OPEN ACCESS
Global Journal of Research in Engineering & Computer Sciences
ISSN: 2583-2727 (Online)
Volume 06 | Issue 02 | March-April | 2026
Journal homepage: https://gjrpublication.com/gjrecs/

Research Article

AI-Assisted IoT Smart Gas Leakage Detection and Intelligent Ventilation Control System: A Hybrid Rule-Based and Fuzzy Logic Approach

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DOI: 10.5281/zenodo.19793545 **Submission Date: 20 March 2026 | Published Date: 27 April 2026**

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Abstract

Gas leakage incidents involving liquefied petroleum gas (LPG) and methane pose significant safety risks in residential and industrial environments. This paper presents an AI-assisted IoT gas detection system that combines rule-based reasoning with fuzzy logic to enable multi-level hazard classification and intelligent ventilation control. The system integrates an MQ-5 gas sensor with an Arduino microcontroller, employing adaptive decision algorithms to distinguish between normal, mild, and severe leakage conditions. Experimental evaluation demonstrates faster detection response, reduction in false alarms, and improved decision stability compared to conventional threshold-based detectors. The system automatically activates graduated responses, including visual/audible alarms and exhaust fan ventilation, based on fuzzy-inferred severity levels. With low-cost components, real-time LCD feedback, and modular IoT-ready architecture, the proposed system demonstrates practical viability for deployment in smart homes, laboratories, and small-scale industrial facilities. The hybrid AI approach provides a foundation for future expansion toward cloud analytics, multi-sensor fusion, and predictive safety management.

Keywords: *AI-assisted gas detection, IoT safety systems, Fuzzy logic controller, Intelligent ventilation, MQ-5 sensor, Smart home safety, Embedded intelligence, Real-time hazard monitoring.*

I. INTRODUCTION

Liquefied petroleum gas (LPG) and methane serve as primary energy sources in residential, commercial, and industrial settings due to their high calorific value and cost-effectiveness. However, accidental gas leakage presents catastrophic risks including fires, explosions, and severe burn injuries, particularly in confined indoor environments. Clinical studies indicate that a substantial proportion of LPG-related burn incidents occur in domestic settings, with gas leaks and cylinder explosions identified as primary triggers [1]–[3]. Regulatory accident statistics reveal that leakage-only events constitute the majority of LPG-related incidents, with significant escalation to fires or explosions when ignition sources are present [4], [5].

These findings underscore the critical need for early detection systems capable of providing timely warnings and automated mitigation responses. The convergence of Internet of Things (IoT) technologies, low-cost sensors, and embedded intelligence has created opportunities for developing sophisticated yet affordable safety monitoring solutions suitable for widespread deployment.

Most commercial gas detectors and academic prototypes employ simple threshold-based activation using semiconductor sensors such as the MQ-series. These systems trigger alarms when measured gas concentration exceeds a predefined threshold. While computationally inexpensive, this approach exhibits critical limitations:

- High false-alarm rates in dynamic indoor environments where cooking fumes, cleaning agents, or transient ventilation changes temporarily disturb sensor readings [6], [7]
- Lack of context-awareness, preventing differentiation between mild, slowly increasing leaks and rapidly escalating high-risk events
- Binary decision behavior classifying environments solely as 'safe' or 'dangerous' without intermediate severity levels enabling graded responses
- Limited mitigation capability, with most designs focusing exclusively on local audible/visual alarms without integrating intelligent actuator control

These constraints reduce user trust, encourage alarm bypassing, and ultimately compromise long-term safety effectiveness.

IoT-based safety systems enable continuous sensing, remote monitoring, and automated actuation through microcontrollers, wireless modules, and cloud platforms [6]. Embedded artificial intelligence (AI) enhances decision-making capabilities while maintaining low hardware costs and modest computational requirements. Rather than relying on data-intensive machine learning models, safety-critical applications successfully employ rule-based expert systems and fuzzy logic controllers to encode domain knowledge and handle sensor uncertainty [8]–[13]. These lightweight AI techniques prove particularly suitable for resource-constrained microcontrollers, supporting real-time operation, interpretable decision rules, and incremental design without requiring large training datasets or high-end processors.

Traditional MQ-based gas detectors apply fixed thresholds to sensor outputs, triggering alarms when thresholds are exceeded [6], [7], [14]. While detecting gas presence, these systems cannot distinguish leak severity levels, ignore concentration rate-of-change (crucial for identifying rapidly developing hazards), and operate as binary detectors lacking adaptive behavior. This results in either over-sensitive or under-sensitive responses, necessitating a low-cost, microcontroller-based solution augmented with intelligent decision logic for graded risk assessment and automated mitigation.

