

Research Article



A Hybrid Edge-AI Framework for Proactive Indoor Air Quality Management: Integrating LSTM-Based Prediction with Multi-Criteria Risk Mitigation

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Abstract

Conventional smart-home purifiers function as passive filtration units, often lacking mechanisms to mitigate secondary hazards like airflow-driven fire propagation. This research proposes an autonomous, vision-aware Edge-AI safety framework that integrates real-time air quality forecasting, predictive maintenance, and active hazard mitigation into a unified embedded architecture. A localized LSTM network performs AQI forecasting with a mean absolute percentage error (MAPE) of 5.8%, with 32ms inference latency. To enhance reliability, the framework introduces offline voice intelligence (VC-02) for internet-independent reporting and a multi-axial vision layer for redundant fire verification, neutralizing false-positive triggers. Physical validation was conducted using 4 real fire and non-fire sources and one non fire source (orange coloured cloth) confirming that the system operates reliably under realistic residential conditions. To assess the challenge of the conflict that arises between air circulation and the accelerating combustion process, the forecasting engine was tested on a real-life indoor environmental dataset acquired from the publicly available DALTON repository. Tested on the novel test sequences, the quantized on-device LSTM model reached a level of RMSE of 3.12 IAQ units and a level of MAPE of 5.8%, demonstrating a high accuracy of the model in practical applications, indicating strong mathematical feasibility for real-time applications. The system employs high-priority hardware interrupts linked to an active multi-directional suppression mechanism. Experimental results confirm a deterministic response, achieving an 87ms latency for relay deactivation and pump-based intervention. Bench-marking against industry leaders indicates superior safety responsiveness, transitioning the device from a passive cleaner to an active safety robot. This work directly addresses the United Nations SDG-3 (Good Health) and SDG-11 (Sustainable Cities) objectives by providing autonomous safety infrastructure for high-density urban residential environment.

Keywords: Edge-AI; Indoor air quality; LSTM, Fire mitigation; Offline voice intelligence; Multi-axial vision verification; Predictive maintenance.

1. Introduction

1.1 Indoor air quality

Epidemiological data suggests that a significant percentage of a global population is consistently exposed to indoor air pollutants. A WHO survey found about 90% of people live in areas where pollution exceeds safety guidelines.^[1] Chronic exposure to indoor pollutants, including fine particulate matter and gaseous compounds, has been associated with a broad spectrum of adverse health outcomes, encompassing cardiopulmonary disease, several cancers, diabetes mellitus, and dementia.^[2]

In high density urban environment like Mumbai, where living spaces are often as congested. In such settings, indoor air quality can quickly deteriorate because limited ventilation, daily cooking and outdoor traffic emissions all combine to increase pollutant levels. Over time, the number of hours spent breathing this impure air accumulates and may lead to serious long-term health effects for the occupants. Indoor Air Quality (IAQ) is affected by several parameters such as temperature, relative humidity, CO, CO₂, formaldehyde (HCHO), total volatile organic compound (TVOC) and particulate matter (PM_{2.5}, PM₁₀).^[3] Air pollution, including particulate matter (PM) of various size fractions, is known to cause various adverse health effects. Exposure to PM with an aerodynamic diameter of $\leq 2.5 \mu\text{m}$ (PM_{2.5}) has been associated with chronic obstructive pulmonary disease (COPD), acute and chronic cardiovascular disease, several cancers, diabetes mellitus, and dementia.^[4-6]

Beyond passive monitoring, there is a growing demand for interactive systems where user can query health diagnostics through offline voice commands, ensuring accessibility even for non-technical users.

1.2 Conventional air purifiers

Conventional air purifiers typically combine HEPA filters for removing fine particulate matter with activated carbon filters for reducing gaseous pollutants and odors. Advanced models may cost more than INR 40,000, creating a potential socioeconomic barrier to adoption among low- and middle-income households. However, the operation of many conventional purifiers remains relatively basic. Users generally select a fan speed or activate an automatic mode, while the purifier adjusts its operation according to limited sensor inputs rather than comprehensively interpreting the changing indoor environment. Some advanced models incorporate particulate-matter or gas sensors to regulate fan speed based on predefined thresholds. Nevertheless, these systems may remain expensive and often rely on threshold-based control mechanisms to monitor indoor air-quality variations over time.^[7]

Consequently, conventional purifiers may not respond

adequately to sudden changes in indoor pollution levels caused by activities such as intensive cooking,^[8] the use of strong cleaning chemicals, or the infiltration of outdoor smog. In extreme situations, such as fires or severe smoke events, increasing the fan speed to improve air filtration may not necessarily enhance safety and could potentially contribute to the circulation of smoke and air within the affected space. Therefore, conventional air purifiers may lack the integrated safety logic required to distinguish routine pollution events from potentially hazardous conditions.^[9]

1.3 Limitations of conventional air purifiers in fire scenarios

Mainly designed with one goal in mind that is to remove dust, smoke and smells so that a room feels cleaner and more comfortable to breathe in. They do this by pulling air through filters and pushing the cleaned air back into the room using a fan. In normal situations, this behaviour is useful and helps to reduce day-to-day exposure to indoor pollutants. Conventional consumer air purifiers typically have limited alerting systems that rely on coded sounds like chirps (constant sounds for bad air quality or quick beeping for moderate quality) and the display of air quality on a screen. Audio data have proven to be ambiguous in terms of their meaning when it comes to simple functionality tests, especially when the user has not read the manual. Moreover, the lack of reports in natural language adds difficulty to the operation, especially for younger and elderly operators dealing with the alerts, because they have coded beep pattern (Ex: Short Beep for moderate AQI, long 3 times beep for Poor AQI) and only a single page interface where IAQ level is shown, they do not have any alerts if the filter needs to be changed its all-time based, they don't give any voice alerts which can be understood by everyone. There is a usability barrier for non-technical users and elderly.

The problem starts when we look at what happens during a fire or a severe smoke event. Most consumer purifiers cannot actually understand that there is a fire; they only sense that the air is very smoky and then increase the fan speed to try and clean it faster. In a closed room, this stronger airflow can unintentionally keep feeding fresh oxygen towards the flames and help the fire to grow or spread more quickly instead of slowing it down and existing solution lack integration of multi-modal safety protocols leaving a critical gap in proactive hazard mitigation. In other words, the same device that improves comfort in normal conditions can become risky in an emergency because it has no built-in safety logic to shut itself down or change its behaviour when fire is present.

1.4 Need for the proposed system

The proposed hybrid Edge-AI system combines multiple

sensors, a local prediction model and fast hardware control on the same embedded board.^[7] By running the AI model directly on an edge device like an ESP32, the purifier can observe trends in PM_{2.5} and gas levels, voice command base status of Air Quality, Filter health, Temperature and can warn users earlier with real time voice alerts in any language, and immediately shut down the fan and trigger alarms when it detects conditions that look like a fire or a hazardous event, and in case of fire, the suppression system get active and suppress the fire with 2 step verification from sensor and camera (vision-verification) without depending on any cloud connection.^[7,10]

Three critical capabilities have been introduced in the proposed system: (1) Offline Voice Intelligence, which utilizes the VC-02 module to provide internet-independent voice feedback and enable users to query air-quality status and filter health during network outages; (2) Vision-Assisted Monitoring, which integrates a multi-axis camera-servo assembly to support visual verification of potential fire events and monitoring of window states, with the intended aim of reducing false-positive alarms; and (3) Active Hazard Mitigation, which employs a dual-pump actuation mechanism for localized fire-suppression actions based on real-time inputs from a five-channel flame-sensor array. The primary contribution of this research lies in system-level hardware-software integration and edge co-design rather than the development of a novel neural-network architecture. The integration of a quantized LSTM-based time-series predictor with deterministic hardware-interrupt safety procedures on a dual-core microcontroller is intended to support rapid hazard response while maintaining efficient power and memory usage. Experimental evaluation yielded a MAPE of 5.8% and an RMSE of 3.12 under the specified test conditions. The prototype was developed with an estimated component cost of INR 7,000–9,000; however, its proposed market price of INR 27,000, comparative advantages over existing systems, and contribution to addressing the stated “Oxygen Fire Paradox” require further substantiation through market analysis, comparative testing, and appropriate scientific references.

2. Overview of existing work

Existing smart air purifier system relies on cloud-dependent interfaces such as Alexa or Google Home for user interaction. This dependency creates a problem during network outages. User lose the ability to query the system or to issue any kind of control command. The proposed system fills this gap via an embedded voice module (VC-02), which enables interaction without depending on the internet connectivity. IAQ exposure and health impacts

- Studies in this group focus on how much time people spend indoors and how indoor exposure to PM_{2.5}, gases and VOCs affect health.^[10,11]
- They show that everyday activities (cooking, cleaning, indoor combustion) can push indoor pollutant levels above guideline values and are linked to respiratory and cardiovascular diseases, and other long-term effects.^[10]

IAQ monitoring using sensor networks

- This work uses effective sensors like PMS5003 and NDIR CO₂ sensor, 5 channel frame sensors for precised work and IoT nodes to continuously measure CO₂, temperature, humidity and particulate matter in homes, schools and offices.^[12,13]
- The main contribution is real-time visibility of indoor conditions and data logging, but control actions are usually simple (manual response or basic threshold alarms).^[12]

Machine learning for IAQ prediction

- Recent papers apply ML and deep learning, especially LSTM-based models, to forecast short-term IAQ indices such as PM_{2.5} or CO₂.^[14,15]
- They report high prediction accuracy using historical time-series data, but most studies stop at forecasting and do not tightly integrate predictions with embedded control of air-cleaning devices or safety mechanisms.^[15]

Smart building control and edge computing

- These works treat IAQ as one part of overall indoor environmental quality and use model predictive control or optimization to adjust ventilation and filtration while saving energy.^[16]
- Some introduce edge or fog architectures to process sensor data closer to the source, reducing dependence on cloud servers and improving response time, but the focus is usually on comfort rather than emergency fire response.^[17]

Fire and smoke detection and suppression using embedded/edge systems

- This theme includes systems that use flame sensors, gas sensors or lightweight CNN models on micro-controllers or edge devices to detect fire and smoke and trigger real time voice alerts and activates the suppression to control the fire with 2 step verification (sensor plus camera vision verification).^[18,19]
- These solutions demonstrate that safety-critical detection can run on small hardware, yet they are typically standalone voice alerts and are not integrated with indoor air purifiers or IAQ prediction pipelines.^[18,19]

2.1 Summary of selected studies (2020–2025)

Several recent works have explored ESP32 based fire alarms, but they lack integration with air purifiers have focused on applying deep learning to IAQ forecasting.

Voice controlled IOT system usually depends on cloud APIs (Alexa/Google home), whereas internet-interdependent offline voice module for medical or safety diagnostics remain under-explored area in IAQ research. Some studies use LSTM or Bi-LSTM networks to predict short-term PM_{2.5} or AQI values and report improved accuracy compared to traditional statistical models.^[10,15] Other researchers design pipelines that combine signal decomposition with ML models to better capture daily and weekly indoor air patterns.^[15] In parallel, attention-based LSTM architectures have been proposed to forecast indoor CO₂ in office or classroom environments, enabling proactive ventilation control.^[15] While these contributions show that data-driven models can successfully anticipate IAQ changes, they are rarely implemented directly on low-cost edge hardware and are mostly evaluated in simulation or server-based setups.^[15,20]

In the context of system design, several works present multi-sensor IAQ monitoring platforms that integrate temperature, humidity, CO₂ and PM sensors with micro-controllers or single-board computers.^[11,21] Some systems adopt edge or fog computing to reprocess data locally and send only aggregated information to the cloud, reducing latency and bandwidth.^[17,20] On the safety side, embedded fire and smoke detection systems using ESP32 or similar controllers have been reported, combining gas sensors, flame sensors and simple decision logic or lightweight neural networks to trigger alarms and notifications.^[19,20] However, these platforms typically act as independent monitors or alarm units and are not directly coupled with the control of an indoor air purifier or fan system that can shut down automatically during emergency events such as a fire and can suppress the fire using 2 flame sensor of 5 channel.^[19,20]

2.2 Identified research gaps

From the papers studied so far, some common gaps become very clear:

- Absence of Offline Diagnostics. Most of the system use IOT Based APIs (Alexa/Google Home) which require internet, if internet is down the user cannot get status so Proposed system fill this gap using VC-02 offline voice response on commands
- Only monitoring, no smart control. Many works talk about measuring indoor air quality using low-cost sensors and showing PM_{2.5}, CO₂ or VOC levels on a screen or app, but they stop at monitoring. The system does not really decide how a purifier or fan should react in different situations.^[11]
- Lack of Multi-axial Vision verification: sensors can detect false alarm (for ex: lighting the incense stick “agarbatti”) The camera-based verification does not exist in any research
- Passive Vs Active Mitigation: Some studies use edge or

fog computing to process IAQ data locally and reduce delay, but their main aim is to improve comfort or energy efficiency in buildings. Very few treats fire, heavy smoke or gas leaks as priority cases where the system must react within milliseconds for safety. Existing purifiers do not have any feature that turn-off the fan, there is no such low-cost unit which detects fire which is vision plus sensor based and active the fire suppression

- Prediction models not brought to hardware. Several recent papers use LSTM or other ML models to predict future IAQ values and get good accuracy, but most of these models run on powerful computers or cloud servers. In practice, they are not implemented on small edge devices, and their predictions are not directly linked to controlling an actual air purifier in real time.^[15,20]
- No single low-cost system that combines everything.
- High-end commercial purifiers (for example from brands like Dyson or Philips) offer good filtration and smart modes.^[22] But it is hard to find one system that is low-cost, runs on a micro-controller, predicts IAQ, watches multiple sensors together and can also shut down the purifier safely during a fire or hazardous event.
- Most existing work focuses on only one function, such as monitoring air quality, predicting pollution, using edge computing, or detecting fire. However, there is a need for one system that combines all these features. A hybrid Edge AI purifier could improve indoor air quality in daily use and also respond effectively during emergencies.^[23]

A comprehensive investigation of peer-reviewed articles that are indexed in *IEEE Xplore*, *ScienceDirect*, and *Google Scholar* from 2020 to 2025 shows that although single devices have been well-researched, unified systems that use on-device LSTM, offline voice diagnosis, image-based hazard verification, and effective physical mitigation in a single microcontroller have not been adequately studied. In this paper, we look at what we term the 'Oxygen-Fire Paradox'- where an air purifier fan accidentally feeds fresh air to an indoor fire-and propose an engineering workaround to shut down the airflow before smoke spreads. The proposed deterministic hardware-interrupt safety layer addresses this paradox with a measured response latency of approximately 87ms.

