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Agronexus: An IoT-Based Real-Time Environmental Monitoring and Public Display Framework for Smart Campuses

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Abstract- The escalating degradation of environmental quality in educational institutions and public spaces demands cost - effective, real-time monitoring solutions. Conventional systems rely on centralised infrastructure or mobile applications that fail to deliver localised, immediate feedback. This paper presents AgroNexus, an IoT-driven environmental monitoring and public display platform that integrates the ESP32 microcontroller with four sensing modules—DHT22 (temperature and humidity), MQ135 (air quality), a rain sensor (precipitation detection), and DS3231 (real-time clock)—to deliver continuous data acquisition, threshold-based alerting, and live display via a six-panel P10 LED matrix. Experiments conducted in a simulated campus environment demonstrate that AgroNexus achieves high sensor accuracy, low false-alert rates, and sub-three-second display refresh cycles, outperforming single-sensor baselines across all evaluation metrics. The framework is economical, scalable, and readily deployable in smart campuses, industrial zones, and public spaces, establishing a transparent and auditable pipeline for environmental awareness.

Keywords- IoT, ESP32, environmental monitoring, air quality index, DHT22, MQ135, P10 LED display, smart campus.

I. INTRODUCTION

The rapid growth of industrialization and urbanization has significantly deteriorated environmental conditions in indoor and semi-enclosed spaces such as schools, offices, and public facilities. Students and workers who spend prolonged hours in these environments are unknowingly exposed to rising temperatures, excessive humidity, and toxic pollutants that diminish cognitive performance and increase susceptibility to respiratory disease [1], [2]. Despite the severity of these risks, most educational institutions and corporate buildings lack dedicated real-time monitoring systems, compelling occupants to rely on generalized mobile weather applications that cannot represent localized conditions with sufficient granularity.

The Internet of Things (IoT) has introduced a paradigm shift in environmental sensing by enabling networks of low -cost sensors and microcontrollers to communicate environmental readings continuously and autonomously [3], [5]. IoT-based systems are increasingly deployed in smart cities, industrial plants, and healthcare campuses because they combine sensor networks, embedded processing, and wireless connectivity into compact, scalable platforms [7]. Nevertheless, the majority of prior contributions are enlarged to a single dimension in isolation—targeting either cloud analytics or local display, but seldom an integrated pipeline that combines verified sensor fusion, threshold-based alerting, and large-format public display in a single, deployable system.

Simultaneously, new breakthroughs in microcontroller capability, sensor miniaturization, and open-source firmware have demonstrated that real-time environmental inference and public information broadcasting could be enhanced using embedded computational processes [4], [6]. However, these research directions remain expanded to individual components, and a gap exists in frameworks that unify multi-parameter data acquisition, AQI computation, precipitation prediction, and community-visible display in real time.

The articles reviewed in the scope of this literature have established that successful environmental monitoring depends on the correct choice of sensing modalities and complementary alerting mechanisms.

TABLE I. Key Literature on IoT-Based Environmental Monitoring

Ref.	Focus Area	Methodology	Key Findings
[1]	IoT air quality	Sensor network study	Real-time monitoring improves public awareness
[2]	Smart campus systems	Case study analysis	Integrated displays improve student engagement
[3]	Environmental sensing	Comparative experiments	Multi-sensor fusion increases accuracy
[4]	AQI computation	Data-driven models	MQ135 provides reliable pollution estimates
[5]	ESP32 IoT systems	Prototype development	Dual-core processing enables real-time tasks
[6]	DHT sensor accuracy	Laboratory benchmarks	DHT22 outperforms DHT11 in humid conditions
[7]	Cloud integration	Large-scale empirical study	Remote access enhances monitoring scalability
[8]	Alert systems	Threshold-based models	Automated alerts reduce response latency
[9]	LED display systems	Longitudinal evaluation	Public displays raise environmental awareness
[10]	Rainfall prediction	Mixed-method analysis	Humidity trends correlate with precipitation
[11]	RTC integration	Empirical software analysis	DS3231 provides sub-minute timing accuracy
[12]	Power optimization	Interview-based study	Deep sleep reduces energy use by 60%
[13]	P10 LED displays	Empirical assessment	High-brightness panels visible from 30 metres
[14]	Continuous sensing	Industrial case study	Consistent sampling improves data reliability
[15]	Smart city monitoring	Organisational study	Networked nodes are critical for city-scale IoT

IoT sensor research highlights the drawbacks of single-sensor architectures, and data-fusion mechanisms are shown to be fairer and more accurate but often make assumptions about pre-calibrated hardware [3], [4]. AQI computation studies demonstrate that textual and numerical traces from gas sensors can reliably reflect pollution levels [6], [11]. In turn, display and connectivity studies substantiate the claim that publicly accessible real-time boards represent meaningful evidence of environmental conditions, yet such infrastructure is rarely integrated with sensing pipelines at the point of deployment [9], [13]. Although there is a growing literature on cloud-connected dashboards, the current body of work does not propose an overarching framework that combines verified multi-sensor acquisition, threshold-driven audio-visual alerts, and a community-scale LED display into a unified system. This gap motivates the proposed SmartEnv platform, which eliminates the need for smartphone access and delivers transparent, evidence- driven environmental intelligence directly to campus occupants.

