Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

Behavioral Refrigerator Shelf Monitoring Using Sequential Image Analysis and Embedded Gas Sensing

Vihaan Madhur

Abstract

Household food waste remains a significant global challenge, often caused by forgotten, expired, or improperly stored food items inside refrigerators. While industrial food-monitoring systems exist for food production and transportation environments, consumer households still lack practical embedded monitoring solutions for monitoring food freshness and spoilage risk in real-world refrigerator conditions. This research presents an embedded monitoring system for behavioral refrigerator shelf monitoring using sequential image analysis and embedded gas sensing. The proposed system integrates MQ-series gas sensors, a fisheye camera, an ESP32-S3 microcontroller, and a Python-based backend to continuously monitor refrigerator environments and collect environmental telemetry and shelf images over time.

Initial experiments focused on direct spoilage detection using gas sensor telemetry and computer vision analysis of fresh and decomposing fruits and vegetables in controlled environments. However, real-world refrigerator deployment revealed several practical limitations affecting direct spoilage detection reliability. As a result of these findings, the research evolved beyond direct spoilage classification and led to the development of a behavioral computer vision approach based on sequential refrigerator shelf image analysis. Instead of relying solely on direct food recognition, the system analyzes shelf-state changes and interaction patterns over time to identify low-movement regions associated with potentially forgotten food items.

Experimental observations suggest that combining embedded gas sensing with behavioral shelf interaction analysis may provide a more practical and deployable household food-monitoring approach than gas sensing or image-based spoilage detection alone.

1. Introduction

Reducing food loss and waste is widely recognized as one of the most important strategies for improving global food sustainability, increasing food system efficiency, and reducing environmental impact. According to the Food and Agriculture Organization (FAO), reducing food waste can help lower production costs, improve food security and nutrition, conserve natural resources, and decrease greenhouse gas emissions associated with food production and disposal [2].

Globally, an estimated 30–40% of food intended for human consumption is wasted each year [1] [2], with a significant portion occurring at the household level. Consumer food waste is commonly caused by poor meal planning, excessive purchasing, confusion regarding “best before” and “use by” labels, oversized packaging, and improper storage practices. In many homes, food stored deep inside refrigerators or behind newer items is frequently forgotten and left unused beyond safe consumption periods.

Modern refrigerators provide cold storage but offer little intelligence regarding food freshness, storage duration, or spoilage risk. Most consumers rely on memory, visual inspection, or smell to determine whether food is still safe to consume. As a result, spoiled or forgotten food is often discovered only after visible decay or unpleasant odors appear, leading to unnecessary waste.

Recent advances in embedded systems, Internet of Things (IoT) technologies, and computer vision create opportunities for developing intelligent household food monitoring systems. Gas sensors are capable of detecting volatile organic compounds and decomposition-related environmental changes[3] [4] [5] , while computer vision systems can analyze shelf conditions and monitor refrigerator activity over time. However, implementing these technologies reliably in real household refrigerator environments presents several engineering challenges.

During this research, significant practical limitations were discovered with both gas-sensor-only and direct image-based spoilage detection approaches. Gas readings inside refrigerators were affected by the presence of multiple food items, environmental mixing, airflow variation, and temperature conditions, making it difficult to isolate spoilage signals from individual specimens. Similarly, computer vision analysis was impacted by inconsistent lighting, reflections, restricted camera positioning, shelf occlusion, and image quality constraints within refrigerator environments.

These findings led the research to evolve beyond its original scope. Instead of relying solely on direct spoilage classification, the project introduced a behavioral computer vision approach based on sequential refrigerator shelf image analysis. Rather than attempting to continuously classify food freshness from isolated images, the system analyzes shelf-state changes and refrigerator interaction patterns over time. Food items or shelf regions that remain stationary for extended durations are treated as indicators of potentially forgotten food and elevated spoilage risk.