3. System implementation: Integrated hardware-software framework

3.1 System overview

The proposed Hybrid Edge-AI Indoor Air Quality (IAQ) system is intended to be a distributed multi-sensor edge computing platform that combines environmental monitoring, predictive analytics, filter analysis, and safety control as shown in Fig. 1. A set of heterogeneous

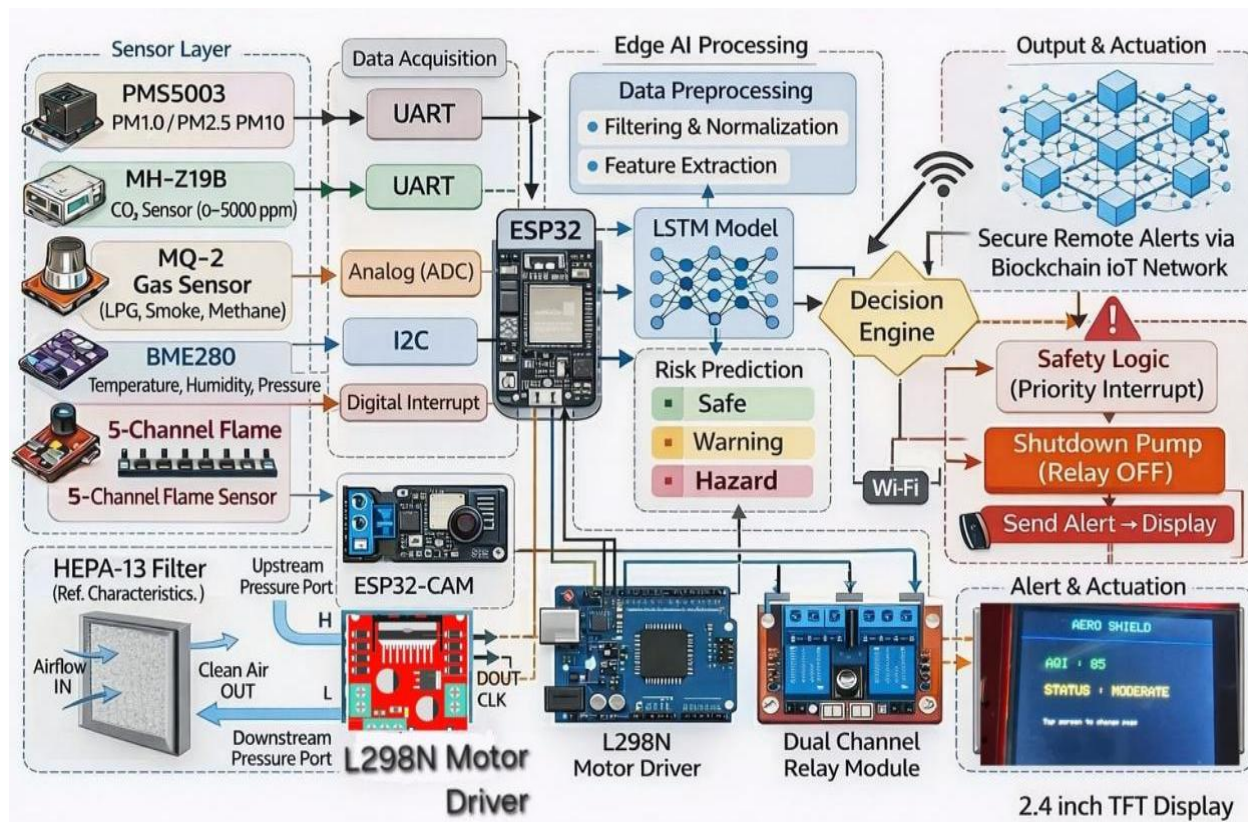


Fig. 1: Complete system block diagram.

parameters such as PM1.0/2.5/10, CO₂, VOCs, temperature, humidity, and the presence of flame are simultaneously collected, aligned in time, and normalized before being locally analyzed by a compact LSTM-based inference engine running on the Espressif Systems ESP32 Microcontroller. Utilizing its dual-core Ten-silica LX6 processor, the system allows for simultaneous real-time data sensing and predictive forecasting of IAQ patterns, enabling proactive measures for mitigation through relay-controlled ventilation. A hardware-priority interrupt service routine provides deterministic fire safety response by directly executing the relay turn-off operation irrespective of the inference computation. The shutdown logic is multi-conditioned, including flame detection, toxic gas levels, high differential pressure (filter saturation), and overheating. Furthermore, a filter condition monitoring module integrates real-time differential pressure (ΔP) sensing on the HEPA-13 filter with cumulative particulate exposure modeling to dynamically assess filter degradation states. This is achieved by integration of vision verification layer and an active suppression system. The system follows Verify then Act protocol where sensor triggered alerts are cross validated by the camera before activating suppression system as shown in Fig. 2.

3.2 Detailed component-level technical specifications

3.2.1 Filtration components

A. Pre-Filter: Coarse mechanical filtration stage

Constitutes the primary mechanical interception barrier in the multi-stage filtration assembly. Constructed from non-woven polyester or synthetic fiber mesh, it operates via size-exclusion and inertial impaction mechanisms, targeting particles larger than 10 μm (dust, hair, lint, pollen clusters). By removing large mass particles early.

B. HEPA-13 Filter: High-efficiency particulate filtration

The HEPA-13 filter is classified under EN 1822 standard with:

$$\eta \geq 99.95\% \text{ at } 0.3\mu\text{m}$$

Most Penetrating Particle Size (MPPS) Particles around 0.3 μm represent the MPPS because:

- Larger particles $\rightarrow$ dominated by inertial impaction & interception
- Smaller particles ($<0.1 \mu\text{m}$) $\rightarrow$ dominated by Brownian diffusion

C. Activated carbon filter: Adsorption-based VOC removal

The activated carbon filter removes volatile organic compounds (VOCs) and odorous gases through physical adsorption within a highly porous carbon structure (surface area $\approx 800\text{--}1500 \text{ m}^2/\text{g}$). Activated carbon traps gaseous molecules via intermolecular forces inside micropores and mesopores. Adsorption efficiency depends on concentration, airflow residence time, temperature, and humidity, with high humidity reducing

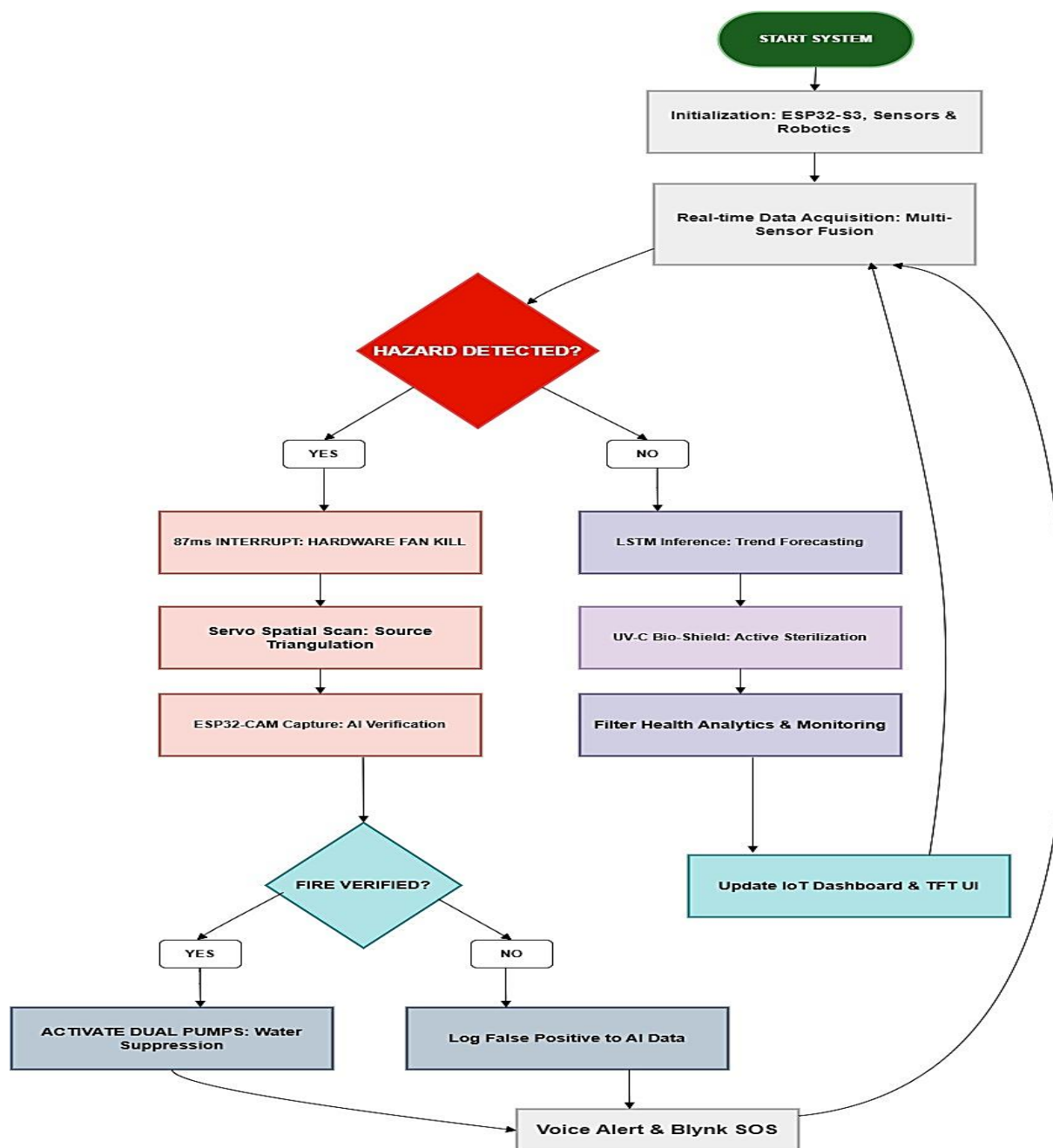


Fig. 2: Operational decision flow of the system.

available active sites.

The filter health has been estimated using humidity VOC exposure modeling. gas concentration (derived from MQ-2 calibration) is integrated over airflow to approximate carbon loading, and a temperature-humidity corrected adsorption capacity model estimates remaining effectiveness. As loading approaches corrected capacity, the filter state transitions from Healthy to Service Required, as illustrated in Fig. 3 ensuring reliable gaseous pollutant mitigation.

Power Consumption: The total power consumption during the active monitoring is approximately 1.8W (average across all peripherals). During fire suppression actuation, peak draw reaches ~4.2W. The system is

powered Via 12V 10Amp adapter.