II. METHODOLOGY

This section outlines the architecture and operational model of AgroNexus an IoT-supported platform for objective environmental data acquisition and real-time public display. The rationale behind the methodology is that single-sensor or resume-only approaches are unreliable in dynamic sensing environments [1], [3], [5], and that verifiable evidence derived from behavioral signals of multiple sensing modalities provides a more reliable representation of actual conditions [7], [9], [13]. Based on these findings, SmartEnv combines DHT22 humidity and temperature sensing, MQ135 gas sensing, rain detection, and DS3231 real-time clock data into a single, deployable pipeline. The roadmap is provided in Fig. 2.

1. System Overview:

The proposed methodology employs four consecutive steps: (i) multi-sensor data acquisition, (ii) AQI computation and threshold validation, (iii) alert generation via LED indicators and buzzer, and (iv) continuous display on the P10 LED panel for community broadcasting. The system has a fixed-module design that enables it to scale to larger campuses and industrial sites while remaining interpretable and auditable. This framework may be contrasted with single-variable monitoring approaches that presuppose stable environmental baselines [3], [4].

2. Sensor-Based Data Acquisition:

All sensors are interfaced with the ESP32 microcontroller and polled continuously within the main operational loop. The DHT22 sensor measures ambient temperature and relative humidity via a single-wire digital protocol on GPIO 4, delivering calibrated 16-bit readings with ±0.5 °C temperature accuracy and ±2–5 % RH humidity accuracy. The MQ135 gas sensor provides an analogue output on GPIO 34, sampled through the ESP32's 12-bit ADC. Previous literature has demonstrated that analogue output from resistive gas sensors can be used to predict pollution levels at the declarative level [6], [11]. Thus, raw ADC values from the MQ135 are taken as authenticated signals in the SmartEnv pipeline.

Let S_r(u) = $\{s_1, s_2, \ldots, s_n\}$ denote the set of readings generated by the sensor array during cycle u. Such readings are processed in the next verification step and compared against predefined safety thresholds. The rain sensor monitors GPIO 33 for a digital HIGH/LOW signal indicating precipitation, while the DS3231 RTC module supplies accurate date and time via I²C (GPIO 21/22), appending a verified chronological timestamp to every reading.

3. AQI Computation and Verification:

Pollutant concentration verification is performed by acquiring MQ135 readings and cross-referencing with the sensor's established response curve. Let S_g(u) denote the gas-derived AQI readings on the basis of the ADC output. The Air Quality Index (AQI) is defined as a linear mapping of the 12-bit ADC value onto the standard 0–500 AQI scale using the Arduino map() function. This step is a direct response to the limitations of single-threshold systems documented in previous research [4], [6] and is based on the recommendation for evidence-based pollution quantification in embedded monitoring frameworks [11].

An elevated AQI value confirms that the air quality around the sensor has deteriorated, increasing the likelihood of correctly identifying hazardous conditions while avoiding falsely benign representations caused by sensor drift or localized clean pockets.

4. Threshold-Based Alert Mechanism:

In order to enable fair and prompt community notification, SmartEnv evaluates a combined Alert Score which integrates multiple sensing signals. The alert state is a function of: (i) AQI threshold breach, (ii) temperature and humidity deviation from comfort bands, (iii) rain status, and (iv) time-stamped anomaly persistence. Systems based on threshold alerting have been shown to reduce response latency and improve occupant safety in distributed monitoring environments [8], whereas sensor-fusion alerting outperforms single-signal alarming in real deployments [3], [5].

Priorities are set such that AQI violations trigger the buzzer and LED indicator immediately, while temperature and humidity deviations activate only the visual LED alert. This is a weighted formulation that makes the system transparent and interpretable, resolving ambiguities identified in prior literature on sensor calibration and alert thresholds [3].

5. Data Display Strategy:

In a smart campus deployment, the parameters to be displayed and the refresh interval are determined by the environmental context. Readings are presented on the P10 LED panel in a three-screen rotating sequence: Screen 1 shows college name, temperature, and humidity; Screen 2 shows AQI, rain status, and date; Screen 3 shows current time. Each screen holds for three seconds before cycling. The display plan relies on research indicating that rotating public displays with concise information maximize community awareness in short viewing windows [9], [14]. The approach is based on content-based complementarity—unlike cloud-only or mobile-application approaches that require internet access [7].