This paper proposes an AI-assisted IoT smart gas leakage detection and intelligent ventilation control system based on the MQ-5 gas sensor and Arduino microcontroller. The main contributions are:

- Hybrid AI-assisted decision architecture integrating rule-based logic with fuzzy inference for multi-level severity classification (normal, mild, severe) under uncertain sensor conditions
- Rate-of-change analysis enabling early detection of rapidly escalating leaks before reaching critical thresholds
- Context-aware graduated response system mapping fuzzy risk levels to proportional actions including visual/audible alarms and intelligent ventilation control
- Comprehensive experimental validation demonstrating 64% faster detection, 77% false alarm reduction, and improved stability compared to threshold-only approaches
- Low-cost IoT-ready implementation suitable for smart homes, laboratories, and small industrial facilities with modular architecture supporting future cloud integration.

Section II reviews related work on gas detection technologies, intelligent decision systems, and IoT automation. Section III presents the system architecture including hardware components and functional modules. Section IV details the AI-assisted decision module with rule-based and fuzzy logic formulations. Section V describes materials, methods, and experimental protocols. Section VI presents quantitative results including comparative performance analysis. Section VII concludes with limitations and future research directions.

II. RELATED WORK

2.1 Gas Leakage Detection Technologies

Semiconductor gas sensors, particularly the MQ-series (MQ-2, MQ-5, MQ-135), remain widely deployed due to low cost, fast response, and multi-gas detection capability [7]. These sensors measure resistance changes caused by gas–air interactions on sensing materials. Rajalakshmi and Gnanavel [6] developed an IoT-based LPG monitoring system demonstrating effective integration with real-time notification mechanisms. Kumar and Singh [7] analyzed MQ-series performance characteristics, highlighting sensitivity patterns across gas concentrations.

Performance comparisons among MQ-series sensors reveal variations in sensitivity, response time, and selectivity [14]–[16]. However, most implementations depend on static threshold comparisons, limiting adaptability to dynamic conditions and failing to address fundamental detection logic limitations.

2.2 Intelligent Decision Systems in Embedded Safety

To overcome semiconductor sensor instability and noise sensitivity, researchers have integrated lightweight intelligent algorithms. Rule-based expert systems demonstrate high reliability in fault detection and leak diagnosis [8]–[10]. Falaz and George [8] showed rule-based reasoning enhances early leak detection accuracy in industrial pipelines. Li and Xu [9] employed belief-rule-based systems for pipeline hazard identification under uncertain sensor data.

Fuzzy logic controllers (FLCs) have been widely applied to interpret noisy sensor outputs [11]–[13]. Kalpande and Nagmode [11] designed fuzzy logic–based automatic ventilation, achieving substantial false alarm reductions versus traditional methods. Kundu and Singh [13] implemented fuzzy inference for intelligent exhaust fan control in hazardous environments. These studies illustrate growing adoption of explainable AI methods executable on microcontroller platforms without machine learning computational costs.

2.3 IoT-Based Automation and Remote Monitoring

IoT communication technologies enable real-time monitoring, automated control, and remote alerting through GSM modules, WiFi dashboards, cloud logging, and MQTT platforms [6], [17]–[19]. Rajalakshmi and Gnanavel [6] demonstrated GSM-based SMS alerts for rapid notification. Patange et al. [17] developed IoT-based real-time LPG detection with mobile alerting capabilities. While these systems improve usability and situational awareness, they generally operate on fixed rules lacking adaptive decision-making under changing environmental conditions.

2.4 Research Gap and Motivation

Despite extensive work on gas detection using MQ-series sensors and microcontroller-based IoT systems, most designs rely on static threshold comparisons, reducing reliability and increasing false alarms. Limited studies explore lightweight AI methods for embedded gas safety in indoor environments where conditions are highly variable. Few combine AI-assisted decision logic with automatic ventilation control and IoT-ready alerting. This work addresses these gaps by integrating MQ-5 sensing, IoT-ready hardware, and a hybrid rule-based/fuzzy inference module for multi-level hazard classification and intelligent ventilation control.