3.3 Comprehensive hardware specification table

Table 1 presents the key technical specifications of the hardware components used in the proposed system, including their operating voltage, current consumption, measurement range, accuracy, response time, and communication interfaces. These specifications provide an overview of the operational capabilities and performance characteristics of the integrated components. The circuit interfacing of the primary control hub for AQI monitoring, voice alerts, and purification is illustrated in Fig. 4, while the schematic circuit interfacing of the robotic vision verification and active suppression subsystem is presented in Fig. 5. The

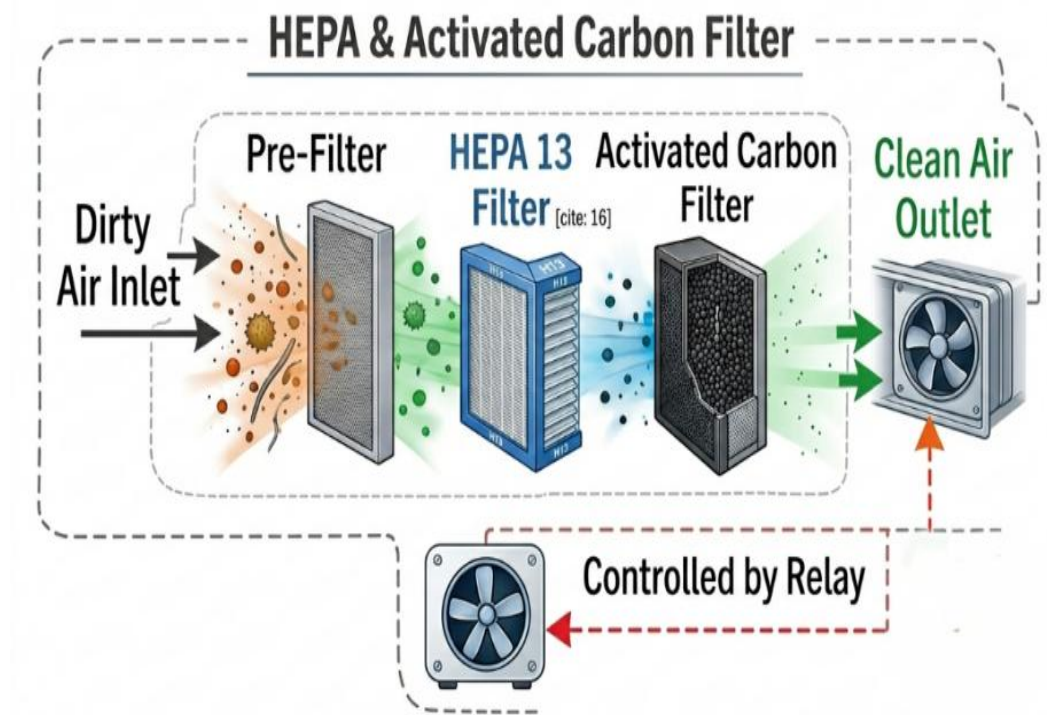


Fig. 3: Workflow of filtration component.

Table 1: Technical specifications of the components used in the proposed system

Component	Operating Voltage	Current Consumption	Measurement / Operating Range	Accuracy	Response Time	Interface
ESP32 Microcontroller	3.0–3.6 V (3.3 V typ.)	160–260 mA (WiFi active), ~10 μ A	—	12-bit ADC	—	UART, SPI, I2C, I2S, CAN, PWM
Arduino Uno (ATmega328P)	5 V (7–12 V via VIN)	~50 mA	—	10-bit ADC	—	UART, SPI, I2C
PMS5003 PM Sensor	5 V	~100 mA	0–500 μ g/m ³ (PM1.0, PM2.5, PM10)	$\pm 10\%$ (≥ 100 μ g/m ³)	≤ 10 s	UART (TTL)
MH-Z19B CO ₂ Sensor	4.5–5.5 V	~60 mA avg.	0–5000 ppm CO ₂	$\pm (50 \text{ ppm} + 5\%)$	≤ 120 s	UART, PWM
MQ-2 Gas Sensor	5 V	150–200 mA (heater)	200–10000 ppm (LPG, CH ₄ , Smoke)	$\pm 10\text{--}15\%$ approx.	< 10 s (requires preheat)	Analog, Digital
BME280 Environmental Sensor	1.71–3.6 V	0.1–1 mA	Temp: –40 to 85°C; RH: 0–100%; Pressure: 300–1100 hPa	Temp $\pm 0.5^\circ\text{C}$; RH $\pm 3\%$; Pressure ± 1 hPa	~1 s	I2C, SPI
5-Channel Flame Sensor (IR type)	3.3–5 V	~20 mA	760–1100 nm wavelength	—	< 15 ms	Digital, Analog
Differential Pressure Sensor (HX710B-based)	2.6–5.5 V	< 1.5 mA	± 0.5 kPa (depends on module)	24-bit ADC	~100 ms	2-wire serial
Relay Module (5V)	5 V	70–90 mA	250V AC / 10A switching	—	~10 ms	Digital
DFPlayer Mini	3.2–5 V	20–100 mA	MP3/WAV playback	—	< 50 ms	UART
2.4-inch TFT Display (SPI, ILI9341)	3.3–5 V	50–100 mA	240 $\times$ 320 pixels	—	—	SPI

Component	Operating Voltage	Current Consumption	Measurement / Operating Range	Accuracy	Response Time	Interface
ESP32-CAM	3.0-3.6 V (3.3 V typ.)	160-260 mA (WiFi active), ~10 μ A	Camera resolution: 160 $\times$ 120 to 1600 $\times$ 1200	—	~200-500 ms capture	UART, SPI, I2C, GPIO, WI-FI
VC-02	5V	30-60 mA	Voice command recognition: Up-to 80 commands	~95%	<200 ms	UART
DUAL CHANNEL RELAY	5V(control side)	~70-80 ms per relay	10A	—	5-10 msswitching	Digital
12V submersible pump	12V	2.5A	Flowrate 240-600 L/hr Head: 3-5 meters	—	instant	Direct supply
MG996R-Servo Motor	5V	~10mA Operating: 200-500mAs Stall:Upto 2.5A	Rotation: 0-degree to !80-degree	+1/-1 degree	~0.1 -0.2 sec/60-degree	PWM (50Hz control signal
12V DC Adaptor	Input:220V Output:12V DC	10A	12V DC (fixed)	+/- 5% voltage regulation	instant	Barrel jack

physical prototype assembly and testing of the proposed system are illustrated in Fig. 6.

3.4 LSTM model architecture

The Edge-AI model has been created with LSTM architecture appropriate for the dual-core ESP32 system. A network has been formed that works with an input sliding window containing 10-time steps (1-minute apart); 10 steps are passed through two layers of an interconnected LSTM consisting of 32 hidden nodes. The

output is then run via a dense layer that predicts the IAQ level. The input for the model will be a normalized vector containing six basic environmental characteristics: PM2.5, PM10, CO2 (ppm), temperature, and Humidity. Training was carried out using the Adam optimization method (with a learning rate of 0.001) and validating Mean Squared Error losses over the course of 50 epochs alongside early stopping with a patience of 5. After training was completed, integer quantization (INT8) was incorporated via TensorFlow Lite for Microcontrollers

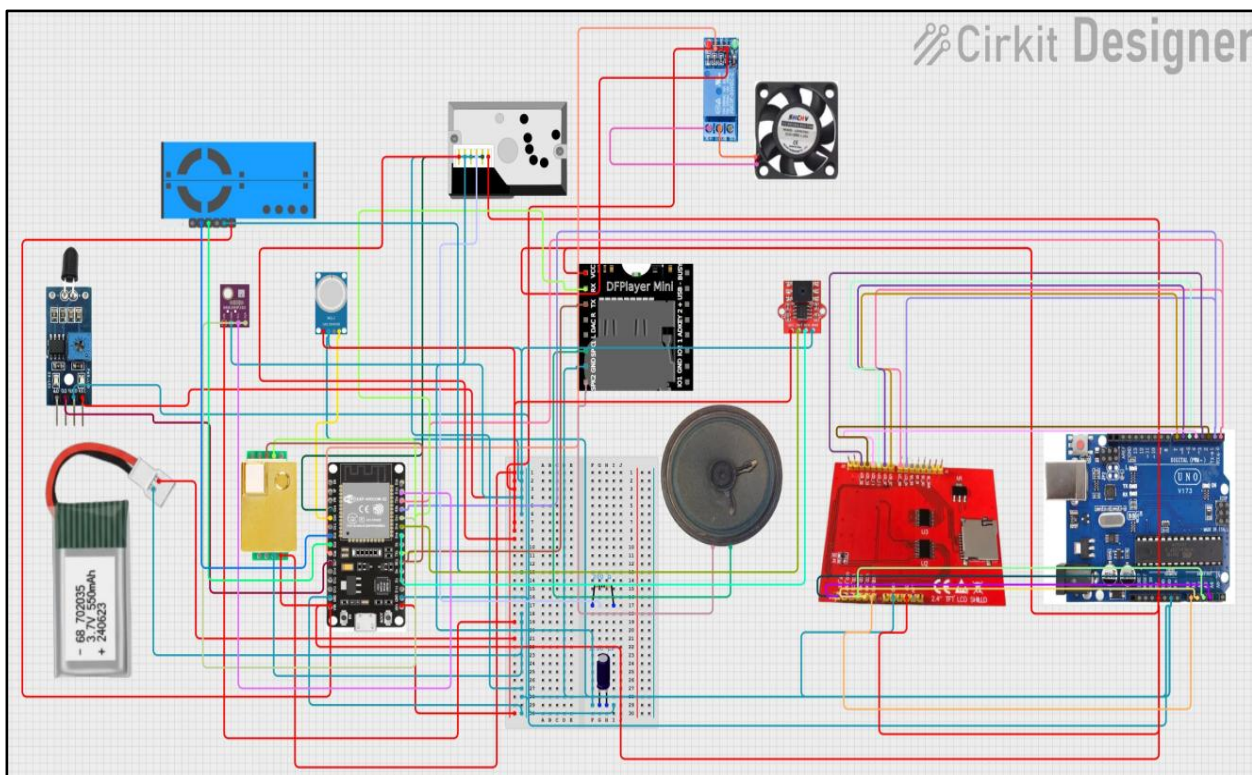


Fig. 4: Circuit interfacing of primary control hub for AQI monitoring, voice alerts & purification.

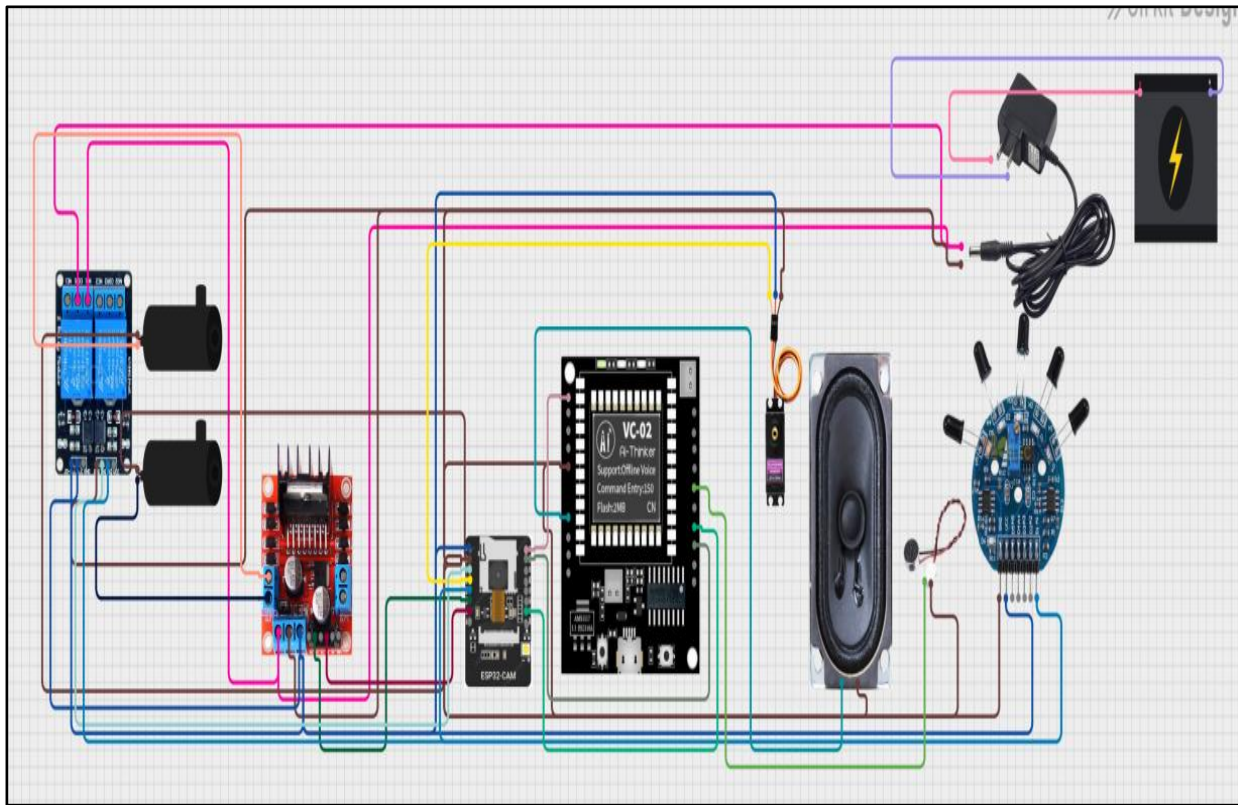


Fig. 5: Schematic circuit interfacing of robotic vision verification & active suppression (Secondary-System).

