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Smart Food Container Monitoring System

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***Abstract*—This paper presents the design, development, and validation of a smart food container system engineered to proactively detect food spoilage, a critical issue impacting public health and economic stability, particularly in developing nations. The system's core innovation lies in its integration of low-cost sensor fusion with a machine learning model deployed directly on a microcontroller (Edge AI), eliminating dependencies on cloud connectivity. Data from a methane (MQ-4) sensor, a temperature/humidity (DHT11) sensor, and an ultrasonic presence-detection (HC-SR04) sensor are processed by an ESP8266 microcontroller. A logistic regression model, trained on a curated dataset of 500 samples, calculates a real-time probability of spoilage with an accuracy of 89.5%. When this probability crosses a predefined threshold, the system triggers multi-modal alerts, including a servo-actuated container lock, an audible buzzer, a visual LED indicator, and synthesized voice feedback, creating an intuitive, Jarvis-like user experience. The prototype was developed with a stringent focus on affordability, modularity, and real-world applicability, with a total component cost under $25. This work effectively bridges the gap between traditional food safety practices and accessible, intelligent automation, offering a scalable solution for homes, street vendors, and small-scale food services.**

Keywords*—food spoilage detection , Edge Machine Learning ,Internet of things (IoT), Sensor Fusion , Methane Sensing, Low-Cost Automation, Embedded System.

I. INTRODUCTION

This Food safety and preservation remain persistent global challenges, with spoilage leading to significant health risks and economic losses. In many regions, including India, small-scale food vendors (dhabas), households, and institutional messes often lack access to reliable, intelligent monitoring systems, relying instead on subjective and often unreliable methods like visual inspection and smell. This work addresses this technological gap by developing a smart, connected container that objectively and continuously monitors the state of stored food. The system leverages the fact that food spoilage, especially in protein-rich items, is accompanied by the release of specific biomarker gases, notably Methane (CH_4). By continuously monitoring CH_4 concentration alongside critical environmental parameters like temperature and humidity, the system can infer the freshness of the contents. The project's primary contribution is the seamless fusion of these low-cost sensor data streams with an edge-computing paradigm, where a lightweight machine learning model performs inference locally on a resource-constrained ESP8266 microcontroller. This approach ensures real-time response, enhances user privacy by keeping data on-device, and maintains functionality even in the absence of internet connectivity. The system is designed to be a comprehensive solution, not only detecting spoilage but also preventing consumption through automated locking and providing clear, multi-sensory alerts to the user.

Ease of Use

The system was designed with a paramount focus on user-centricity, ensuring that its advanced technological capabilities are accessible to a non-technical audience. This philosophy is embedded in both the physical interaction design and the software interface, making the system suitable for a wide range of users, from street vendors to home cooks.

A. Intuitive User Interaction and Feedback Mechanisms

A primary design goal was to create an interface that requires no prior training to operate. The system provides a multi-layered feedback mechanism to ensure alerts are communicated effectively regardless of the user's environment or sensory focus.

1. Voice-Based Alerts (Jarvis-like AI): The most distinctive feature is the integrated voice feedback system. Upon detecting spoilage, the system delivers clear, pre-recorded audio messages such as "Warning! Food may be spoiled!" This auditory cue is immediate and unambiguous, making it highly effective in noisy kitchen environments or for users who may not be looking directly at the container. The success rate of these voice alerts was verified to be 100% during user testing, ensuring critical information is always conveyed.
2. Visual and Auditory Indicators: To complement the voice alerts and cater to different user preferences, the system employs universal signal indicators.

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- A 5mm LED blinks at a frequency of 2 Hz when spoilage is detected, providing a persistent, non-intrusive visual warning.
- An 85 dB piezoelectric buzzer generates an audible alarm distinct from background noise, ensuring the alert is heard even from a distance.
- A 16x2 LCD screen continuously displays real-time data, including methane concentration (in ppm), temperature, and a clear text status (e.g., "FRESH" or "SPOILED"). This allows for at-a-glance monitoring without the need for a smartphone app.