This project therefore explores the feasibility of an embedded monitoring system combining gas sensing, behavioral computer vision, sequential image analysis, and machine learning to identify spoilage-related environmental conditions and detect potentially forgotten food items inside household refrigerators. The proposed system integrates MQ-series gas sensors, a fisheye camera, an ESP32-S3 microcontroller, and a Python-based backend for environmental monitoring and behavioral shelf analysis.

By shifting the focus from direct spoilage classification toward behavioral refrigerator interaction monitoring, this research explores a more practical and deployable approach for intelligent household food monitoring. Ultimately, the project aims to contribute toward reducing preventable household food waste, improving food safety awareness, and promoting more sustainable household consumption practices.

2. Novel Contributions

The key contributions of this research include:

1. Behavioral Refrigerator Shelf Monitoring: Instead of relying solely on direct spoilage classification, this research introduces a behavioral monitoring approach that analyzes refrigerator shelf interaction patterns over time using sequential image analysis.

2. Sequential Shelf-State Change Analysis: A lightweight computer vision pipeline based on image differencing and spatial change detection was developed to identify low-movement shelf regions associated with potentially forgotten food items.
3. Real-World Refrigerator Deployment Evaluation: The project evaluates the practical challenges of deploying an embedded sensing system inside real household refrigerators, including environmental gas mixing, low-light imaging constraints, airflow variation, reflections, and sensor interference.
4. Hybrid Embedded Monitoring Architecture: The proposed system combines embedded gas sensing, behavioral computer vision, machine learning, and mobile monitoring into a unified IoT-based food monitoring platform.
5. Practical Shift from Direct Spoilage Detection to Behavioral Monitoring: One of the major findings of this research was that behavioral refrigerator interaction analysis may provide a more practical and deployable approach for household food waste monitoring compared to direct spoilage classification alone.

3. Related Work

Electronic nose ("e-nose") systems using gas-sensing technologies have been widely researched for agricultural monitoring, food quality analysis, and spoilage detection[3] [4]. These systems analyze volatile organic compounds (VOCs) and gases released during microbial activity and organic decomposition processes in fruits, vegetables, dairy products, and meats [3] [4] [5]. Prior research has shown that gas-sensing approaches can detect chemical changes associated with food deterioration under controlled experimental conditions.

Recent smart refrigerator and IoT-based food monitoring systems have combined embedded sensors, wireless communication, and computer vision technologies to improve household food management [9] [10]. Existing approaches commonly focus on inventory tracking, expiration-date reminders, barcode scanning, RFID systems, or direct object-recognition methods for estimating food freshness. However, many of these systems depend heavily on manual user input, labeled datasets, or controlled imaging conditions that may not generalize reliably to real household refrigerator environments involving occlusion, lighting variability, and changing shelf arrangements.

Computer vision techniques have additionally been applied to food classification, freshness estimation, and scene-change detection. Prior research in image differencing and sequential scene analysis has explored methods for identifying visual changes between images over time [8]. These techniques have been used in broader applications involving motion analysis, environmental monitoring, and activity detection.

Inspired by these approaches, this research explores a behavioral refrigerator shelf-monitoring approach using sequential image analysis and embedded gas sensing.

4. Research Hypothesis

The research evaluates the following hypotheses:

H1: Gas sensor readings from MQ-series sensors correlate with food spoilage progression in controlled food storage environments.

H2: Low shelf-interaction activity detected through sequential image analysis can identify potentially forgotten food items before visible spoilage occurs.

H3: Combining behavioral computer vision with gas sensing improves monitoring reliability compared to gas sensing alone in real household refrigerator environments.

H4: An ESP32-S3-based embedded monitoring platform can support continuous environmental telemetry and sequential shelf-image collection for household refrigerator monitoring applications.

5. System Architecture

The Food Waste Monitoring System is designed as a distributed embedded sensing platform that continuously monitors refrigerator conditions using a combination of gas sensing, computer vision, and machine learning. The system collects environmental sensor data and refrigerator shelf images in real time and transmits them to backend analysis services for spoilage assessment and behavioral monitoring.