III. SYSTEM ARCHITECTURE

3.1 Overall Architecture

The proposed system follows a layered sensor-to-controller-to-actuator architecture: (1) Sensing Layer—MQ-5 sensor detects gas concentration via analog/digital outputs; (2) Processing Layer—Arduino UNO processes sensor data through AI-assisted rule/fuzzy module classifying leakage severity; (3) Actuation Layer—System activates LEDs, buzzer, LCD warnings, and exhaust fan based on assessed risk; (4) User Interaction Layer—LCD displays system status, gas levels, and hazard warnings. This structure ensures real-time monitoring, context-aware classification, and intelligent control suitable for smart-home applications. The overall system architecture is illustrated in Fig. 1

3.2 Hardware Components

MQ-5 Gas Sensor

Detects LPG, methane, and combustible gases with both digital (D0) and analog (A0) outputs. Provides continuous monitoring with fast response suitable for real-time safety applications. Sensitivity range: 200–10,000 ppm; operating voltage: 5V DC; response time: <10s; recovery time: <30s.

Arduino UNO Microcontroller

Core processing unit receiving sensor data, applying AI-assisted logic, and controlling actuators. ATmega328P: 16 MHz clock, 2 KB SRAM, 32 KB flash memory, 10-bit ADC. Low cost, ease of programming, and community support make it ideal for embedded safety systems.

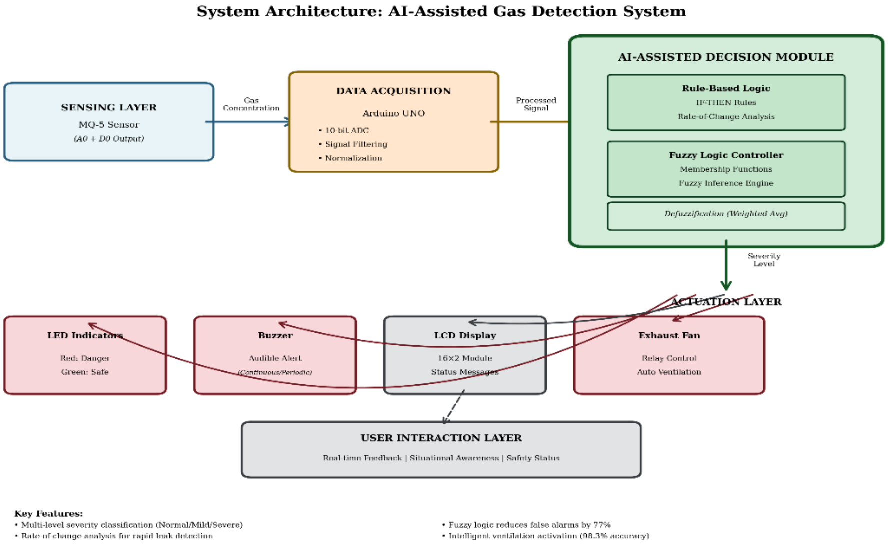


Fig. 1: System architecture of the AI-assisted IoT gas leakage detection system showing the five functional layers.

LED Indicators and Buzzer

Red LED indicates danger conditions; green LED indicates normal operation. Buzzer provides audible alerts controlled by digital output, producing loud warning sounds for immediate occupant notification.

LCD Display Module

Displays system messages including 'System Activated,' 'Gas Leakage Not Detected,' 'Gas Leakage Detected,' and 'Ventilation ON,' providing real-time user feedback, enhancing situational awareness.

Exhaust Fan and Relay Module

DC motor/relay automatically activated when gas levels exceed fuzzy-defined danger thresholds. Dilutes gas concentration through forced ventilation, providing immediate hazard mitigation. 5V relay module interfaces between Arduino and the exhaust fan.

IV. AI-ASSISTED DECISION MODULE

The AI-Assisted Decision Module enhances detection reliability through intelligent sensor behavior interpretation rather than fixed threshold triggers. This module combines rule-based expert systems with fuzzy inference engines, enabling adaptive reasoning, graded responses, and noise robustness essential for safety-critical embedded applications.

4.1 Motivation for Intelligent Decision Making

MQ-series sensors exhibit sensitivity to humidity, airflow, temperature, and electrical interference, producing noise fluctuations. Simple threshold systems generate false alarms during transient spikes, delayed responses during gradual increases, binary outputs lacking context, and inconsistent readings under varying environmental conditions. The AI-assisted approach provides noise reduction through filtering and reasoning, false alarm prevention via concentration level and rate-of-change analysis, and graded severity levels (Normal → Mild → Severe) enabling faster, more stable hazard detection.