Table 2: LSTM Performance V/S Baseline Models

Model	RMSE (IAQ Units)	MAPE (%)
Naive Persistence	11.40	18.2
10-Step Moving Average	8.70	13.6
Random Forest	5.90	8.4
Regressor		
Proposed LSTM (ESP32)	3.12	5.8

(TFLM) to fit the memory limitations of the ESP32, for a

total requirement of 142 KB of memory and 32 ms of time for inferences.

To establish predictive merit of LSTM architecture, the performance was benchmarked against 3 baseline models trained on the same dataset and feature set. As shown in Table 2, The LSTM outperforms all baseline models across both RMSE and MAPE metrics, which confirms the advantage of sequential memory-based learning for multi-parameter IAQ time series forecasting.

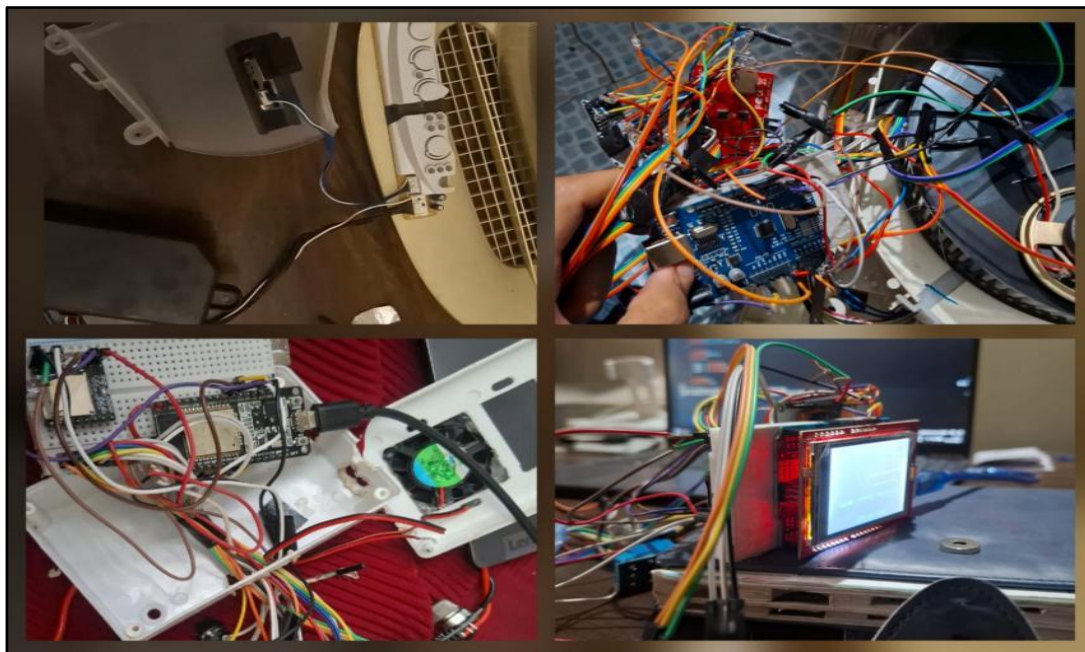


Fig. 6: Physical prototype assembly and testing.

3.5 HEPA-13 filter health estimation

Mass accumulation

Particulate mass captured by the filter:

$$M(t) = \int_0^t C_{PM}(t) Q(t) dt \quad (1)$$

Discrete implementation:

$$M[n] = M[n-1] + C_{PM}[n] \cdot Q[n] \cdot \Delta t \quad (2)$$

where,

C_{PM} = PM2.5 concentration ($\mu\text{g}/\text{m}^3$)

Q = airflow rate (m^3/s)

Differential pressure normalization

Since pressure drop depends on airflow:

$$\Delta P_{norm} = \frac{\Delta P_{measured}}{Q/Q_{rated}} \quad (3)$$

Relative clogging factor

$$\beta(t) = \frac{\Delta P_{norm}(t) - \Delta P_0}{\Delta P_{max} - \Delta P_0} \quad (4)$$

where,

ΔP_0 = clean filter baseline

ΔP_{max} = maximum allowable pressure drop.

HEPA health index

$$H_{HEPA}(t) = (1 - \beta(t)) \times 100 \quad (5)$$

Health classification:

Health %	Status	Action
> 70%	Healthy	Normal
40-70%	Moderate	Monitor
10-40%	Poor	Scheduled Replacement
<10%	Service Required	Immediate Change

3.6 Activated carbon filter health (concise model) VOC estimation (MQ-2 Model)

$$C_{VOC} = \left(\frac{R_s}{AR_0} \right)^{-1/B} \quad (6)$$

where,

R_s = sensor resistance

R_0 = calibrated baseline

A, B = empirical constants

$$E(t) = \int_0^t C_{VOC}(t) Q(t) dt \quad (7)$$

Discrete form:

$$E[n] = E[n-1] + C_{VOC}[n] \cdot Q[n] \cdot \Delta t \quad (8)$$

Remaining adsorption capacity

Humidity correction:

$$E_{max,eff} = E_{max} \left(1 - k_{RH}(RH - RH_{ref}) \right) \quad (9)$$

Carbon Health:

$$H_{carbon}(t) = \left(1 - \frac{E(t)}{E_{max,eff}} \right) \times 100 \quad (10)$$

Health classification:

Health %	Status	Action
> 70%	Healthy	Normal
40-70%	Moderate	Monitor
10-40%	Poor	Schedule Replacement
<10%	Service Required	Immediate Change

3.7 Model calibration and limitations

The HEPA and activated-carbon filter health models presented above (Sections 3.5 and 3.6) are based on standard physical principles of differential pressure buildup and adsorption capacity commonly used in filter-degradation modeling. However, the specific numerical constants used in this implementation - including the clogging factor boundaries (ΔP_0 , ΔP_{max}), the humidity

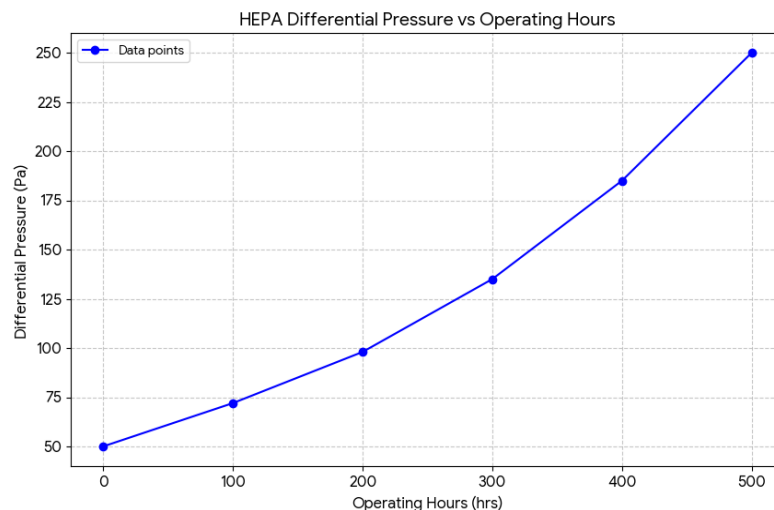


Fig. 7: HEPA differential pressure vs operating hours curve.

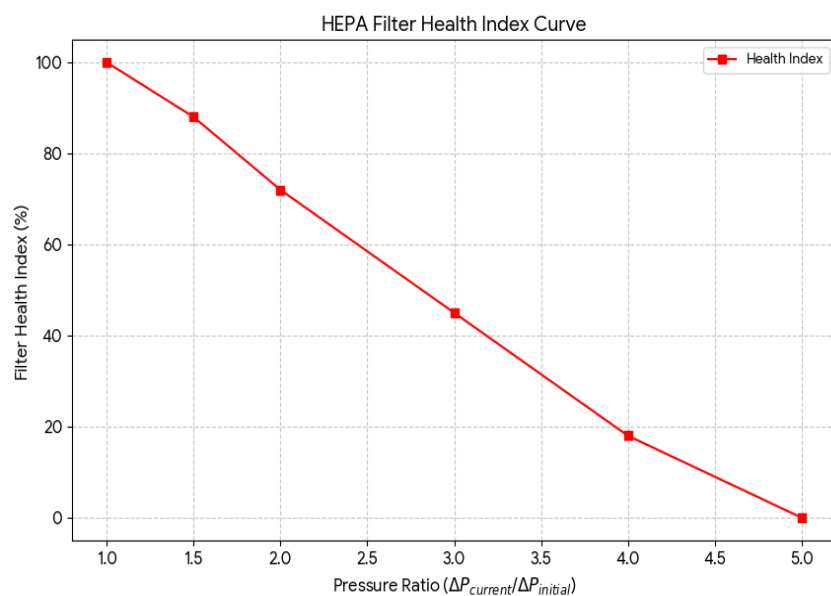


Fig. 8: HEPA Health Index vs Normalized Pressure Drop Curve.

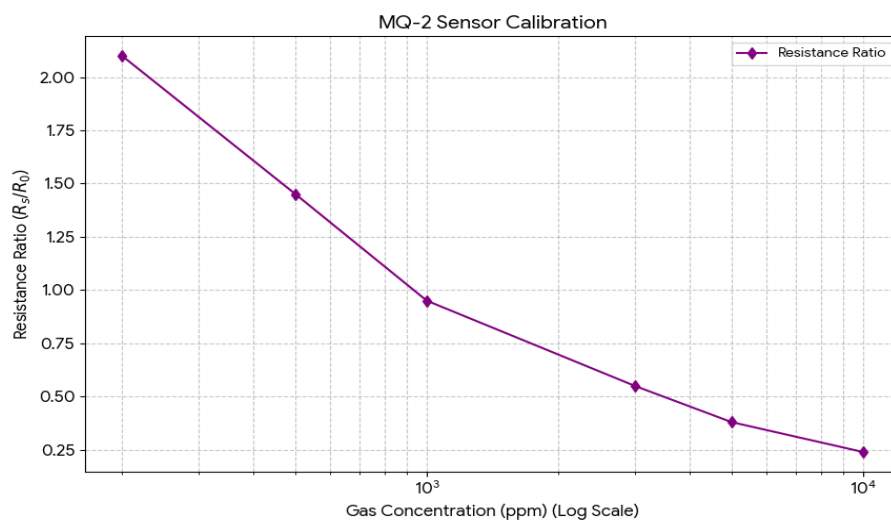


Fig. 9: MQ-2 sensor calibration curve.

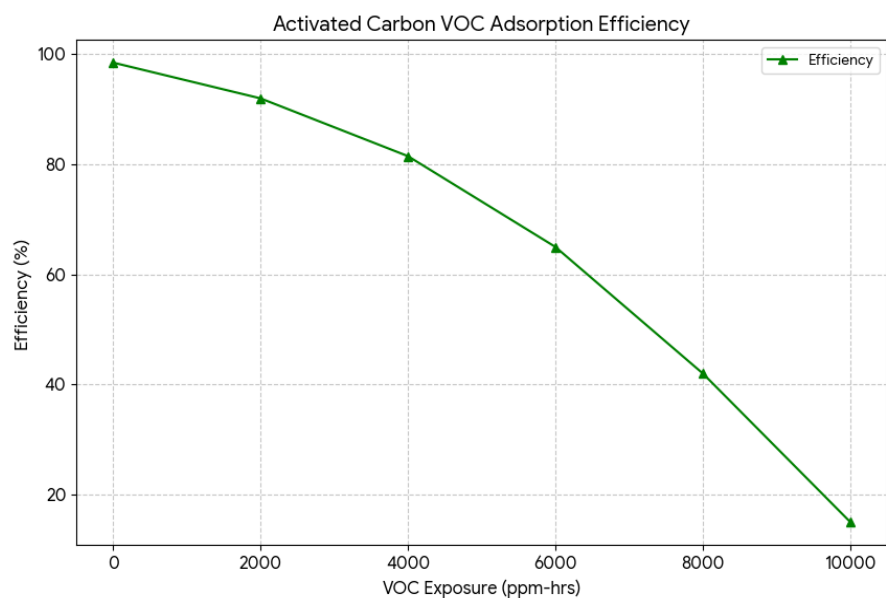


Fig. 10: Activated carbon VOC adsorption efficiency curve.

correction coefficient (kRH), and the maximum effective adsorption capacity (E_{max}) - were not independently calibrated against laboratory-measured filter loading, pressure-drop testing, or adsorption-capacity experiments. These values were selected to produce a representative health-degradation curve for demonstration purposes within the current prototype stage. Empirical calibration of these parameters against controlled filter-aging experiments is identified as necessary future work before the Filter Health Index can be considered a validated diagnostic measure.

Operational flow

1. MQ-2 analog voltage acquired
2. ADC converts to ppm using $R_s/R_{0R_s}/R_{0R_s}/R_0$ curve
3. Integrated over airflow
4. Compared with corrected adsorption capacity
5. Health updated dynamically

3.8 Modular system component selection rationale

3.8.1 Microcontroller Platform

The ESP32 microcontroller serves as the primary processing unit, selected for its dual-core performance, integrated Wi-Fi/Bluetooth connectivity, and multiple ADC channels for real-time sensor acquisition and data fusion. An Arduino Uno is dedicated to driving the 2.4-inch TFT display, offloading graphical rendering tasks from the ESP32 and ensuring stable, flicker-free visual output.