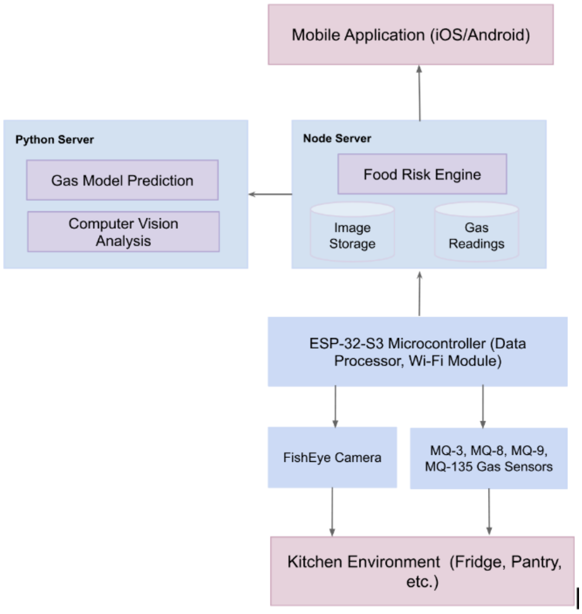


Figure 1: System architecture diagram of Food Waste Monitoring System

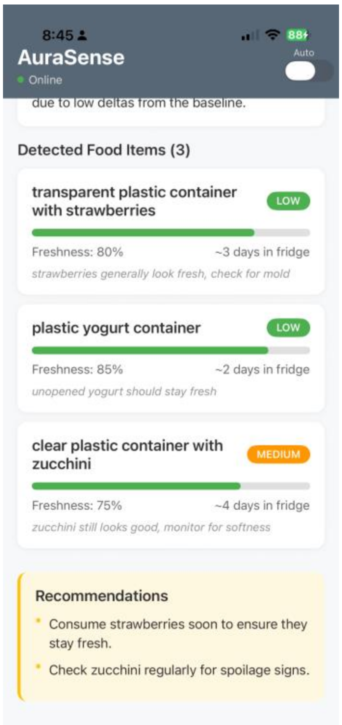
The embedded device consists of an ESP32-S3 microcontroller connected to multiple MQ-series gas sensors and a fisheye camera module mounted inside the refrigerator. The sensing array includes MQ-8, MQ-3, MQ-135, and MQ-9 sensors, which detect chemical compounds commonly associated with food decomposition, including ammonia (NH_3), hydrogen sulfide (H_2S), ethanol (EtOH), methane (CH_4), and carbon dioxide (CO_2). These gases are frequently released during microbial spoilage and organic decay processes.

The ESP32-S3 periodically captures sensor telemetry and shelf images and transmits the collected data through WiFi to a backend server infrastructure. Sensor telemetry is stored as time-series data within a SQL database, while captured images are stored within a filesystem-based repository for sequential analysis.

A Python-based backend service processes incoming telemetry data and executes machine learning inference workflows. Statistical analysis and Decision Tree classification models are used to identify abnormal gas concentration patterns potentially associated with spoilage conditions. In parallel, computer vision algorithms analyze sequential refrigerator shelf images to detect shelf-state changes and monitor shelf interaction activity over time.

Processed results, spoilage likelihood estimations, and shelf activity summaries are displayed to users through a mobile application interface. Although the current implementation monitors a single refrigerator shelf, the modular system architecture allows future expansion to multiple storage zones and larger smart kitchen environments.

Figure 2: Mobile App - AuraSense displaying detected food items using image analysis.



6. Materials and Methods

The prototype system consists of a shelf-mounted embedded monitoring device containing a gas sensor array, fisheye camera, ESP32-S3 microcontroller, rechargeable battery module, and WiFi communication interface. The embedded device is positioned on a refrigerator shelf or door compartment to capture both environmental sensor data and sequential shelf images.