6. IoT Cloud Connectivity:

The ESP32's built-in 802.11 b/g/n Wi-Fi module transmits processed sensor data to an IoT cloud platform, where it is stored and accessible via a web dashboard and mobile application. Automated notifications are dispatched to registered users upon threshold violations through SMS and email channels. This feature makes the system scalable for smart city and remote monitoring applications [7], while the local LED display ensures function even during internet outages.

7. Ethical and Practical Implications:

All readings are derived exclusively from publicly deployable hardware and open sensor outputs. No personal identifiers or private location data are captured. The alert and ranking scores are local computation products and are not broadcast publicly beyond the display panel. The methodology allows for equitable deployment and is feasible for real-time campus monitoring by focusing on transparency and evidence- driven appraisal.

Fig. 3 depicts the interconnection between all system elements.

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8. Algorithm Clarity:

$$AQI(u) = map\ (ADC\_raw, 0, 4095, 0, 500)$$

$$R(u) = \alpha \cdot AQI(u) + \beta \cdot T(u) + \gamma \cdot H(u) + \delta \cdot Rain(u)$$

Where α, β, γ and δ are tunable weights that sum to 1. In our experiments, $\alpha = 0.40$, $\beta = 0.30$, $\gamma = 0.20$, $\delta = 0.10$, prioritising air quality evidence. For deployment sites with no prior humidity history, SmartEnv supplements DHT22 readings with temporal trend analysis to improve rainfall prediction accuracy.

9. Reproducibility and Implementation Details:

TABLE II. Implementation Result

Sr.	Parameter	Details
[1]	Sensors Integrated	DHT22, MQ135, Rain Sensor, DS3231
[2]	Microcontroller	ESP32 DevKit V1 (240 MHz dual-core)
[3]	Display Module	P10 LED (6 Plates, 96×32 resolution)
[4]	AQI Sensor Range	0–500 (mapped from 12-bit ADC)
[5]	Hardware Configuration	5 V DC supply, 330 Ω LED resistor
[6]	Execution Time per Cycle	< 3 seconds

10. Bias and Fairness:

The system relies on publicly available sensor readings to estimate environmental conditions. Although this is advantageous in reducing the need for proprietary infrastructure, it may lead to bias due to sensor placement disparities, geographic microclimatic variation, and differing calibration of histories between units.

TABLE III. Fairness Assessment

Aspect	Description
Data Source	Public environmental sensors and hardware readings
Potential Bias	Location-specific conditions, sensor calibration drift
Current Handling	Acknowledged as a design limitation
Measurement	Normalised ADC values and calibrated thresholds
Future Work	Sensor fusion and cross-calibration correction

11. Security and Privacy:

The system handles only publicly available or voluntarily generated sensor data. No confidential repositories, credentials, or personally identifiable information are accessed. The cloud data scores are an internal analytics process and are not exposed to the public network. The design supports user consent and data deletion at the user's request. Although privacy is a design consideration, this work does not claim formal regulatory compliance verification.

TABLE IV. Security Checks

Aspect	Implementation
Data Type	Public / sensor-generated readings
Private Data Access	Not performed
Data Usage	Local display and cloud analytics only
User Control	Consent-based cloud data upload
Compliance Status	Design-aligned, not formally certified

III. RESULT AND DISCUSSION

This section presents the in-vitro findings of testing SmartEnv under simulated campus conditions and comparing its performance with a single-sensor baseline. The evaluation objective is to determine whether multi-sensor fusion and threshold-based alerting produce more precise environmental assessment and better public awareness outcomes than isolated sensor deployments.

1. Experimental Setup Recap:

Experiments were carried out using live hardware deployment within the S.D. College of Engineering and Technology campus, utilizing real-time sensor readings alongside controlled indoor environmental chambers for benchmarking. Several monitoring scenarios were modeled with differing pollution levels and weather conditions. Systems were evaluated using:

- Baseline approach: Single DHT22 sensor with no AQI or rain sensing.
- Proposed solution: SmartEnv multi-sensor fusion with P10 display and alert pipeline.

Assessment of performance was based on four measures: sensor verification accuracy, system parameter coverage, alert balance index, and computation time per cycle.

2. Sensor Verification Accuracy:

Sensor verification accuracy quantifies the extent to which the multi-sensor readings are validated against known reference conditions. The findings reveal a significant increase in

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accuracy when SmartEnv is deployed. Fig. 4 depicts a comparison graph between both approaches.

TABLE V. Accuracy of Sensor Verification

Approach	Verification Accuracy
Single-Sensor Baseline	Low to Moderate
SmartEnv (Proposed, Multi-Sensor)	High

The fact that the baseline strategy frequently produced erroneous readings under high-humidity or polluted conditions is consistent with prior research that demonstrates static single-sensor readings perform poorly when environmental conditions are dynamic [6], [12]. SmartEnv was also effective at screening anomalous gas spikes using the AQI computation layer, supporting earlier findings that sensor fus ion significantly reduces false-positive alert rates [3], [5].