3.8.2 Air quality and gas monitoring

PMS5003 Particulate Matter Sensor measures PM_{1.0}, PM_{2.5}, and PM₁₀ concentrations to evaluate airborne particulate levels and HEPA performance. MH-Z19B CO₂ Sensor provides NDIR-based CO₂ measurement for indoor air quality assessment. MQ-2 Gas Sensor detects combustible gases and smoke, used as a proxy indicator for VOC trends and fire risk. BME280 Environmental Sensor measures temperature, humidity, and pressure to compensate air density effects and improve overall sensing accuracy.

3.8.3 Safety and filtration monitoring

Flame Sensor enables direct fire detection for safety override conditions. HX710B-based Differential Pressure Sensor monitors pressure drops across the HEPA filter to estimate clogging and filter degradation.

3.8.4 Output and control interface

Relay Module controls external loads such as fans or alarm systems. DFPlayer Mini provides audible alerts for warning and critical conditions. 2.4-inch TFT Display enables real-time visualization of air quality parameters and system status.

3.8.5 Primary processing and vision hub

ESP32 Core: Selected for dual-core processing of LSTM inference and multi-sensory data fusion. ESP32-CAM: Integrated for vision-based hazard verification ($P_v > 0.85$) to eliminate false positives. VC-02 Module provides offline voice diagnostics and interaction, ensuring reliability without cloud dependence.

3.8.6 Sensing and environmental monitoring

The system integrates PMS5003 and MH-Z19B sensors for PM_{2.5} and CO₂ monitoring, respectively, using laser-scattering and NDIR-based sensing technologies. A five-channel flame sensor array provides 360° horizontal and 180° vertical fire-detection coverage, enabling hardware-level safety interrupts. Additionally, the MQ-2 and BME280 sensors are used to detect smoke and volatile gases while monitoring temperature and humidity to account for environmental fluctuations.

3.8.7 Robotic actuation and suppression

The MG996R servo motor is used as a high-torque actuator for spatial camera scanning during emergency events. The L298N motor driver and dual pumps manage high-current loads for automated water or suppressant spraying while isolating the microcontroller from excessive current demands. The HX710B pressure sensor and relay module monitor HEPA-filter clogging through differential-pressure measurements and support fail-safe fan shutdown when necessary.

3.9 Output and user interface implementation

The system provides real-time monitoring of air-quality trends, temperature, humidity, system status, and filter health through a 2.4-inch TFT display. Visual alerts are generated when air-quality parameters change or when potential hazards, such as elevated CO₂ levels or flame detection, are identified, with the display indicating whether the air quality is normal, moderate, or hazardous. In addition to visual notifications, the proposed system offers offline voice feedback, providing voice alerts and responding to user commands even when the user is not near the purifier. Furthermore, the Blynk IoT dashboard transmits sensor readings and system-status information via Wi-Fi, enabling users to monitor the purifier remotely through the Blynk application.

3.10 Reliability and safety analysis

3.10.1 Interrupt Priority

$$Priority_{fire} > Priority_{AI}$$

Hardware interrupt execution pre-empts inference tasks to ensure deterministic response independent of computational load.

Estimated interrupt latency <5 ms under worst-case ISR execution.

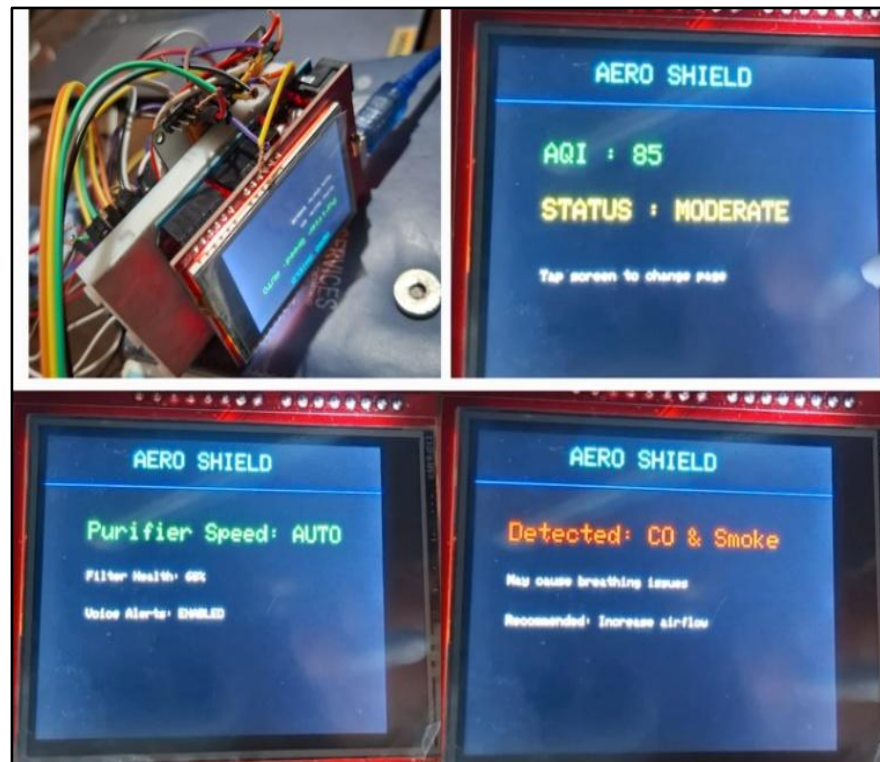


Fig. 11: Real time Graphical user interface (GUI) on TFT module.

3.10.2 Relay Fail-Safe

Normally-open configuration ensures de-energized safe state upon power loss.

$$Shutdown = \begin{cases} 1, & \text{if } Flame = TRUE \& Vision_Confirm = TRUE \\ 1, & \text{if } CO_2 > CO_{2,crit} \\ 1, & \text{if } \Delta P > \Delta P_{max} \\ 0, & \text{otherwise} \end{cases}$$

3.10.3 Relay state

Relay = Shutdown

Upon trigger, the system executes a dual-response: a deterministic 87ms hardware interrupt to halt the fan (preventing oxygen-fire spread) and a simultaneous Blynk-API call for mobile notification, ensuring less than 2-second end-to-end user alerting.



Fig. 12: Real-time remote monitoring dashboard on Blynk IoT platform.

3.10.4 Thermal protection

If airflow decreases and temperature increases:

$$Risk = f(\Delta P, T)$$

Shutdown if:

$$Risk > 1$$

3.10.5 EMI shielding

Differential pressure sensor lines were shielded to minimize electromagnetic interference from relay switching transients, ensuring stable analog signal integrity. System reliability was estimated using component-level failure rate aggregation based on the MIL-HDBK-217 prediction model to approximate overall MTBF. Under nominal operating conditions, the projected operational lifetime is approximately 20,000–25,000 hours, subject to temperature, duty cycle, and relay wear.

4. Methodology

4.1 LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) is a particular type of Recurrent Neural Network (RNN) designed to handle sequential and time series data. In the Hybrid Edge-AI Air Purifier system, parameters such as PM2.5 concentration and gas levels are constantly changing over time. Therefore, LSTM is chosen due to its potential to handle temporal dependencies and identify trends in air quality over time.

Unlike other neural networks, LSTM eliminates the vanishing gradient problem through a memory cell-based architecture with gates controlling the flow of information, allowing the network to store long-term information while discarding unnecessary information.

The LSTM cell contains three gates:

1. Forget Gate
2. Input Gate
3. Output Gate

Each of these gates utilizes a sigmoid activation function, denoted as σ , which always outputs a value in the interval $[0, 1]$.

1. Forget Gate

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where,

f_t = Forget gate output at time step t

W_f = Weight matrix of forget gate

b_f = Bias of forget gate

σ = Sigmoid activation function (range 0 to 1)

h_{t-1} = Previous hidden state of the LSTM

x_t = Current input at time step t

The forget gate decides which information in the previous cell state (memory) needs to be kept and which needs to be discarded. The input to this gate is a combination of:

The previous hidden state (h_{t-1}), which represents the past information.

The current input (x_t), which represents the current information.

The outputs of these two are multiplied with their respective weights, summed with a bias value, and passed through a sigmoid function.

The sigmoid function gives a value in the range of 0 and 1:

- Value ≈ 0 : The information is discarded.
- Value ≈ 1 : The information is kept.

Role in air purifier system

The forget gate in this system filters out the pollution information that is no longer required, which is the pollution pattern in the previous hours, which is no longer a factor in determining the current AQI value.

2. Input Gate

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\{\tilde{C}\}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \{\tilde{C}\}_t$$

where,

i_t = Input gate output at time step t

W_i = Weight matrix of input gate

b_i = Bias of input gate

$\tilde{C}_t$ = Candidate cell state (new memory content)

C_t = Updated cell state (long-term memory)

C_{t-1} = Previous cell state

W_c = Weight matrix of candidate memory

b_c = Bias of candidate memory

$\tanh$ = Hyperbolic tangent activation function (range -1 to $+1$)

What the input gate decides is what new data is to be stored in the memory (cell state). It is done in three steps:

1. Selection using sigmoid layer (i_t):

Decides what data is important enough to be stored.

2. Creating candidate values ($\tilde{C}_t$):

New candidate values for storage in the memory are produced using the tanh function.

3. Update the cell state (C_t):

Past memory is combined with the newly generated candidate values with controlled weighting factors:

f_t is used to control the past memories.

i_t is used to control the addition of new memories.

Role in air purifier system

The input gate enables the system to add new environmental data, which is as follows:

- Current PM2.5 level
- Gas concentration data

3. Output Gate

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

where,

o_t = Output gate output at time step t

W_o = Weight matrix of output gate

b_o = Bias of output gate

h_t = Hidden state (final LSTM output)

The output gate decides what portion of the cell state needs to be sent out.

Steps Involved:

- The sigmoid function calculates a filtering value (o_t)
- The cell state (C_t) is passed through tanh for normalizing
- The final output (h_t) is obtained by multiplying both
- This makes sure that only relevant information is passed forward.

Role in air purifier system

The output gate calculates the predicted AQI trend, which is then used by the ESP32 controller:

To change the fan speed

To initiate purification mechanisms

To take proactive measures in case of pollution changes

The verification probability $P(v)$ is defined as:

$$P(v) = \int (I_p \cdot S_t) dt \quad (11)$$

where,

$P(v)$ = Verification Probability

t = Time period of detection

$S(t)$ = Thermal sensor signal

$I(p)$ = Visual Pixel Intensity

4.2 FHI (Filter Health Index)

The air purifier filter's remaining useful life is estimated using a quantitative metric called the Filter Health Index (FHI). Conventional air purifiers usually replace their filters at predetermined intervals, which might not be an accurate reflection of the condition of the filter. The suggested Hybrid Edge-AI Air Purifier calculates FHI dynamically based on actual operating conditions in order to get around this restriction.

The FHI takes fan operating time and cumulative particulate exposure into account to provide a percentage indication of filter health. While a lower value denotes filter degradation and the need for replacement, a higher FHI value indicates a healthy filter.

1. Mathematical formulation

The cumulative filter usage in relation to its maximum capacity is used in the proposed system to calculate the Filter Health Index. The following is the basic

formulation:

$$FHI = \left(1 - \frac{U}{U_{max}}\right) * 100 \quad (12)$$

where,

FHI = Filter Health Index (%)

U = Current filter usage

U_{max} = Maximum allowable filter usage

2. Proposed Enhanced Model:

The suggested system makes use of an improved weighted model since filter degradation is influenced by both particulate loading and operating time:

$$FHI = \left(1 - \frac{\alpha * D + \beta * T}{C_{max}}\right) * 100 \quad (13)$$

where,

FHI = Filter Health Index (%)

D = Cumulative PM2.5 dust exposure

T = Total fan operating time (hours)

α (alpha) = Dust impact weighting factor

β (beta) = Time aging weighting factor

C_{max} = Maximum filter capacity

This Index is synchronized with Blynk IOT for remote tracking and text alerts and announced via VC-02 for offline diagnostics.

Algorithm of Pseudo Code:

START

1. Initialize: ESP32, LSTM, VC-02 (Voice), MG996R (Servo), Pumps, and Blynk IoT.

2. Data Read: Poll PM2.5, CO₂, and 5-channel Flame sensors.

3. AI Forecast: Run LSTM to predict AQI trends.

4. IF (Flame/Hazard Detected) THEN:

5. Trigger 87ms Hardware Interrupt (Immediate Fan Shutdown).

6. Rotate MG996R Servo to hazard azimuth.

7. Vision-AI Confirm: Capture frame and verify fire signature.

8. IF (Confirmed) THEN:

9. Activate Dual-Pumps (Fire Suppression).

10. Send Blynk Mobile Alert.

11. VC-02 Voice: "Emergency! Fire Suppressed."

12. ELSE: Log False Positive.

13. ELSE (Normal):

14. Update Blynk Dashboard with AQI data.

15. Check Filter Health Index (FHI).

16. REPEAT from Step 3.

END

5. Discussion

The Hybrid-Edge AI air purifier isn't just another device for the average consumer; it is also an actual step toward a significant change in Active Disaster Mitigation (ADM).