The fisheye camera captures images during refrigerator door-open and door-close events to maximize available lighting conditions and improve image consistency. Sensor telemetry and image data are transmitted to a Node.js-based backend server through wireless communication protocols. The backend infrastructure stores sensor telemetry within a SQL database while image frames are archived within the server filesystem for temporal analysis.

Python-based analysis pipelines were developed to process gas sensor telemetry and computer vision outputs. Time-series sensor analysis was performed to identify gas concentration trends associated with food decomposition. A Decision Tree machine learning model was trained using experimentally collected gas sensor data from both fresh and warning-stage food samples.

Initial computer vision experiments focused on direct food-image analysis and spoilage detection. However, refrigerator environments introduced practical limitations including inconsistent lighting, restricted camera angles, reflections, and food occlusion. These challenges reduced the reliability of direct object-level spoilage classification.

As a result, a sequential image analysis pipeline was developed to compare sequential shelf images and identify refrigerator regions with varying levels of interaction activity. The algorithm computes shelf-state differences across time intervals to generate spatial heatmaps representing user interaction frequency.

High-movement zones correspond to frequently accessed food regions, while low-movement zones indicate areas where food may remain forgotten for extended durations. These low-interaction regions are used as behavioral indicators of potential spoilage risk and forgotten food accumulation.

7. Gas Sensor Machine Learning Analysis

Gas sensor telemetry was analyzed using a supervised machine learning approach. Each collected sample was labeled according to observed food condition status categories: fresh, caution, and warning. These labels represented increasing levels of spoilage-related environmental change observed during decomposition experiments.

The categorical labels were converted into numerical classes for model training, where fresh = 0, caution = 1, and warning = 2.

The dataset was divided into training and testing subsets using an 80/20 train-test split. A Decision Tree classifier was selected because the experimental dataset was relatively small and interpretable classification behavior was preferred for exploratory prototype analysis. The Decision Tree classifier with a maximum depth of 4 was trained on the collected sensor telemetry data. Model performance was evaluated using a confusion matrix, precision, recall, F1-score, and overall classification accuracy.

The classifier achieved strong performance for identifying fresh food conditions, while intermediate decomposition stages produced greater classification ambiguity due to overlapping gas emission patterns during gradual spoilage progression. These findings suggest that gas sensor telemetry can effectively identify spoilage progression trends, although precise stage separation remains challenging in transitional decomposition states.

Figure 3: Gas readings collected from the gas sensors in a csv file written by the python program