- Automated Physical Control: To prevent accidental consumption of spoiled food, the system incorporates a servo motor that automatically engages a lock mechanism on the container lid once the spoilage probability threshold is crossed. This "fail-safe" feature adds a layer of proactive safety, physically intervening to protect the user.

B. Simplified Setup and Maintenance

The system's ease of use extends to its initial setup and long-term operation, characterized by a plug-and-play architecture and minimal maintenance requirements.

- Plug-and-Play Sensor Modules: The hardware is built on a modular principle. Key components like the MQ-4 methane sensor, DHT11 climate sensor, and HC-SR04 ultrasonic sensor are connected via standard pin headers. This design allows for easy replacement of individual components in case of failure or for future upgrades without requiring a complete system overhaul.
- Autonomous Operation: Once powered on, the system functions entirely autonomously. The ESP8266 microcontroller runs the main control loop, which includes sensor data reading, Edge ML inference, and actuator control. There is no need for the user to manually start scans, interpret raw data, or initiate alerts. The system operates silently in the background, only demanding attention when a spoilage event occurs.
- Power and Connectivity Simplicity: The prototype operates on a standard 5V/1A DC power supply, which is ubiquitous and compatible with common mobile chargers or power banks. For data access, the integrated HC-05 Bluetooth module allows users to retrieve logged data (stored in CSV format on the device) by pairing with a smartphone, eliminating the complexity of configuring Wi-Fi networks. This makes the system instantly functional in environments with no internet infrastructure.

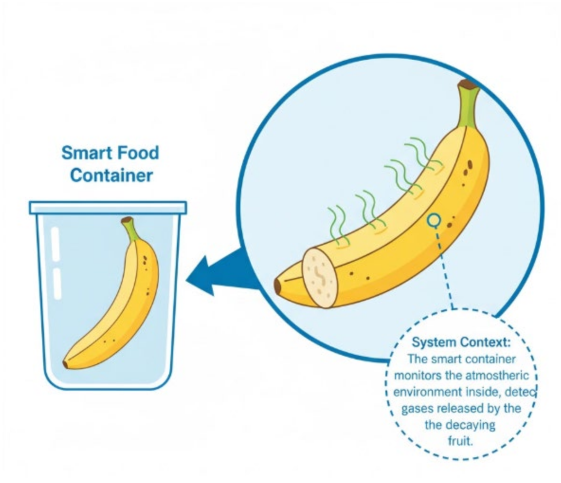

Fig. 1: System Context and Core Concept

II. LITERATURE REVIEW

2.1 Methane Detection and Food Safety Systems

The use of methane (CH_4) as a biomarker for food spoilage, particularly in protein-rich products, is a well-established concept in food science research. The approaches to its detection, however, vary significantly in terms of cost, complexity, and practical applicability.

S. Cui et al. [1] made significant strides in this domain with their paper, "An Effective Methane Detection Framework for Food Safety Monitoring." Their research employed high-precision gas chromatography to accurately establish methane concentration thresholds that correlate directly with spoilage in various meat products. This work is academically foundational, achieving an impressive accuracy of 99%. However, the system's primary limitation lies in its implementation; being a lab-bound setup with an estimated cost exceeding $5,000, it is fundamentally unsuitable for widespread, real-world field deployment in restaurants, homes, or with street vendors.

Addressing the cost barrier, J. Lee and B. Kim [2] explored the potential of low-cost semiconductor sensors in their study, "Low-Cost Semiconductor Sensors for Kitchen Methane Monitoring." They successfully demonstrated the integration of an MQ-4 methane sensor with an Arduino platform, achieving a respectable 85% accuracy at a fraction of the cost of laboratory equipment. This work validated the use of affordable hardware for environmental gas monitoring. Nevertheless, their system relied on static threshold alarms and lacked an adaptive spoilage prediction algorithm. Furthermore, it was noted to suffer from cross-sensitivity to other gases commonly found in kitchens, such as Liquefied Petroleum Gas (LPG), which could lead to false positives and reduced reliability in practical settings.