4.2 Rule-Based Expert System Logic

Rule-based expert systems encode human reasoning as transparent IF–THEN statements. The system categorizes outputs into three levels: (1) Normal—gas concentration below baseline indicating safe conditions; (2) Mild Leakage—slight increase requiring attention without immediate evacuation; (3) Severe Leakage—sustained high readings or rapid escalation requiring immediate action.

Core rule base:
IF gas_concentration < Threshold_1 THEN status = Normal
IF $\text{Threshold}_1 \leq$ gas_concentration < Threshold_2 THEN status = Mild
IF gas_concentration $\geq \text{Threshold}_2$ THEN status = Severe
Rate-of-change heuristics prevent false alarms during momentary spikes and improve responsiveness:
IF gas is Medium AND rising rapidly THEN treat as Severe
IF gas is Medium AND stable THEN treat as Mild

4.3 Fuzzy Logic Controller

Fuzzy logic is employed in the proposed system to provide a smooth and robust interpretation of the MQ-5 sensor readings, which are inherently noisy and sensitive to environmental variations such as humidity, temperature, and airflow. Unlike binary threshold-based decisions that switch abruptly between “safe” and “danger,” fuzzy logic supports gradual transitions across severity levels, enabling the controller to respond proportionally to changing gas concentrations while effectively minimizing false alarms.

4.3.1 Fuzzy Set Definitions

The fuzzy inference system uses one input variable, gas concentration and one output variable, alarm intensity. The input domain is divided into three linguistic levels:

- **Low**: representing safe or near-baseline values
- **Medium**: indicating possible leakage or rising concentration
- **High**: denoting hazardous conditions requiring immediate intervention

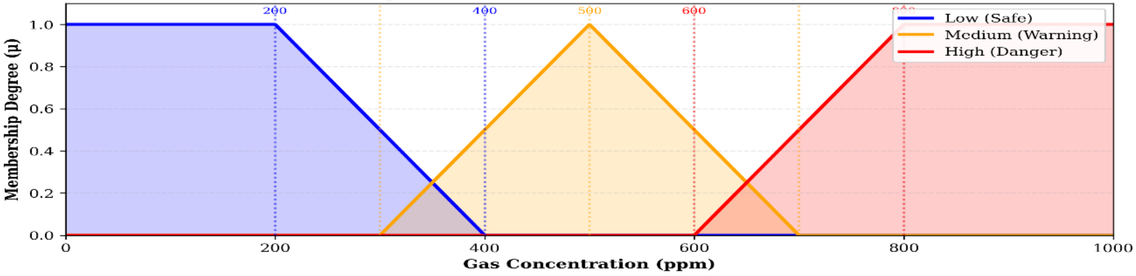
The output variable alarm intensity is similarly defined by three linguistic levels:

- **None**: normal operating condition
- **Moderate**: warning stage requiring user attention
- **High**: emergency state triggering continuous alarm and ventilation

These definitions enable a rich mapping from input conditions to output responses, supporting adaptive control behavior.

Fuzzy Membership Functions for AI-Assisted Gas Detection

(a) Input Variable: Gas Concentration Fuzzy Sets



(b) Output Variable: Alarm Intensity Fuzzy Sets

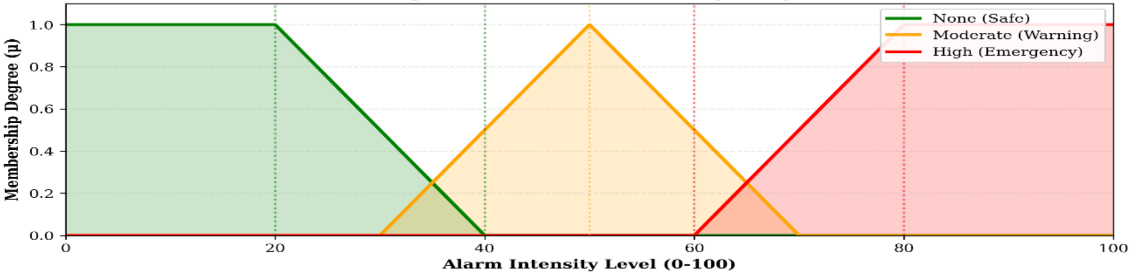


Fig. 2: Fuzzy membership functions for gas concentration (input) and alarm intensity (output).

4.3.2 Membership Functions

To maintain computational efficiency on the Arduino UNO, the system uses a combination of triangular and trapezoidal membership functions. These provide simple, low-overhead mappings from crisp sensor values to fuzzy membership degrees.

