and critical events generated by the system. During experimentation, the system generated 5 Critical Alerts and 3 Warning Alerts. Each alert included the gas type, current value, predicted value, and timestamp. The predictive alert mechanism enabled the identification of potential hazardous situations before threshold violations occurred, thereby improving response time and safety.

Gas Type	**Current Value**	**Predicted Value**	**Alert Type**
Combustible Gas	143 ppm	505 ppm	Warning
AQI	35	396	Warning
AQI	55	297	Critical

Table 2: Alert Records

Total Alerts Generated: Warning Alerts: 3

Critical Alerts: 5

Total Alerts: 8

The system successfully identified hazardous conditions and generated notifications based on predefined threshold values. The alert cooldown mechanism reduced repetitive alert generation and improved dashboard usability.

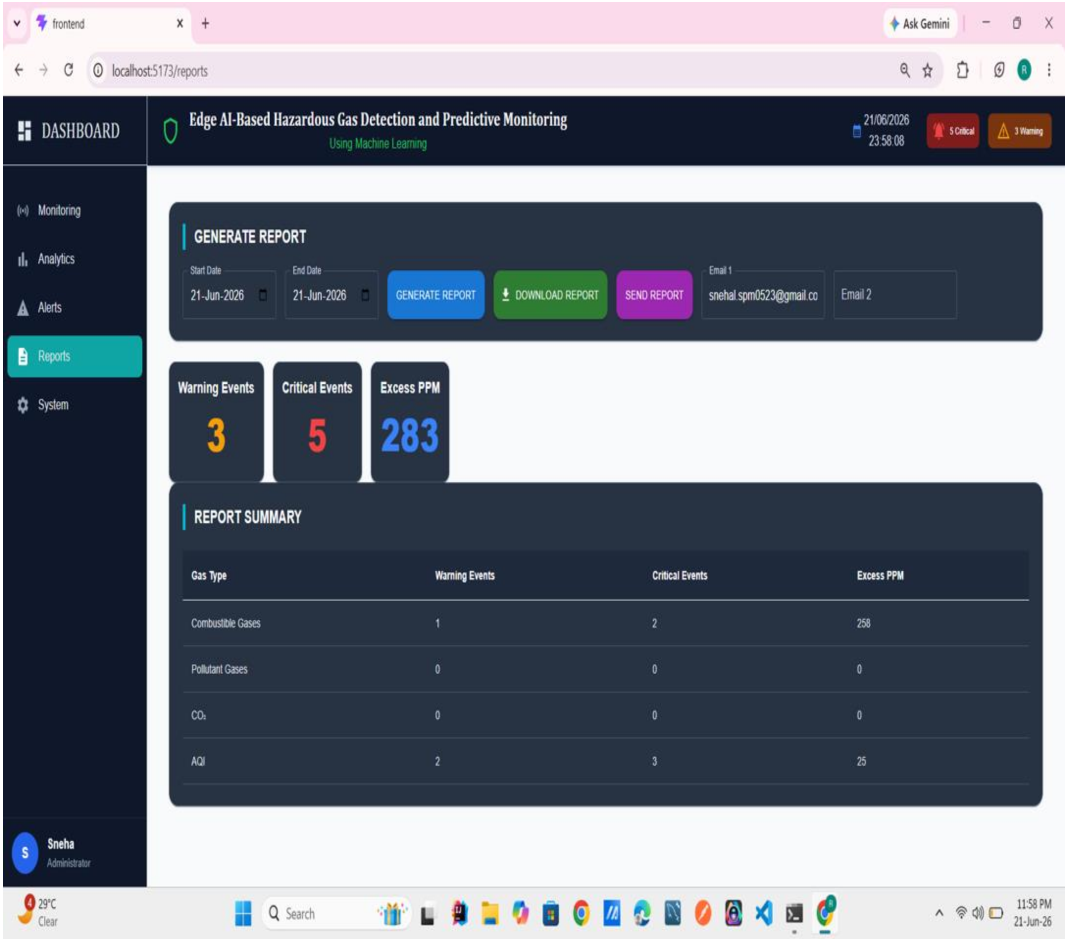

Figure 5: Report Generation Performance

The Report Generation module summarizes hazardous gas events over a selected time period. The generated report included warning events, critical events, and excess pollutant concentration values. For the test period, 3 warning events, 5 critical events, and 283 excess PPM were recorded. The module successfully generated downloadable reports and provided a concise overview of environmental safety conditions.