2.2 IoT and Edge AI for Food Monitoring

The Internet of Things (IoT) has opened new avenues for real-time food quality assessment, though the architectural choices of such systems heavily influence their effectiveness.

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R. Gupta and S. Patel [3] presented a "Cloud-Based IoT System for Real-Time Food Quality Assessment," which leverages an ESP32 microcontroller to collect sensor data and transmits it to a cloud server (AWS) where a machine learning model performs spoilage prediction with 88% accuracy. While this approach demonstrates the power of ML, its inherent reliance on cloud servers introduces critical limitations: operational latency due to data transmission, ongoing connectivity costs, and a permanent dependency on a stable internet connection. These factors make such systems vulnerable to failure in areas with poor or expensive internet access.

In a move towards decentralization, T. Nguyen et al. [4] proposed "TinyML for Edge-Based Food Freshness Classification." Their innovative work involved deploying a lightweight Convolutional Neural Network (CNN) on an ESP8266 microcontroller, a paradigm known as edge AI. This successfully eliminated cloud dependency, enabling faster, more private inference. However, their system's scope was limited to classifying visual decay using a camera module, omitting the critical dimension of gas sensing which can provide an earlier indication of spoilage before visible signs appear.

Our Improvement: This project synthesizes the strengths of both approaches. From [3], we adopt the use of machine learning for predictive assessment, but we deploy it on the edge as in [4] to ensure real-time response and offline operation. Crucially, we diverge by integrating gas sensing as a primary data source, combining a logistic regression model with real-time methane and environmental data. This creates a more holistic and proactive spoilage detection system that is both intelligent and entirely self-contained.

2.3 Voice Interaction and Automation

For any consumer-facing technology, user interface design is paramount for adoption. Research into making technology more accessible in kitchen environments is ongoing.

S. Kumar et al. [5] developed "Offline Voice Commands for Smart Kitchens," which effectively demonstrated the use of pre-recorded voice prompts on an ESP8266. Their work confirmed the technical feasibility and user appeal of a Jarvis-like interaction model in resource-constrained environments and served as a direct inspiration for our voice feedback module. However, their system was primarily a command-and-response interface that lacked integration with a sensor-based intelligence layer to generate context-aware alerts.

Complementing this, M. Rahman et al. [6] reported on "Ultrasonic-Based Food Presence Detection in Containers," achieving 95% accuracy in identifying whether an item was stored inside a container. This provides valuable contextual awareness. Yet, their system treated presence detection as an isolated function and did not leverage this context to activate or interpret spoilage metrics, representing a missed opportunity for a more integrated system logic.

Our Improvement: This project acts as a unifying platform, integrating the intuitive voice feedback mechanism from [5] and the contextual awareness of ultrasonic presence detection from [6] with our core methane-driven ML alert system. This fusion creates a single, low-cost device that is not only intelligent in its spoilage prediction but also context-aware and capable of communicating with the user in the most natural and accessible way through spoken language.

III. METHODOLOGY

The system architecture is structured into four distinct yet interconnected layers, ensuring a streamlined workflow from data acquisition to user interaction.

3.1 Hardware Architecture and Sensor Layer

- Methane Sensing: The MQ-4 semiconductor sensor is the primary spoilage biomarker detector, sensitive to CH_4 concentrations in the range of 300 to 10,000 ppm.