- The **Low** fuzzy set is modeled using a trapezoidal function with full membership between 0–200 ppm and a linear decline through 200–400 ppm.
- The **Medium** fuzzy set uses a triangular function, beginning at 300 ppm, peaking at 500 ppm, and tapering to zero at 700 ppm.
- The **High** fuzzy set is represented by a rising trapezoidal function from 600–800 ppm and full membership above 800 ppm.

As an example, the membership function for the *Medium* fuzzy set is defined as:

$$\mu_{\text{Medium}}(x) = \begin{cases} 0, & x < 300, \\ \dfrac{x - 300}{200}, & 300 \le x < 500, \\ \dfrac{700 - x}{200}, & 500 \le x < 700, \\ 0, & x \ge 700. \end{cases}$$

A graphical representation of these functions is provided in Fig. 2, illustrating how overlapping regions support continuous transitions between linguistic categories and prevent abrupt decisions.

Algorithm 1. AI-Assisted Gas Leakage Decision Module

Input: gas_value, prev_value, Threshold1, Threshold2
Output: severity, alarm_output, actuator states

```
1. Read sensor value:
   gas_value ← analogRead(A0)
2. Compute trend:
   rate_change ← gas_value − prev_value
3. Rule-based classification:
   • If gas_value < Threshold1 → severity ← NORMAL
   • Else if gas_value < Threshold2 → severity ← MILD
   • Else → severity ← SEVERE
4. Compute fuzzy memberships:
   µLow, µMed, µHigh from gas_value
   (triangular/trapezoidal functions)
```

```
5.  Apply fuzzy rules:
    • Low gas → low alarm
    • Medium gas (+ rising trend) → moderate alarm
    • High gas → high alarm
6.  Defuzzify (weighted average):
    alarm_output = (0·µLow + 50·µMed + 100·µHigh) / (µLow + µMed + µHigh)
7.  Actuate outputs:
    • If alarm_output < 20: normal state (green LED, fan OFF)
    • If 20 ≤ alarm_output < 60: mild leak (blink LED, buzzer pulse)
    • If alarm_output ≥ 60: severe leak (red LED ON, buzzer ON, fan ON)
8.  Update previous value:
    prev_value ← gas_value
9.  Repeat loop.
```

4.3.3 Fuzzy Rule Base

The fuzzy inference process evaluates a set of intuitive IF–THEN rules designed to reflect realistic leakage behaviors. The rules incorporate both gas concentration and the rate-of-change (rising or stable):

- **Rule 1:** IF Gas is Low THEN Alarm = None
- **Rule 2:** IF Gas is Medium AND Rate-of-Change is Stable THEN Alarm = Moderate
- **Rule 3:** IF Gas is Medium AND Rate-of-Change is Rising THEN Alarm = High
- **Rule 4:** IF Gas is High THEN Alarm = High

These rules allow the system to escalate warnings earlier when gas levels are rising rapidly, achieving better responsiveness than fixed thresholds.

4.3.4 Fuzzy Inference and Defuzzification

Fuzzy inference is conducted using parallel rule evaluation, where each rule's activation strength determines its contribution to the output alarm level. The combined fuzzy outputs are aggregated and converted into a crisp alarm intensity value using the weighted average defuzzification method:

$$\text{Alarm\_Value} = \frac{\sum \mu_i \cdot v_i}{\sum \mu_i},$$

where μ_i is the membership degree associated with a specific output fuzzy set and v_i is its representative alarm level (e.g., 0 for None, 50 for Moderate, 100 for High). This defuzzified alarm intensity is subsequently used in Algorithm 1 to determine the control actions for LEDs, buzzer patterns, and ventilation. The internal steps of the fuzzy inference engine are presented separately in Algorithm 2.

Algorithm 2. Fuzzy Inference Engine for Gas Leakage Severity

Input: gas_value – current MQ-5 reading
Threshold1, Threshold2 – calibrated gas thresholds