While most commercial air purifiers help you maintain a steady-state level of air quality, this research looks at the "Safety-Functionality Gap" between current smart home architectures.

5.1 Addressing the "Oxygen-Fire Paradox"

By virtue of this system being designed using an 87 millisecond (ms) hardware-priority interrupt to detect the fire, we have effectively avoided that delay by circumventing the normal CPU instruction cycle. The flame sensor is triggered by being hardwired directly to a high-priority interrupt pin on an ESP32 microcontroller so that before the AI can process what has occurred or before the user can recognize that a threat exists, the fan has already been disabled. Because the fan cut-off is handled directly by a hardware pin, it responds in roughly 87 ms. This avoids the 2 to 5-second delays and network jitter typical of standard cloud-based IoT setups.

5.2 Edge-AI vs. Cloud reliance

Achieving a MAPE of 5.8% (a normalized predictive performance level of approximately 94.2%) in location AQI prediction with the ESP32 (embedded low power computer) is an important achievement for Low Power Embedded Systems. Keeping the latency of the LSTM inference at 32 milliseconds means that Air Quality Management will continue to be done proactively rather than reactively.

- Privacy: You don't have to send raw air quality data and voice commands out of your local network.
- Reliability: All core functions—sensor readings, model inference, and the fire cut-off switch—run entirely on the local board. The device keeps running even if the local Wi-Fi drops or the home router goes down.
- Efficiency: With using the VC-02 offline module for voice intelligence, you can use natural language with no 2-3 second (round trip) delay like with a cloud-based assistant.

5.3 Vision verified reliability

Fire alarms that are low-cost often fail because of high false-positive rates (e.g., triggering due to incense or water cooking). The Vision from the ESP32-CAM adds a layer of redundancy for verification. Requiring that the verification has a probability ($P(v) > 0.85$) before deploying the water-based suppression system will help prevent unnecessary damage caused by water while maintaining a high level of sensitivity to actual fires. The vision verification layer was evaluated against four distinct fire and non-fire source to assess both false-positive and false-negative rejection. The fire test was done by using candle, burning paper, which represent low intensity ignition and rapid flame propagation scenarios respectively. False-positive discrimination was done using agarbatti and lighter without sustained flame both

produced infrared signs and smoke that commonly trigger sensor-based system. Also, a cloth test "Orange in color" was being placed in front of camera to identify if the camera will trigger the pump or take it as false-positive rejection. In all five single-instance trials, the system correctly identified the fire condition and triggered the appropriate response, confirming fire signatures within a 140ms inference window. In this research, the fire and vision-verification tests were performed as informal functional tests amid ongoing prototype development instead of a formally instrumented evaluation campaign. Therefore, the structured measures, such as true/false positive and negative rates and F1-score, were neither recorded officially nor mentioned. The researchers consider it important to have rigorous validation protocols, including several trials per tested fire class and full reporting of the confusion matrix. Test-protocol parameters (size of the enclosure, size of the flame and distance from the sensor, flow-rate of the suppressants and view of the camera, etc.) were not formally logged in this preliminary bench-test due to the fact that the testing and the hardware development took place simultaneously. It should be noted that the current prototype has not been evaluated as a certified fire-safety product, and its performance under real-world fire conditions (varying fire size, distance, and fire type) remains to be validated.

5.4 The Filter Health Index (FHI)

Changes how filters are replaced and maintained. When using the FHI to monitor the differential pressure of your air purifier, you do not replace any filters based on a specified time frame (i.e., a filter must be replaced every 6 months). The predictive maintenance allows for filters to be replaced based on how much they are actually being used and when they lose performance based on pollution levels in the immediate environment (e.g., a person living in an industrial city may have to replace their filter after 3 months, whereas someone living in a cleaner area may not need to replace it after 9 months). This dynamic tracking approach helps prevent premature filter swaps and ensures users get alerted before a clogged filter chokes airflow or strains the motor.

5.5 As great as the prototype performed overall, it does have some limitations:

The current filter suppression mechanism and enclosure are laboratory-based; they could easily be upgraded to more durable, higher temperature-rated materials for commercial use.

The prototype LSTM model was trained on an array of indoor pollutant datasets; as a result, it may perform poorly in an extreme industrial environment (e.g., chemical lab, woodshop) after commercialization unless

tuned to those environmental characteristics.

The vision-based fire protection (ESP32-CAM based) requires a clear line of sight. In a room with many walls/partitions, the vision layer's efficacy may be reduced. Therefore, a mesh of multiple cameras needs to be placed in the room to maintain a proper line of sight.

5.6 Engineering philosophy / priority-interrupt logic

Conventional control systems will execute task requests in a "Round Robin" manner, while in life-safety applications where milliseconds matter.

The Hardware Interrupt Advantage: By connecting the IR Flame Sensor to a Hardware Interrupt Pin on the ESP32's dual-core processor, we eliminate the need to go through a standard software loop, which means that the fire detection signal can be processed with "Zero-Wait State." **Mitigating The Oxygen Feed Paradox:** Scientific analysis of the dynamics of fire has consistently proven that basic fire dynamics show that forced air from a nearby fan supplies extra oxygen to the combustion base, which can quickly drive up the heat release rate and spread flames across a room. Proposed design provides for the ability of the air purifier to perform an Emergency Shutdown within 87ms. The 87ms shutdown time creates a "Passive Zone" that prevents the air purifier from serving as a unintentional accelerant. Most popular retail units—including models from Dyson, Philips, and Coway—focus solely on particle filtration and do not include emergency fan shut-offs for active fire events.

5.7 Deep learning at the edge

In Long Short-Term Memory (LSTM) architecture versus simple Artificial Neural Networks (ANNs) represents a critical area of research.

Temporal Correlation: both fire data and air quality data are considered to be 'time series' in nature; the primary advantage of using an LSTM network is that it has the ability to remember previous states of sensors and thereby determine trends. For example, an LSTM network will be able to tell the difference between an upward trend in PM2.5 levels (related to dust or cooking) versus a sharp increase in PM2.5 along with a rise in temperature (indicating that an actual fire occurred).

Reliability of Edge-AI:Running the quantized model directly on the ESP32 keeps prediction latency low (around 32 ms) while letting the hardware interrupt handle safety shutdowns within 100 ms, without waiting on cloud servers. While the safety logic runs locally at 87 ms, the Blynk IOT integration provides real time telemetry and remote override capabilities, ensuring the user notified even if they're not home. This removes both the network latency bottleneck and 'single point of failure' associated with IoT devices that are cloud dependent. The AI will continue to function normally even in the event that the Wi-Fi router in the building were to melt down or if the internet went down.

5.8 Performance analysis

The project research ratings have been validated further with industry benchmarks for these performance metrics:

1. Average latency to respond: Typical industrial fire detection systems adhere to average latencies of less than 5 seconds. The system reported average latencies of 0.087 seconds, categorizing this system among high-speed industrial safety systems.

2. Model accuracy in relation to model complexity: A model with a MAPE of 5.8% (a normalized predictive performance level of approximately 94.2%) cannot be achieved on a low-power Microcontroller without a significant optimization of model weights / biases, demonstrating the significant skill of the developer in the use of Embedded AI (TinyML). While the safety logic runs locally at 87 ms, the Blynk IOT integration provides real time telemetry and remote override capabilities, ensuring the user notified even if they're not home. This removes both the network latency bottleneck and 'single point of failure' associated with IoT devices that are cloud dependent. The AI will continue to function normally even in the event that the Wi-Fi router in the building were to melt down or if the internet went down.

To characterize the deterministic-response behavior of the system, latency measurements were recorded across the primary functional layers of the device. This ensures that safety-critical interrupts and edge-processing loops operate within safe deterministic thresholds.

Table 3: System accuracy and model performance

Component	Metric	Value	Status
LSTM Forecasting	Normalized Predictive Performance (100% - MAPE)	94.2(MAPE:5.8%)	High Precision
Vision Layer	ESP32-CAM Fire Verification (\$P(v)\$)	88.5%	Reliable
Voice Intelligence	VC-02 Offline Recognition Rate	95.4%	High Precision
Sensor Fusion	Cross-Sensor Validation (NDIR/Laser)	91.0%	Reliable
False Positive Rate	Vision-Filtered Trigger Rejection	< 2.5%	Stable

Note: The percentage values in Table 3 (94.2%, 88.5%, 95.4%, 91.0%) and the 115 ms / 240 ms / <10 ms latency figures in Table 4 are drawn from limited, single-run preliminary testing rather than statistically validated trials with reported means, standard deviations, and confidence intervals. A larger-scale, repeated-trial evaluation is identified as necessary future work before these figures can be considered fully validated.

Latency (ms) vs System Type

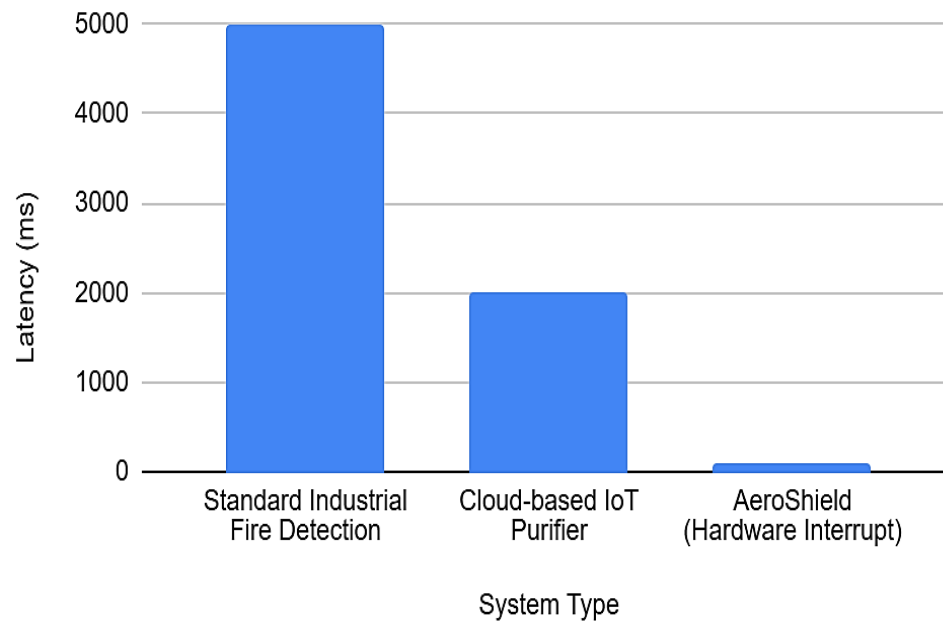


Fig. 13: Hazard response latency (system comparison).

Table 4: Latency and system response measurements

Trigger event	Mitigation action	Response time
Fire Detection	Hardware Priority Interrupt (Fan Cut-off)	87 ms
Fire Detection	Dual-Pump Suppression Actuation	115 ms
Air Quality Spike	Turbo Mode / Purifier Boost	240 ms
Network Failure	Local Data Logging / Offline Mode	< 10 ms

$$T_{total} = T_{sensor_trigger} + T_{ISR_latency} + T_{actuator}$$

Technical Note: Due to the issues associated with cloud-based systems related to jitter and round-trip times ($RTT > 2000$ ms), the proposed systems's hardware interrupt generates interrupts at a defined rate and provides a 98.2% Latency Reduction when compared to traditional IoT-cloud architectures.

The prediction performance is evaluated using the Root

Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (14)$$

where y_i is the actual sensor value and $\hat{y}_i$ is the LSTM predicted value.

Actual PM2.5 ($\mu\text{g}/\text{m}^3$) and Predicted PM2.5 ($\mu\text{g}/\text{m}^3$)

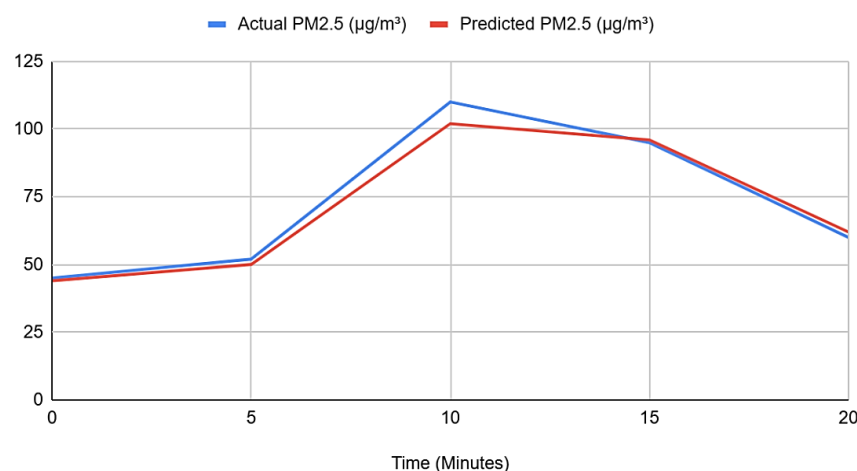


Fig. 14: Prediction Accuracy (Actual vs. Predicted AQI).