timestamp	nh3	h2s	etoh	co2	d_nh3	d_h2s	d_etoh	d_co2	gas_status	overall_status	food_count	foods_detected
2026-01-27T21:52:41.689Z	22	1.9	3.9	220	1.54	-0.08	-0.24	15.4	fresh	fresh	0	
2026-01-27T21:54:39.640Z	19.8	1.5	4	198	-0.66	-0.48	-0.14	-6.6	fresh	fresh	1	apple(80%)
2026-01-27T21:55:40.445Z	21.1	2	4.2	211	0.64	0.02	0.06	6.4	fresh	fresh	1	apple(75%)
2026-01-27T21:56:16.725Z	19.1	1.8	3.6	191	-1.36	-0.18	-0.54	-13.6	fresh	fresh	1	peach(60%)
2026-01-27T21:58:41.278Z	22.4	2	4.1	224	1.94	0.02	-0.04	19.4	fresh	caution	1	small fruit(40%)
2026-01-27T22:00:00.029Z	22.2	2	4.1	222	1.74	0.02	-0.04	17.4	fresh	fresh	1	cucumber(80%)
2026-01-27T22:00:02.898Z	22.2	2	4.1	222	1.74	0.02	-0.04	17.4	fresh	fresh	1	cucumber(85%)
2026-01-27T22:01:08.230Z	21.5	1.9	4.2	215	1.04	-0.08	0.06	10.4	fresh	fresh	1	cucumber(85%)
2026-01-27T22:28:19.362Z	22.9	2.2	4.3	229	2.44	0.22	0.16	24.4	fresh	fresh	1	cucumber(75%)
2026-01-27T22:36:26.651Z	22.4	1.8	4.3	224	1.94	-0.18	0.16	19.4	fresh	fresh	1	cucumber(75%)
2026-01-27T22:48:03.024Z	20.3	1.9	4.1	203	-0.16	-0.08	-0.04	-1.6	fresh	fresh	0	
2026-01-27T22:48:16.529Z	20.3	1.9	4.1	203	-0.16	-0.08	-0.04	-1.6	fresh	fresh	0	
2026-01-27T22:48:48.186Z	19.6	1.9	4.1	196	-0.86	-0.08	-0.04	-8.6	fresh	fresh	1	red onion(90%)
2026-01-27T22:50:49.585Z	23.6	2.1	4.2	236	3.14	0.12	0.06	31.4	warning	caution	1	onion(75%)
2026-01-27T22:51:38.684Z	22.9	1.8	4.5	229	2.44	-0.18	0.36	24.4	fresh	fresh	1	onion(90%)
2026-01-27T23:00:04.439Z	20.4	1.9	4.2	204	-0.06	-0.08	0.06	-0.6	fresh	fresh	1	onion(90%)
2026-01-27T23:38:26.459Z	25	1.7	4	250	4.54	-0.28	-0.14	45.4	warning	caution	1	apple(90%)
2026-01-27T23:38:47.981Z	21.3	2.2	4.4	213	0.84	0.22	0.26	8.4	fresh	fresh	1	apple(90%)
2026-01-27T23:40:25.295Z	23.7	2.3	4.6	237	3.24	0.32	0.46	32.4	warning	warning	1	unidentified item(80%)
2026-01-27T23:40:41.179Z	23.7	2.3	4.6	237	3.24	0.32	0.46	32.4	warning	caution	1	red bell pepper(75%)
2026-01-27T23:40:57.090Z	23.1	2	4.5	231	2.64	0.02	0.36	26.4	fresh	fresh	1	wrapped meat(85%)
2026-01-28T00:00:03.419Z	20.5	1.7	4	205	0.04	-0.28	-0.14	0.4	fresh	fresh	1	wrapped produce (likely a fruit or vegetable)(75%)
2026-01-28T00:17:57.401Z	22.3	2.1	4.6	223	1.84	0.12	0.46	18.4	fresh	fresh	1	wrapped produce(85%)
2026-01-28T00:18:14.640Z	22.3	2.1	4.6	223	1.84	0.12	0.46	18.4	fresh	fresh	1	wrapped food item(70%)
2026-01-28T01:00:03.969Z	23.1	2.1	4.5	231	2.64	0.12	0.36	26.4	fresh	fresh	1	pomegranate(90%)
2026-01-28T02:00:03.944Z	21.7	2.1	4.5	217	1.24	0.12	0.36	12.4	fresh	fresh	1	tomato(70%)
2026-01-28T03:00:03.639Z	21.3	2	4.2	213	0.84	0.02	0.06	8.4	fresh	fresh	1	red cabbage(80%)
2026-01-28T04:00:03.287Z	24.4	2	4.6	244	3.94	0.02	0.46	39.4	warning	caution	1	tomato(60%)

The feature set included gas concentration readings from four sensor channels: ammonia (NH_3), hydrogen sulfide (H_2S), ethanol (EtOH), and carbon dioxide (CO_2). In addition to raw gas values, the model also used change-based features representing variation over time: d_NH_3, d_H_2S, d_EtOH, and d_CO_2. These delta features were included to help capture gas concentration trends associated with food decomposition progression.

This approach allowed the system to evaluate whether MQ-series gas sensor patterns could distinguish between different spoilage stages and whether time-based gas changes improved classification of food condition status.