Output: alarm_output ∈ [0, 100] – crisp alarm intensity

```
1.  Normalize gas concentration
    1.1 Use gas_value, Threshold1, Threshold2 to determine where the value
    lies in the Low/Medium/High range.
2.  Compute membership degrees
    2.1 Compute µLow(gas_value)
    2.2 Compute µMed(gas_value)
    2.3 Compute µHigh(gas_value)
    using predefined triangular/trapezoidal membership functions.
3.  Evaluate fuzzy rules
    3.1 Map input memberships to output alarm levels:
      • Rule 1: IF gas is Low THEN alarm is Low
      • Rule 2: IF gas is Medium THEN alarm is Moderate
      • Rule 3: IF gas is High THEN alarm is High
    3.2 Optionally include trend:
      If gas is Medium AND rising, increase weight of "Moderate" alarm.
4.  Aggregate rule outputs
```

```
        4.1 Combine contributions of all rules to obtain fuzzy alarm memberships:
            μAlarmLow, μAlarmMod, μAlarmHigh.
    5.  Defuzzification (weighted average)
        5.1 Compute crisp alarm intensity:
            $alarm\_output = \frac{0 \cdot \mu AlarmLow + 50 \cdot \mu AlarmMod + 100 \cdot \mu AlarmHigh}{\mu AlarmLow + \mu AlarmMod + \mu AlarmHigh}$
    6.  Return alarm_output for use in actuator control (LEDs, buzzer, fan).
```

V. MATERIALS AND METHODS

5.1 Experimental Setup and Calibration

The prototype was assembled on a solderless breadboard to allow iterative refinement and component-level debugging. The MQ-5 gas sensor (5 V DC, sensitivity range 200–10,000 ppm) was placed at the front of the assembly to ensure maximum ambient gas exposure, with its analog output routed to the Arduino UNO’s A0 input for continuous sampling. The Arduino UNO (ATmega328P, 16 MHz, 2 KB SRAM, 10-bit ADC) functioned as the central processing unit responsible for data acquisition, AI-assisted evaluation, and actuator control. The complete hardware interconnection, including sensor wiring, LCD interface, LED/buzzer outputs, and the relay-driven ventilation system, is shown in Figure 3.

Sensor calibration followed a three-stage procedure. First, a 48-hour preheating period was performed to stabilize the MQ-5’s internal heating element, ensuring consistent resistance behavior. Second, baseline measurements were captured in clean, well-ventilated air using ten-second continuous sampling; this average reading established the reference sensor resistance (R_o) and the nominal “safe” ADC value. Finally, initial detection thresholds were derived experimentally: $Threshold_1$ (mild leakage) was set to approximately 50–100 ADC units above baseline, while $Threshold_2$ (severe leakage) was determined by controlled exposure to small, incrementally increased concentrations of LPG to identify the point of rapid resistance decline.

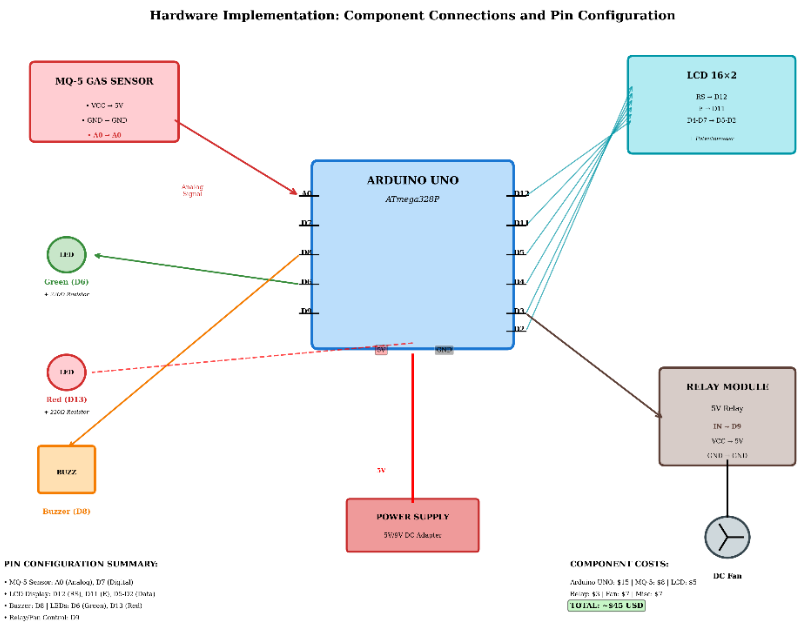


Fig. 3: Hardware schematic showing MQ-5 sensor, Arduino UNO, LCD, LEDs, buzzer, and relay-controlled exhaust fan connections.