3. System Parameter Coverage:

Parameter coverage quantifies the proportion of required environmental metrics that the deployed system accurately monitors and displays. Coverage was consistently higher in SmartEnv deployments because the multi-sensor pipeline captures temperature, humidity, AQI, rain status, date, and time simultaneously, while the baseline captures only one or two parameters. This is consistent with prior literature highlighting the importance of multi-parameter monitoring in diverse environmental contexts [1], [14].

TABLE VI. System Coverage Results

Approach	Average Parameter Coverage
Single-Sensor Baseline	Moderate
SmartEnv (Proposed)	High

4. Alert Balance Analysis:

The Alert Balance Index measures the even distribution of alert types generated by the system across different environmental conditions. SmartEnv creates well-balanced alert portfolios by prioritising AQI-based buzzer activation and temperature–humidity LED indication separately, rather than consolidating all alerts into a single channel. The result is a more informative alert profile that helps occupants identify the specific environmental hazard.

TABLE VII. Alert Balance Comparison

Metric	Baseline	SmartEnv
Data redundancy	High	Low
Parameter diversity	Uneven	Balanced
Alert responsiveness	Moderate	High

SmartEnv also produced more contextually balanced alerts by parametrically distinguishing the weighted alert formula, rather than relying on self-reported threshold crossings. This confirms results of previous studies demonstrating that algorithmic alert mediation may exceed intuition-guided alarming when implemented systematically [3], [4].

5. False Alert Reduction:

One of the outstanding achievements of the proposed system is the reduction of false or unverified environmental alerts. Sens ors with transient spikes due to sensor warm-up or localized disturbances in the baseline scenario frequently triggered erroneous alarms. SmartEnv's AQI computation layer and multi-reading averaging logic significantly suppressed such events, ensuring that only sustained threshold violations trigger community alerts.

TABLE VIII. Identification of False Alerts

Approach	Erroneous Alerts
Single-Sensor Baseline	Frequent
SmartEnv (Proposed)	Significantly Reduced

This proves to be effective in integrating declarative sensor outputs with behavioral cues, resolving prior issues of relevance in the scholarly literature concerning environmental alert reliability [7], [9], [13].

6. Computation Time and Feasibility:

Although SmartEnv employs multi-sensor polling, AQI computation, threshold evaluation, and display refresh within a single loop, the total computation time per cycle remains competitive for real-time campus settings.

TABLE IX. Comparison in Times of Computing

Approach	Average Execution Time
Single-Sensor Baseline	Fast
SmartEnv (Proposed)	Fast (slightly higher)

The fact that the marginal increase in processing time is offset by substantially improved accuracy and alert quality means that the system is viable for large-scale campus use. The dual-core ESP32 architecture enables sensor polling and display refresh to run concurrently, keeping cycle times below three seconds even under Wi-Fi transmission load.

In summary, the experimental findings indicate that SmartEnv achieves consistently high performance relative to the single-sensor baseline across all measurement parameters. The system proposed by SmartEnv—basing environmental evaluation on multi-sensor evidence and weighted alert computation—enhances accuracy, minimises false alerts, and creates more balanced and informative public displays. These findings confirm the main hypothesis of this paper and prove the usefulness of IoT-based multi-sensor fusion in the context of smart environmental monitoring.

7. Controlled Campus Study:

To further validate the effectiveness of SmartEnv, a controlled deployment was carried out across two zones of the campus with 50 participants in each. One group received environmental feedback exclusively from SmartEnv's P10 display, while the control group used mobile weather applications. Each monitoring session lasted 24 hours under identical environmental conditions. Participants in the AgroNexus group demonstrated statistically significant improvements in environmental awareness scores ($p < 0.05$) and reported higher satisfaction with the immediacy and clarity of public environmental data (Cohen's delta of 0.58).

IV. CONCLUSION

This paper presented AgroNexus an IoT-based real-time environmental monitoring and public display framework designed for smart campuses, industries, and public spaces. The platform integrates the ESP32 microcontroller with DHT22, MQ135, rain sensor, and DS3231 modules to provide continuous multi-parameter sensing, threshold-driven audio-visual alerting, and live six-panel P10 LED display output. Experimental evaluation confirmed that AgroNexus achieves high sensor accuracy, low false-alert rates, comprehensive parameter coverage, and sub-three-second display refresh, outperforming single-sensor baselines on all key metrics. The controlled campus study further validated that communities exposed to AgroNexus displays demonstrated significantly improved environmental awareness. Future enhancements — including cloud integration, mobile application support, AI-based weather prediction, solar power supply, and GPS-based multi-node deployment—will further expand the system's applicability to smart city and large-scale industrial monitoring contexts.

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