Gas Type	Warning Events	Critical Events	Excess PPM
Combustible Gas	1	2	258
Pollutant Gas	0	0	0
CO_2	0	0	0
AQI	2	3	25

Table 3: Report Summary

The reporting system successfully summarized alert occurrences and excess gas concentrations. Generated reports can assist safety personnel in analyzing hazardous events and identifying trends.

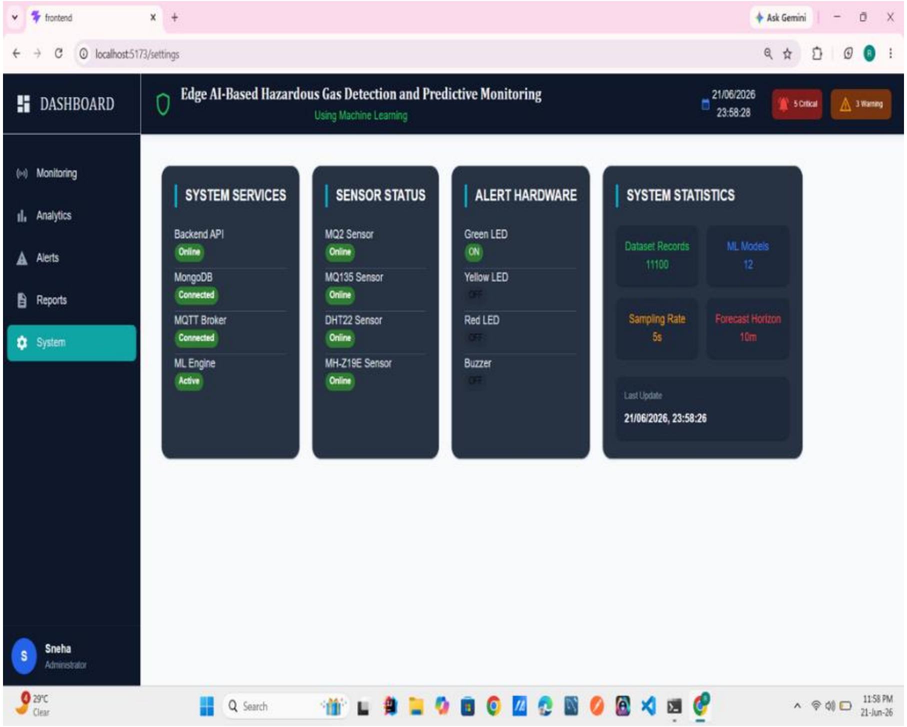

Figure 6: System Performance and Resource Monitoring

The System Statistics dashboard displays the operational status of all system components. Experimental results showed that the MQTT broker, backend services, machine learning engine, and sensors remained active throughout the testing period. The system processed 11,100 dataset records using 12 machine learning models with a sampling interval of 5 seconds and a forecasting horizon of 10 minutes. The successful execution of all modules confirms the suitability of Raspberry Pi Zero 2W for edge-based hazardous gas monitoring applications.

5. Discussion

The experimental results demonstrate that the proposed system effectively integrates IoT sensors, edge computing, machine learning, and web technologies into a unified hazardous gas monitoring platform. The system not only detects hazardous gas conditions in real time but also predicts future gas concentrations, enabling proactive safety measures. The successful deployment on Raspberry Pi Zero 2W validates the feasibility of implementing intelligent environmental monitoring solutions on low-cost edge devices.

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