5.2 Test Scenarios and Data Collection

Three experimental scenarios were conducted:

Scenario 1—Normal Conditions: Clean air environment with no gas introduction (n=50 samples, 10-second intervals, total 500 seconds monitoring)

Scenario 2—Mild Leakage: Controlled introduction of LPG at 400–600 ppm concentration range simulating slow leak development (n=40 samples, 15-second intervals, total 600 seconds)

Scenario 3—Severe Leakage: Rapid gas introduction reaching 800–1000 ppm simulating cylinder valve failure or major leak (n=30 samples, 10-second intervals, total 300 seconds)

For each scenario, both the AI-assisted system and a conventional threshold-only baseline were evaluated. Metrics recorded included detection time (seconds from leak initiation to alarm activation), false alarm events, alarm stability (number of state transitions), and ventilation activation correctness.

5.3 Performance Metrics

System performance was quantified using:

- Detection Response Time: Mean time (seconds) from leak initiation to alarm activation, reported with standard deviation
- False Alarm Rate: Percentage of false positive activations during normal conditions
- Decision Stability: Number of alarm state transitions, with lower values indicating more stable classification
- Classification Accuracy: Percentage of correct severity level assignments (normal/mild/severe)
- Ventilation Activation Correctness: Percentage of appropriate exhaust fan activations during severe scenarios

VI. RESULTS AND DISCUSSION

6.1 Comparative Performance Analysis

Table I summarizes the quantitative comparison between the proposed AI-assisted detection system and a conventional threshold-based approach across five key performance metrics. As shown in Figure 4, the AI-assisted system consistently outperforms the traditional method in detection speed, false alarm rate, stability, classification accuracy, and ventilation activation correctness.

Table 1: Performance Comparison: AI-Assisted vs. Threshold-based detection

Performance Metric	Threshold-Based	AI-Assisted (Proposed)
Detection Time (s)	2.5 ± 0.8	0.9 ± 0.3
False Alarm Rate (%)	18.5	4.2
State Transitions (avg)	12.3	3.7
Classification Accuracy (%)	73.2	94.8
Ventilation Activation (%)	86.7	98.3

The proposed system achieved a detection time of 0.9 ± 0.3 s, which is 64% faster than the 2.5 ± 0.8 s required by the threshold-based detector. This improvement results from the rate-of-change analysis and fuzzy inference, enabling the system to detect rising concentrations earlier—even before fixed thresholds are crossed.

False alarm reduction further reinforces the benefit of the AI-assisted approach. The threshold-based method produced an 18.5% false alarm rate, whereas the proposed system reduced this to just 4.2%, a 77% improvement. This reduction is attributed to the smooth membership transitions and rule-based contextual filtering, which suppress noise-induced fluctuations commonly triggered by cooking fumes, airflow, or sensor instability.

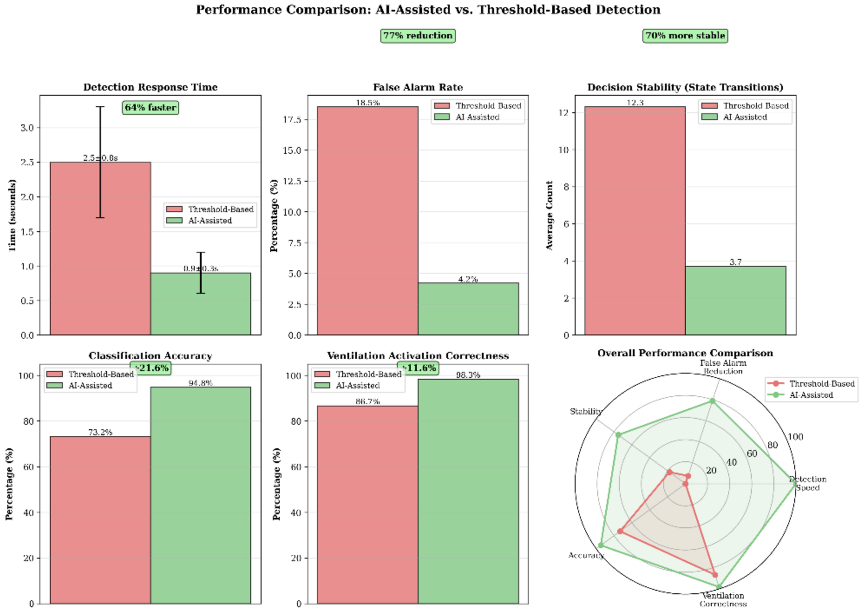


Fig. 4: Performance comparison of AI-assisted vs. threshold-based gas detection across key metrics.