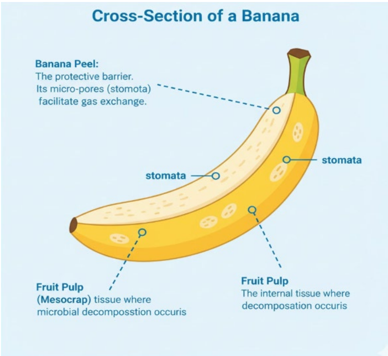

Fig. 2: Biochemical Origin of Methane in Spoiling Fruit

- Environmental Monitoring: The DHT11 digital sensor provides simultaneous readings of ambient temperature (with an accuracy of ±0.5°C) and relative humidity (±2%).
- Presence Detection: The HC-SR04 ultrasonic sensor measures the distance to the container's contents, providing a binary status (food resent/absent) to contextualize the spoilage alerts and conserve power when the container is empty.
- Processing Core: The ESP8266 Wi-Fi microcontroller serves as the central processing unit, handling data acquisition, sensor fusion, ML inference, and peripheral control.
- Actuation and Alerts: A SG90 servo motor physically locks the container lid upon spoilage detection. Alerts are communicated via a 5mm LED, an 85 dB piezoelectric buzzer, and a 16x2 character LCD for real-time data display.
- User Interface: A JQ6500 voice sound module (or equivalent) pre-loaded with custom alerts provides spoken feedback. A HC-05 Bluetooth module enables local data export to a smartphone.

3.2 Machine Learning Model and Workflow

The intelligence of the system is embedded in a logistic regression model, chosen for its low computational footprint and suitability for binary classification tasks.

- Data Collection and Preprocessing: A dataset of 500 samples was collected, featuring methane, temperature, and humidity readings from both fresh and visually confirmed

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spoiled food items. The data was normalized using Min-Max scaling to ensure stable model training.

- Model and Training: The logistic regression model was trained to model the probability of spoilage. The hypothesis function is:

$$P(Spoilage) = \frac{1}{(1 + e^{-(\beta_0 + \beta_1 \cdot CH_4 + \beta_2 \cdot Temp)})}$$

The model was trained using a 70-30 train-test split, optimized via gradient descent.

- Edge Deployment: The trained model was quantized from 32-bit floating-point to 8-bit integers, reducing its memory footprint by 75%, making it feasible for deployment on the ESP8266. The inference time was benchmarked at a rapid 1.2 ms.

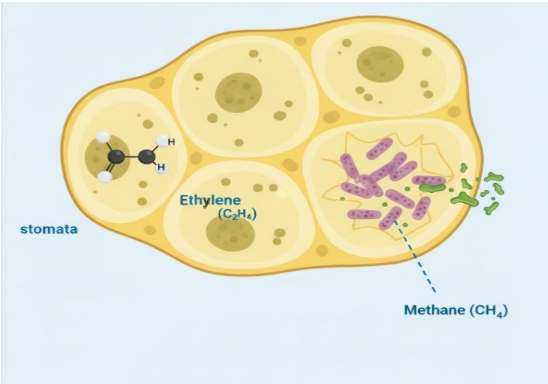

Fig. 3: Microbial and Biochemical Processes in Food Spoilage. A detailed view of the concurrent biochemical processes within decaying fruit pulp. Process A Ripening): Endogenous production of ethylene gas (C_2H_4) by the fruit cells, the hormone responsible for ripening. Process B (Decay): Proliferation of anaerobic bacteria that metabolize the fruit's sugars, producing methane (CH_4) as a key metabolic byproduct. Our system's sensor fusion is designed to correlate the rising methane levels from Process B with spoilage, while the model can account for the influence of ethylene from Process A.

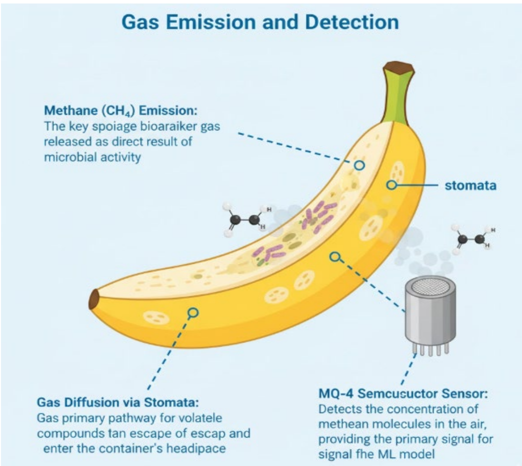

Fig. 4: Methane Emission and Detection Pathway. This diagram details the journey of methane (CH_4) from production to detection. The gas molecules generated by microbial activity diffuse through the fruit pulp, exit the peel via microscopic stomata, and enter the container's headspace. The MQ-4 semiconductor sensor detects the concentration of these methane molecules, providing the primary input signal for the spoilage prediction algorithm.