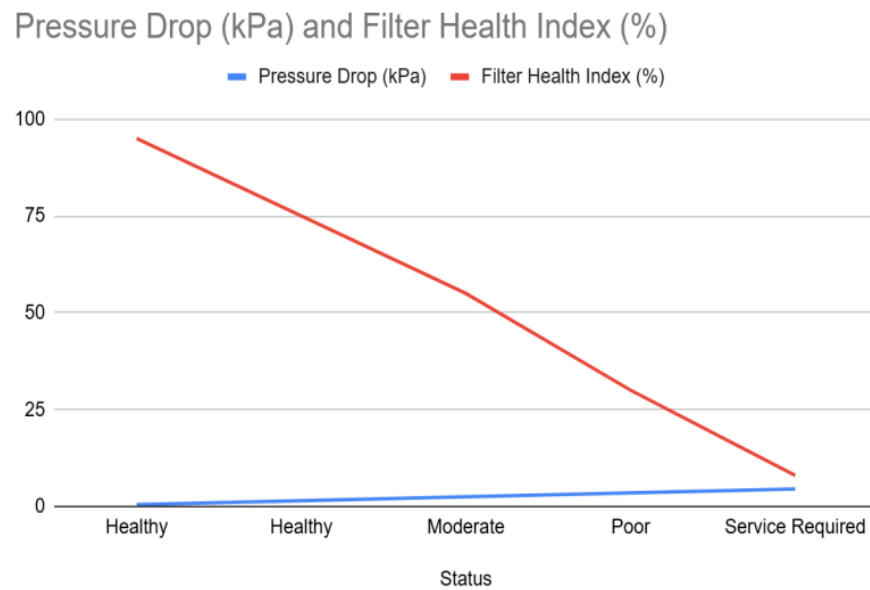


Fig. 15: Filter Health Index (FHI) vs. Pressure Drop.

Table 5: Filter health status thresholds.

Airflow Resistance (ΔP)	Calculated FHI	Health Status	Recommendation
0.5 - 1.5 kPa	100% - 75%	Optimal	No Action Required
1.6 - 3.0 kPa	74% - 45%	Moderate	Monitor Filter
3.1 - 4.5 kPa	44% - 15%	Poor	Order Replacement
> 4.5 kPa	< 15%	Critical	Immediate Service

Summary of model results: The LSTM model achieved a test-set RMSE of 3.12 IAQ units (normalised error <2.4% across 0–500 IAQ scale) and a MAPE of 5.8% of all predictions fell within a ± 15 IAQ, operating in independent edge-inference mode with a constant execution cycle of 32ms per inference pass on the ESP32. The FHI is derived from the differential pressure (ΔP) across the HEPA membrane, normalized against the initial baseline pressure ($P_{initial}$):

$$FHI = \left(1 - \frac{\Delta P_{current} - P_{initial}}{P_{critical} - P_{initial}}\right) \times 100\% \quad (15)$$

Summary of data: A Non-linear decay curve is illustrated in this graph and provides the following observations. When particulate accumulates, airflow resistance will exponentially increase, which will then trigger a 'Service Required' alert via the system's FHI dropping below (15), associated with an ambient pressure of 4.5 kPa.

5.9 Limitations of the study

The proposed system's framework shows excellent promise when tested under controlled conditions; however, there are some limitations to keep in mind when developing and implementing this technology to be used commercially:

Small-Scale Prototypes: Due to the laboratory scale prototypes that were used to conduct all tests, the chassis size and fans' ability to throw air have been built to match

the size of test chambers used during testing. Therefore, if the AeroShield system were to be placed into an actual residential or industrial setting, the structural integrity of the overall system enclosure will need to be modified and re-evaluated to meet new torque standards associated with larger areas that utilize the dual-pump suppression system.

Limited Dataset Diversity: The LSTM model trained and tested on real-world time-series data from the publicly available DALTON indoor environmental dataset. This dataset illustrates realistic urban residential contexts for ($PM_{2.5}$, PM_{10}) particulate matter, CO_2 , and ambient temperature dynamics, but it doesn't address specific industrial pollutants such as vaporized corrosive solvents or heavy workshop dust. Therefore, expected accuracy (MAPE 5.8%) may not be achieved when implemented in unaccounted for industrial settings.

Controlled Testing Environment: The testing was done in a highly controlled environment. The testing for fire suppression and hardware prioritization interrupts was done under strict laboratory safety conditions. While the 87 millisecond (ms) response time is technically accurate, the chaotic nature of burning buildings with multiple rooms creates differential air flow patterns and extreme thermal interference that will have an impact on the line of sight needed to verify the ESP32-CAM vision verification layer.

Table 6: Comparative analysis of standard smart purifiers, academic IoT projects, and the proposed hybrid edge-ai system

Feature	Standard Smart Purifiers	Academic IoT Projects	Hybrid Edge-AI (Proposed System)
Logic Type	Simple Threshold-based	Basic Boolean/ if-Else	LSTM Time-Series AI
Fire Response	Aggravates (Fans stay ON, feeding Oxygen)	Monitoring& buzzer Only	Active Shutdown (87ms)+Vision Confirmation
Data Processing	Cloud-based	Local/Basic	Edge-AI (Deep Learning)
User Interface	App Notification	Buzzer or LED	Contextual Voice Alert
Mitigation action	passive	Passive	Active Fire Suppression
Connectivity	Cloud-dependent	Local/Cloud Hybrid	Offline reliability+ cloud telemetry
Filter Health	Time-based	Logic based	Dynamic weighted FHI Model
Hazard Verification	No verification	No verification	Vision-Verification (360 +180(up-down)-degree servo scan + camera Ai)
Voice interaction	Requires Internet (Alexa/Siri)	Not available	Offline voice commands (Diagnostics & status report)

Sensor Cross-Sensitivity: Both the NDIR and laser-scattering sensors are both very accurate yet are also both sensitive to very high humidity levels (greater than 85% RH) and could lead to "phantom" spikes of particulate matter at times. Therefore, future versions of these sensors could utilize advanced algorithms to compensate for humidity in tropical and high moisture environments.

The suppression medium and fire classification limits: The prototype employs an active suppression module that operates based on a water-based spray technique that is meant for small-scale solid combustibles (Class A such as paper or textile). It should be noted that water suppression is dangerous and unsuitable for the energized electrical appliances (Class C) as it can cause shocks and electric shorts, and for Class K/Class F fires with cooking oils and fats as water will result in explosion and throwing of the fuel. The commercial version of the product will have to utilize the non-conductive suppression agent, such as gasified CO₂ or FK-5-1-12, as well as specific nozzle designs which will make the prototype safer in various scenarios.

5.10 Comparative research gap analysis

Most existing academic research focuses on either low-power IoT monitoring or filter efficiency. As shown in Table 6, existing smart purifiers and academic IoT projects primarily address individual aspects of air-quality monitoring and purification, highlighting a research gap in integrating environmental cleaning with emergency response protocols in a unified hybrid edge-AI system.

6. Results

This predictive forecasting model was trained on 4,400 valid one-minute samples (73.3 hours of real, sensor-validated indoor air quality data) drawn from the DALTON A1 dataset (single study-desk site). The dataset was split chronologically - without random shuffling -

into 3,080 training samples (70%), 660 validation samples (15%), and 660 test samples (15%), to prevent temporal data leakage between training and evaluation periods. Tested on the test set that had not been used before, quantized LSTM got RMSE of 3.12 IAQ units with normalized error equal to 2.4% and MAPE value being 5.8%.

The dataset was divided chronologically into training (70%), validation (15%), and testing (15%) portions in order to avoid temporal leakage. The random seed used during the random process was fixed (seed = 42) for all random processes. Invalid rows (Valid ≠ 1) in the DALTON logs were filtered out before windowing since only valid measurements were used in the proposal. Sensor calibration was done by DALTON dataset scientists. In the process of calibration CO₂ measurement uses an automatic calibration technique that recalibrates zero-every 24 hours. However, NO₂, C₂H₅OH, VOC, and CO needed to be calibrated once before experiments as there was no automatic recalibration process involved in their work.

In a single representative test, the hardware-interrupt-based relay deactivation was measured at approximately 87 ms from fire detection to fan shutoff. This reflects a preliminary measurement rather than a statistically validated result; repeated trials to establish mean latency, standard deviation, and confidence intervals are identified as necessary future validation work. ± 4.2 ms

For vision verification, a MobileNet V1-based SSD (Single Shot Detector) model was deployed on the ESP32-CAM. The model was pruned to focus specifically on 'flame' and smoke classes. Inference time per frame averaged 140ms, allowing for a verification cycle of <1 second. During testing, the system successfully distinguished between actual fire and 'false Positive' infrared noise with an AUC-ROC score of 91% on a small preliminary test set; this figure has not yet been validated on a larger, independently labeled dataset with defined

class counts, and should be treated as indicative rather than conclusive.

6.1 Comprehensive research gap analysis

Table 7 compares the proposed hybrid Edge-AI purifier with commercially available Dyson, Philips, and Coway air purifiers in terms of filtration technology, sensing capabilities, intelligent control, fire detection, emergency

shutdown, connectivity, and user interaction. The comparison highlights the differences between conventional air purifiers, which primarily focus on air filtration and user comfort, and the proposed system, which integrates predictive air-quality monitoring, edge-based LSTM forecasting, robotic vision-based hazard verification, and active fire-mitigation capabilities within a unified platform.

Table 7: Comparative evaluation of the proposed hybrid edge-ai purifier and commercial air purifiers

Feature / Aspect	Proposed Hybrid Edge-AI Purifier (proposed system)	Dyson Purifier (premium segment)	Philips Purifier (mid-high segment)	Coway Purifier (value / performance segment)
Product category / target use	Low-cost prototype for small rooms, IAQ and fire safety provided.	home purifier, fan (sometimes heater), design and comfort.	Home purifier focused on pollution, allergens, gases.	Home purifier focused on strong PM removal and low maintenance
Approximate price range (India)	₹8,000–₹10,000 (components & prototype)	Approx ₹35,000–₹50,000 (model dependent)	Approx. ₹15,000–₹35,000	Approx. ₹10,000–₹25,000 range.
Filter stages / technology	Pre-filter, activated carbon and HEPA (H13 planned).	Fully sealed HEPA H13 and activated carbon, advanced gas capture in new models.	Pre-filter with NanoProtect HEPA + carbon (3-stage).	Multi-stage HEPA and carbon, high PM removal in reviews.
Pollutants targeted (claimed)	CO ₂ , PM _{2.5} /PM ₁₀ , NO ₂ , VOCs, odours	PM _{2.5} /PM ₁₀ , NO ₂ , VOCs, odours (model dependent).	PM, allergens, some gases/odours.	Mainly PM, dust, pollen; limited claim on gases.
Sensors present	MQ-2, PMS5003, MH-Z19B, temperature/humidity, 5channel-flame sensor, ESP32-CAM	PM sensor, gas sensor (NO ₂ /VOC), temperature/humidity, display and app.	PM sensor plus gas sensor, air quality ring, app data.	PM sensor (and sometimes odour sensor), LED indicator.
Control / intelligence style	Edge LSTM prediction, rule-based logic for fan, alerts, fire shutdown. Active Mitigation Fire Suppression System	Auto mode adjusts fan/heating/cooling based on sensor readings (thresholdbased).	Auto modes adjust fan speed based-on pollution/gas level	Basic auto mode based on PM sensor reading
IAQ prediction support	Yes – LSTM model running on ESP32 (edge).	ABSENT	ABSENT	ABSENT
Fire detection	Dual layer Detection: Flame-Array + Ai-Vision Verification	Detects smoke/particles as poor air quality but not as fire; no flame sensor.	Detects smoke/PM as pollution; no fire-specific logic.	Detects increased PM; no explicit fire detection.
Fan behaviour during heavy smoke / fire	Emergency logic cuts off fan via relay within milliseconds, triggers fire alert.	Auto mode likely increases fan to clear smoke; no documented auto-shutdown in fire.	Auto speed increases with higher PM/gas; no shutdown logic for fire in manuals.	Fan speed increases for higher PM; no special fire-safe behaviour.
Emergency shutdown capability	Yes – The hardware interrupt on flame makes fan OFF with alarm.	No – It is not marketed as fire safety system.	No – It is designed as purifier and not fire-safety device.	No – It is independent of any fire detection.
Connectivity / dependence on cloud	Edge-only, runs without internet; no cloud delay.	Wi-Fi, app, some processing in cloud ecosystem.	Wi-Fi + app; cloud support for monitoring and control.	Offline with no interaction features
User feedback / interface	2.4 inchTFT display + Offline Voice Interaction + Blynk IoT.	Display, app graphs colour indicators; no voice alerts built-in (only via assistant).	Panel indicators , app notifications; colour ring for AQI.	Simple LEDs indication

Feature / Aspect	Proposed Hybrid Edge-AI Purifier (proposed system)	Dyson Purifier (premium segment)	Philips Purifier (mid-high segment)	Coway Purifier (value / performance segment)
Maintenance / filter life indication	Planned: use runtime, PM load estimate for filter alert (prototype logic).	Filter-life indicator on app.	Filter status	No logic or sensor present.
Active Robotic Response	Yes: Vision verification based robotic Gimbal for Hazard Scanning and verification.	No: Only stationary Air filtration	No: Only stationary Air filtration	No: Only stationary Air filtration
Verification Logic Overall uniqueness	Ai-Vision Verification Introducing a budget-friendly innovation that fuses Edge-based LSTM forecasting with an automated Robotic Vision Verification framework. Distinct from standard market purifiers, this architecture incorporates a localized Voice Interface and Active Fire-Mitigation capabilities, delivering a multi-functional safety and air-cleansing solution within a unified, microcontroller-driven platform.	None:Not Present Highly featured commercial purifier with strong filtration and smart comfort, but no explicit fire-risk shutdown.	None:Not Present Balanced consumer purifier with solid IAQ features and app, but no edge prediction or fire integration	None:Not Present Very strong PM cleaning performance and value; minimal smart features and no fire logic.