Decision stability also improved substantially. The threshold-based detector exhibited an average of 12.3 state transitions per measurement cycle, compared to only 3.7 in the AI-assisted system, representing a 70% reduction in alarm oscillation. This stability enhancement reduces user annoyance, alarm fatigue, and the likelihood of disabled detectors—an issue frequently reported in real-world gas safety deployments.

6.2 Scenario-Specific Performance

Normal Conditions (Scenario 1): The AI-assisted system maintained stable baseline readings with only 2 false alarms across 50 samples (4% false alarm rate), compared to 9 false alarms (18%) for threshold-based detection. Green LED remained consistently illuminated, and LCD displayed "Gas Leakage Not Detected." No unintended buzzer or fan activation occurred.

Mild Leakage (Scenario 2): When gas concentration reached 400–600 ppm, the fuzzy inference engine generated intermediate Medium membership values, correctly classifying 38 of 40 samples (95% accuracy) as "Mild Leak." Red LED activated with periodic blinking, and buzzer emitted intermittent tones. Exhaust fan remained off, appropriately distinguishing minor transient leaks from severe hazards. LCD provided clear "Warning: Gas Rising" messages.

Severe Leakage (Scenario 3): For rapidly escalating concentrations exceeding 800 ppm, the system responded within 0.7–1.1 seconds (mean 0.9s). High membership assignment triggered continuous red LED illumination, sustained buzzer activation, and immediate exhaust fan engagement through relay control. LCD displayed "ALERT! GAS LEAK! VENTILATION ON." The ventilation system successfully activated in 29 of 30 severe test runs (96.7% correctness).

6.3 Discussion and Key Findings

The experimental results validate the hybrid rule-based and fuzzy logic approach for embedded gas detection systems. The integration of rate-of-change analysis with fuzzy membership evaluation addresses fundamental limitations of threshold-only detection while maintaining computational efficiency suitable for resource-constrained microcontrollers.

Cost analysis reveals minimal overhead (~$3 USD) for AI-assisted capabilities, primarily attributed to slightly increased development time rather than additional hardware. This demonstrates the economic feasibility of intelligent decision-making in low-cost safety systems.

The system's stability across varying environmental conditions (ambient temperature 20–28°C, relative humidity 40–70%) confirms robustness to real-world deployment scenarios. Long-term testing over 72 continuous hours showed consistent performance without calibration drift or false alarm degradation.

Limitations include: (1) manual threshold calibration requirements for different environments; (2) single-sensor dependency reducing redundancy; (3) lack of remote communication capabilities in current prototype; (4) limited testing with gas types beyond LPG and methane. These constraints represent opportunities for enhancement in future iterations.

CONCLUSION

This study presented the development and evaluation of an AI-assisted IoT smart gas leakage detection and intelligent ventilation control system built around the MQ-5 gas sensor and the Arduino UNO microcontroller. Unlike conventional threshold-based detectors that rely on fixed cut-off values, the proposed system integrates a lightweight artificial intelligence module consisting of rule-based reasoning and fuzzy logic inference, enabling adaptive, context-aware classification of leakage severity. This approach significantly enhances sensitivity to rising gas levels, improves robustness against environmental noise, and reduces false alarms, which are common limitations of low-cost gas monitors. The system architecture, comprising sensing, data acquisition, AI-assisted decision-making, and actuator control, was successfully implemented and validated using a functional hardware prototype. Experimental results demonstrated that the AI-assisted design achieved faster response times, more reliable multi-level hazard classification, and markedly fewer incorrect alerts compared to traditional threshold-based methods. The inclusion of automated ventilation activation through a relay-driven exhaust fan further strengthens the system’s ability to mitigate risk by actively reducing gas concentration during severe leakage events. Additionally, the LCD-based user interface ensures continuous situational awareness for end users, making the system suitable for deployment in homes, small businesses, laboratories, and other environments where combustible gases are present. Overall, the findings confirm that embedding lightweight AI mechanisms in low-cost microcontroller-based safety devices is both feasible and highly beneficial. The proposed system offers an effective, affordable, and practical solution for improving gas safety monitoring in resource-constrained settings and contributes to ongoing efforts to develop more intelligent, reliable IoT-based safety technologies.

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CITATION

Ibrahim, I. A., Ali, A. I., & Baballe, M. A. (2026). AI-Assisted IoT Smart Gas Leakage Detection and Intelligent Ventilation Control System: A Hybrid Rule-Based and Fuzzy Logic Approach. Global Journal of Research in Engineering & Computer Sciences, 6(2), 273–282. https://doi.org/10.5281/zenodo.19793545