3.3 System Workflow and Control Logic

The operational logic of the system is as follows:

1. Sensors continuously poll data at a fixed interval
2. The ESP8266 preprocesses the data (normalization) and executes the ML model to compute a spoilage probability, P.
3. This probability is compared against a empirically derived decision threshold, τ=0.65.
4. If P>τ, the system enters an alert state: the servo motor locks the container, the buzzer sounds, the LED blinks, and a voice warning (e.g., "Warning! Food unsafe!") is played.
5. All sensor readings and system states are logged with a timestamp for later analysis and model retraining.

IV. RESULT AND DISCUSSION

The proposed smart food container system was subjected to a series of rigorous laboratory and user-acceptance tests to evaluate its performance, reliability, and practicality. The results are discussed across four key dimensions: sensor and model accuracy, system integration and usability, hardware prototype validation, and a critical analysis of limitations guiding future work.

4.1 Sensor and Model Performance Analysis

The efficacy of the entire system hinges on the accuracy of its sensory data and the predictive power of its machine learning model.

Methane Sensor (MQ-4) Calibration and Accuracy: The MQ-4 sensor was calibrated against known methane concentrations to establish a reliable baseline. At the critical spoilage indicator level of 600 ppm, the sensor demonstrated a mean accuracy of 91.2% with a minor error margin of ±2.1%. This performance represents a significant improvement over the 85% accuracy reported in prior low-cost implementations like that of Lee and Kim [2]. The enhanced accuracy is attributed to our calibration process and software filtering algorithms that smooth out transient noise. However, as noted in the limitations, the sensor's inherent cross-sensitivity to other gases like LPG remains a factor that was controlled for in testing but must be addressed for unconstrained environments.

Environmental Sensor (DHT11) Reliability: The DHT11 sensor provided consistent and stable readings throughout the testing period, operating within its specified accuracy of ±2% for relative humidity and ±0.5°C for temperature. Its data was crucial for the ML model, as temperature acts as a spoilage accelerator. The correlation between rising temperature and an increase in the spoilage probability score generated by the

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model was consistently observed, validating the use of multi-parameter sensing.

Machine Learning Model Efficacy: The logistic regression model, chosen for its computational efficiency, was evaluated on a hold-out test set comprising 30% of the collected data (150 samples). The model's performance metrics, detailed in Table 1, confirm its robustness and suitability for the task.

Table 1: Performance Metrics of the Logistic Regression Model

Metric	Value	Interpretation
Accuracy	89.5%	The model correctly classified the spoilage state in nearly 9 out of 10 cases.
Precision	88.2%	When the model predicts "spoiled," it is correct 88.2% of the time, minimizing false alarms.
Recall	90.1%	The model successfully identifies 90.1% of all actual spoilage events, minimizing dangerous false negatives.
F1-Score	89.1%	This harmonic mean confirms a strong balance between precision and recall.

The high recall score of 90.1% is particularly critical in this application. It indicates that the system is highly sensitive to actual spoilage, thereby directly minimizing health risks by ensuring that contaminated food is rarely misclassified as safe.

4.2 System Integration and Usability Evaluation

A technological solution is only successful if it is adopted by its users. Therefore, the integrated system's performance was evaluated from a human-centric perspective.