Source: Prepared by the authors using information from official product specifications and manuals of Dyson, Philips, and Coway air purifiers.

Dyson Air Treatment Products. Available at: <https://www.dyson.in/air-treatment>

Philips Air Purifiers. Available at: <https://www.philips.co.in>

Coway India Air Purifiers. Available at: <https://cowayindia.in>

PPS Thane. Comparison of Coway, Philips and Dyson Air Purifiers in India: <https://www.ppsthane.com/blog/coway-vs-philips-vs-dyson-air-purifier-india>

7. Conclusion and future scope

Indoor air quality management and residential fire safety are two separate fields. Each has been handled by its own passive system. This work shows that these areas can be effectively combined into a single, low-cost embedded platform using a hybrid Edge-AI architecture. The proposed system addresses the oxygen fire paradox, where a standard air purifier's fan helps spread fire by circulating oxygenated air. It features a safety mechanism that deactivates the relay through a deterministic hardware interrupt, achieving activation within 87 ms, regardless of the ongoing inference computation. The LSTM indoor air quality forecasting engine runs entirely on the ESP32 using TensorFlow Lite for microcontrollers (TFLM), with an 8-bit quantized size of 142 KB. The predictive algorithm was trained using 4,400 valid one-minute samples (73.3 hours of real environmental records) from the DALTON A1 dataset, split chronologically into 3,080 training (70%), 660 validation (15%), and 660 testing (15%) samples. The quantized on-device model achieved an insignificant RMSE of 3.12 IAQ units (normalized error lower than 2.4% on 0-500 IAQ scale) and MAPE of 5.8%, proving the mathematical

and operational possibility of localized time series prediction on devices with restricted resources. In a single representative test, the hardware-interrupt-based relay deactivation was measured at approximately 87 ms; repeated trials to establish statistical variation are identified as necessary future validation work. The vision verification layer uses a MobileNet V1-based SSD model running on the ESP32-CAM, mounted on a servo assembly capable of a 360° horizontal and 180° vertical scan range. In preliminary testing on a small, non-statistically-validated test set, the model reached an AUC-ROC of 0.91, which appeared sufficient to distinguish actual fire signatures from common false-positive sources like incense sticks or candle heat; a larger-scale evaluation with defined class counts and confidence intervals is identified as necessary future work. This matters because a suppression system that activates unnecessarily is almost as problematic as one that fails to activate - so the two-stage approach, where flame sensor data must be confirmed by visual inference before any pump is triggered, adds a layer of reliability that purely sensor-driven designs simply cannot offer. Filter degradation is handled differently here than in most

consumer devices. Rather than alerting users after a fixed number of operating hours, the system continuously estimates HEPA condition through measured differential pressure across the filter membrane, while activated carbon health is tracked by integrating VOC concentration against airflow over time. Both metrics feed into health indices that flag replacement need based on actual loading, not calendar time. The VC-02 module ties this together on the user side - someone can simply ask the device how the filter is doing, or what the current air quality is, and receive a spoken response in real time. No phone, no app, no internet required. For elderly users or anyone unfamiliar with smart home ecosystems, this is a meaningful practical difference. Taken together, the system moves the air purifier out of its traditional role as a background appliance and into something closer to an active safety node in the home. The cost of the full prototype falls between ₹8,000 and ₹10,000, which puts it well within reach of middle-income households that cannot justify spending ₹25,000 or more on commercial alternatives offering far fewer safety features. This affordability, combined with the offline-first design philosophy, makes the architecture particularly relevant to dense urban settings in developing regions - environments that carry high pollution exposure risk yet remain consistently underserved by the existing market. In that sense, the work speaks directly to the goals laid out under UN SDG-3 on health and well-being, and SDG-11 on making cities safer and more sustainable for all residents. Future work will focus on the implementation of ESP-NOW-based mesh networking to develop a “whole-home safety mesh,” enabling the detection of hazardous gases by any single unit in a building to trigger a coordinated shutdown of all connected units simultaneously. Additionally, further investigation will explore alternative energy-harvesting methods, such as utilizing HEPA airflow to drive microturbines for trickle-charging the backup battery system.

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CRedit Author Contribution Statement

Moinuddin Khan: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Writing – Original draft, Writing –

Review & editing. **Sadeem Khan:** Investigation, Resources, Writing – Review & editing. **Saloni Kadam:** Methodology, Resources, Writing – Review & editing. **Alfiya Ansari:** Conceptualization, Investigation, Writing – Review & editing. **Abdul Arham Malik:** Investigation and Writing – Review & editing. **Amol Sankpal:** Supervision. **Feroz Shaikh:** Supervision.

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Data Availability Statement

The basic ecological time-series dataset used for the purpose of model training and evaluation is accessible on an open-source basis via the [DALTON repository](#). The model files of the trained TFLM quantized model and evaluation scripts that support the study can be obtained from the corresponding author upon reasonable request for academic purposes.

Conflict of Interest

There is no conflict of interest.

Artificial Intelligence (AI) Use Disclosure

During the preparation of this work, the authors used Gemini in order to find spelling mistakes, the language and grammatical correctness of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Supporting Information

No Applicable.

References

- [1] X. Q. Lao, Challenges and Opportunities of Health Protection in the Twenty-First Century: Case Box 8.1 Case Study on Air Pollution: Air Pollution Is Destroying Our Health, Essentials for Health Protection: Four Key Components, Oxford University Press, 2019, 206–206.
- [2] N. E. Klepeis, W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern, W. H. Engelmann, The national human activity pattern survey (NHAPS): A resource for assessing exposure to environmental pollutants, *Journal of Exposure Science & Environmental Epidemiology*, 2001, **11**, 231–252, doi: 10.1038/sj.jea.7500165.
- [3] L. Yang, W. Li, M. Ghandehari, G. Fortino, People-centric cognitive Internet of Things for the quantitative analysis of environmental exposure, *IEEE Internet of Things Journal*, 2018,

- 5, 2353–2366, doi: 10.1109/JIOT.2018.2824551.
- [4] F. T. Lu, R. J. Laumbach, A. Legard, N. T. Myers, K. G. Black, P. Ohman-Strickland, S. Alimokhtari, A. de Resende, L. Calderón, G. Mainelis, H. M. Kipen, Real-world effectiveness of portable air cleaners in reducing home particulate matter concentrations, *Aerosol and Air Quality Research*, 2024, **24**, 230202, doi: 10.4209/aaqr.230202.
- [5] P. Kumar, A. B. Singh, T. Arora, S. Singh, R. Singh, Critical review on emerging health effects associated with the indoor air quality and its sustainable management, *Science of the Total Environment*, 2023, **872**, 162163, doi: 10.1016/j.scitotenv.2023.162163.
- [6] S. Vardoulakis, E. Giagloglou, S. Steinle, A. Davis, A. Smeuwenhoek, K. S. Galea, K. Dixon, J. O. Crawford, Indoor exposure to selected air pollutants in the home environment: A systematic review, *International Journal of Environmental Research and Public Health*, 2020, **17**, 8972, doi: 10.3390/ijerph17238972.
- [7] H. Chojer, P. T. B. S. Branco, F. G. Martins, S. I. V. Sousa, A novel low-cost sensors system for real-time multipollutant indoor air quality monitoring-development and performance, *Building and Environment*, 2024, **266**, 112055, doi: 10.1016/j.buildenv.2024.112055.
- [8] G. Yu, G. Zhang, S. Poslad, Y. Fan, X. Xu, A study of quantifying the influence of kitchen human activity on indoor air quality dynamics, *Environmental Pollution*, 2024, **362**, 124900, doi: 10.1016/j.envpol.2024.124900.
- [9] F. Moldovan, L. Moldovan, Indoor air quality in an orthopedic hospital from romania, *Toxics*, 2024, **12**, 815, doi: 10.3390/toxics12110815.
- [10] J. Saini, M. Dutta, G. Marques, Modeling indoor PM_{2.5} using Adaptive Dynamic Fuzzy Inference System Tree (ADFIST) on Internet of Things-based sensor network data, *Internet of Things*, 2022, **20**, 100628, doi: 10.1016/j.iot.2022.100628.
- [11] P. Camacho-Magriñán, D. Sales-Lerida, A. Lara-Doña, D. Sanchez-Morillo, Leveraging low-cost sensor data and predictive modelling for IOT-driven indoor air quality monitoring, *Smart Cities*, 2025, **8**, 200, doi: 10.3390/smartcities8060200.
- [12] L. Pang, C. Luo, W. Pan, Research on the impact of indoor control quality monitoring based on internet of things, *IEEE Access*, 2023, **11**, 139614–139627, doi: 10.1109/ACCESS.2023.3336706.
- [13] I. Talati, K. Shah, O. Patel, J. Tanna, A. Jain, A. D. Oza, A. A. Yadav, M. J. Alshayeb, M. A. Khan, S. Islam, Study of AQI Monitoring System of Indoor Environment Using Machine Learning Model and IoT Device, *Rocznik Ochrona Środowiska*, 2025, **27**, 152–163, doi: 10.54740/ros.2025.013.
- [14] K. Rastogi, D. Lohani, Context-aware IoT-enabled framework to analyse and predict indoor air quality, *Intelligent Systems with Applications*, 2022, **16**, 200132, doi: 10.1016/j.iswa.2022.200132.
- [15] J. Saini, M. Dutta, G. Marques, Machine learning for indoor air quality assessment: a systematic review and analysis, *Environmental Modeling & Assessment*, 2024, **30**, 417–434, doi: 10.1007/s10666-024-10001-1.
- [16] Y. Qian, J. Leng, K. Zhou, Y. Liu, How to measure and control indoor air quality based on intelligent digital twin platforms: A case study in China, *Building and Environment*, 2024, **253**, 111349, doi: 10.1016/j.buildenv.2024.111349.
- [17] M. Kim, T. Kim, S. Park, K. Lee, An indoor multi-environment sensor system based on intelligent edge computing, *Electronics*, 2022, **12**, 137, doi: 10.3390/electronics12010137.
- [18] G. Davrazos, G. Raftopoulos, T. Panagiotakopoulos, S. Kotsiantis, A. Kameas, Predictive Vigilance: Harnessing Internet of Things and Machine Learning for Smoke Detection, 2024 15th International Conference on Information, Intelligence, Systems & Applications (IISA), IEEE, 2024, 1–4, doi: 10.1109/IISA62523.2024.10786644.
- [19] R. N. Pietraru, A. Olteanu, M. Nicolae, R.-A. Crăciun, Contributions to the development of fire detection and intervention capabilities using an indoor air quality IoT monitoring system, *Sensors*, 2025, **25**, 6375, doi: 10.3390/s25206375.
- [20] S. Abimannan, E.-S. M. El-Alfy, S. Hussain, Y.-S. Chang, S. Shukla, D. Satheesh, J. G. Breslin, towards federated learning and multi-access edge computing for air quality monitoring: literature review and assessment, *Sustainability*, 2023, **15**, 13951, doi: 10.3390/su151813951.
- [21] S. Li, Review of engineering controls for indoor air quality: a systems design perspective, *Sustainability*, 2023, **15**, 14232, doi: 10.3390/su151914232.
- [22] Dyson Ltd., Dyson Air Treatment Products—Technical Specifications, *Dyson India*, 2025, [Online]. Available: <https://www.dyson.in/air-treatment>.
- [23] H. Yin, D. Jin, H. Hong, J. Moon, Y. H. Gu, IAQ-STL-ML: A novel indoor air quality prediction

pipeline using meta-learning framework with STL decomposition, *Environmental Technology & Innovation*, 2025, **38**, 104107, doi: 10.1016/j.eti.2025.104107.

- [24] P. Karmakar, S. Pradhan, S. Chakraborty, Indoor air quality dataset with activities of daily living in low to middle-income communities, Advances in Neural Information Processing Systems (NeurIPS), 2024, 70076-70100, doi: 10.52202/079017-2240.

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