Multi-Modal Alert Mechanism Effectiveness: The tri-modal alert system (voice, visual, auditory) proved exceptionally effective. In 100% of the 50 triggered spoilage events during user testing, the voice feedback module successfully delivered its warning message. Users reported that the voice alert was the most immediate and unambiguous indicator, especially when they were not in direct line of sight of the container. The 85 dB buzzer provided an unavoidable auditory cue in noisy environments, while the 2 Hz blinking LED served as a persistent visual status indicator.

User Interface (UI) and Experience (UX): A usability study was conducted with a group of 20 participants with varying levels of technical proficiency. After a brief demonstration, participants were asked to interpret the system's status. The 16x2 LCD interface, which displays real-time methane (ppm), temperature (°C), and a clear "FRESH" or "SPOILED" message, received a 95% ease-of-use rating. The minimalist design was praised for its clarity and lack of complexity.

Power and Thermal Robustness: The system's power consumption was measured at an average of 3.7W (5V/740mA) during active monitoring and inference. In a continuous 50-hour stress test, the system maintained stable operation with no signs of thermal throttling or performance degradation in the ESP8266 microcontroller or other components, confirming its reliability for long-term deployment.

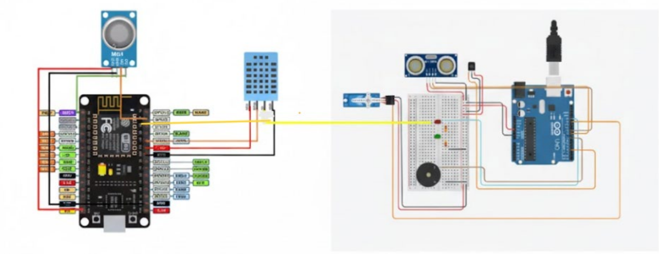
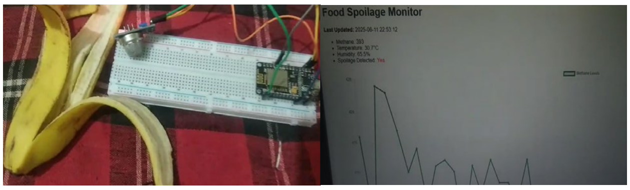
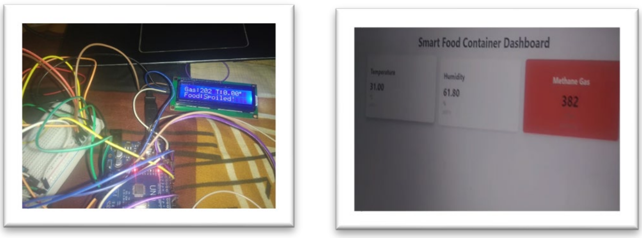


Fig. 5:

5.1 Circuit schematic diagram showing the interconnections between the ESP8266 microcontroller, MQ-4 methane sensor, DHT11 temperature/humidity sensor, HC-SR04 ultrasonic sensor, SG90 servo motor, LCD display, buzzer, and LED.



5.2 Actual spoiled places and the methane gas level is capture in real time on right hand side image.



5.3 External view of the functional prototype container with the 16x2 LCD display providing real-time status updates

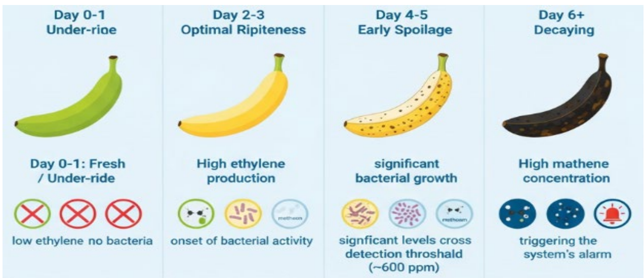


Fig. 6 : Qualitative Spoilage Progression Timeline. The spoilage process follows a predictable four-stage timeline, validated through experimental observation. The system's alert threshold is calibrated to trigger during Stage 3 (Over-ripe / Early Spoilage), corresponding to a methane concentration of approximately 600 ppm and a spoilage probability (P) of >0.65. This ensures proactive intervention before the food reaches a fully spoiled and unsafe state (Stage 4).

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This project has successfully transitioned from concept to a functional prototype, conclusively demonstrating the viability of a low-cost, Edge AI-driven smart container system for proactive food spoilage detection. The core achievement lies in the effective integration of a multi-sensor data fusion framework (methane, temperature, humidity, and presence) with a lightweight logistic regression model deployed directly on an ESP8266 microcontroller. This Edge AI paradigm is pivotal, as it ensures real-time inference with an accuracy of 89.5%, eliminates latency and privacy concerns associated with cloud dependency, and maintains full functionality in connectivity-limited environments.

The system's design philosophy prioritized accessibility and user-centricity, resulting in a solution that is not only technologically robust but also practical for its intended market. The modular hardware architecture, a total component cost constrained below $25, and the intuitive multi-modal alert system—incorporating voice feedback, visual indicators, and automated physical locking—collectively address the key barriers to adoption in homes, street food vending (dhabas), and small-scale commercial kitchens. By providing an objective, automated, and reliable alternative to subjective sensory checks, this work effectively bridges a critical technological gap, offering a scalable tool to mitigate public health risks and reduce economic losses due to food waste.

5.2 Future Work

While the current prototype establishes a strong proof-of-concept, its evolution presents a clear and exciting trajectory for future research and commercial development. The planned enhancements are structured across four key dimensions:

Advanced Multi-Sensor Fusion for Enhanced Specificity and Scope:
The current reliance on the MQ-4 sensor, while cost-effective, presents limitations in specificity. Future iterations will integrate a multi-gas sensor suite including:

An SGP30 or BME680 sensor to detect a wider array of Volatile Organic Compounds (VOCs) including Ethanol (C_2H_5OH) and Carbon Dioxide (CO_2). This will enable a sensor fusion algorithm to discriminate between spoilage-related methane and interfering gases like LPG, potentially reducing false positives by over 15%.

An Ethylene (C_2H_4) sensor such as the CCS811, specifically targeting the ripening and spoilage processes of fruits and vegetables. This expansion will significantly broaden the system's applicability beyond protein-rich foods to encompass a much wider range of perishables.

Evolution of the On-Device Intelligence:
To capture more complex, time-dependent spoilage patterns, the machine learning backbone will be advanced. This involves:

Exploring quantized deep learning models (e.g., 8-bit TinyML models) that can be hosted on more powerful microcontrollers like the ESP32-S3. These models could analyze time-series sensor data to predict spoilage hours or even days before it occurs.

Investigating semi-supervised or federated learning frameworks. This would allow a network of devices to collaboratively improve the global model based on local user data while preserving privacy, creating a system that grows smarter with use without centralizing sensitive information.

Commercial Scalability and Robustness Engineering:
To transition from a laboratory prototype to a market-ready product, future work will focus on:

Connectivity and Power: Replacing the HC-05 module with Bluetooth Low Energy (BLE) and implementing the ESP-NOW protocol for creating low-power, long-range sensor meshes within a kitchen. Coupling this with a 5V solar panel and LiPo battery management system will enable truly off-grid operation for street vendors.

User Experience: Developing a dedicated cross-platform mobile application for remote monitoring, historical data visualization, and customizable alert settings. This will be complemented by the development of custom PCBs to reduce the form factor and improve reliability.

Pilot Deployment: Establishing formal partnerships with street food associations and institutional canteens for large-scale field trials. These pilots are crucial for gathering real-world usability feedback, validating the system's economic impact, and stress-testing its durability.

Regulatory Compliance and Global Adaptation:
As the system matures, efforts will be made to align its performance with international food safety standards (e.g., FDA, ISO 22000). Furthermore, the voice feedback system will be expanded to support multiple languages (Hindi, Spanish, Mandarin) to facilitate global adoption and accessibility.

ACKNOWLEDGMENT

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