8. Experimental Procedure

The experimental procedure for this project began by purchasing fresh fruits and vegetables from local markets to establish baseline readings for healthy food samples. In addition, intentionally spoiled and rotting food specimens were tested to compare changes in gas emissions during decomposition. A Decision Tree machine learning model was then trained using the collected sensor data to classify and predict food spoilage levels based on gas concentration patterns.

To create a controlled testing environment, the food specimens were first placed individually inside an insulated ice box. Fresh and spoiled samples were positioned at the center of the chamber alongside the sensing device. The system, built using an ESP32-S3 microcontroller connected to gas sensors and a fisheye camera, continuously recorded gas readings. These readings were transmitted and stored in a database through a Python-based data collection program for further analysis and model training.

Figure 4: Initial isolated spoilage-testing environment.

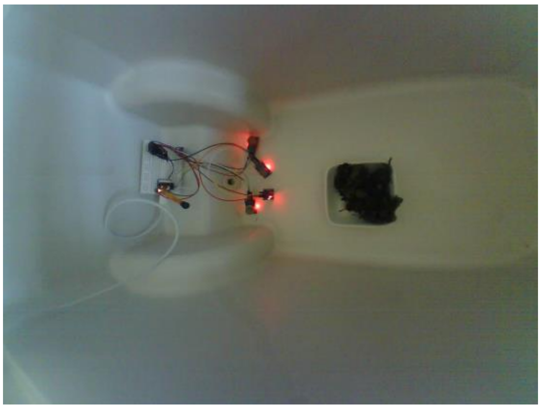
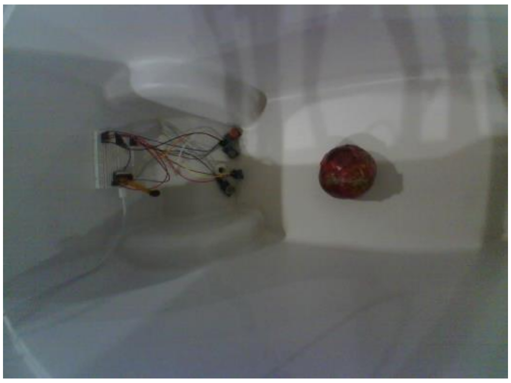


Figure 5: Gas sensor placement during controlled decomposition experiment.

Figure 6: Rotten food tested in an ice box with a fisheye camera and gas sensors connected to an ESP32-S3 microcontroller.



After successful isolated testing, the device was installed inside a household refrigerator to simulate real-world operating conditions. Real-world refrigerator testing exposed several practical challenges that were not observed during controlled experiments. One major limitation was the lack of lighting inside the refrigerator when the door remained closed, which significantly reduced the camera's ability to capture usable images.

Figure 7: Fisheye camera connected to an ESP32-S3 micro-controller attached to the fridge door to collect images of the shelf right in front.

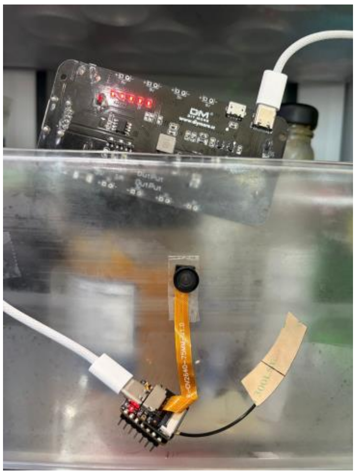


Figure 8: Low-light refrigerator image captured with refrigerator door closed.

With sufficient lighting, the device was able to capture clear images from the refrigerator door shelf. However, testing within the refrigerator environment revealed additional engineering constraints. The exposed battery experienced rapid cooling, leading to reduced performance and highlighting the need for an insulated battery enclosure for long-term deployment.

Another challenge involved gas isolation. Unlike the controlled ice box experiments, refrigerators contain multiple food items, containers, and materials simultaneously. As a result, gas sensor readings represented the overall condition of the refrigerator environment rather than a single food item, making precise spoilage attribution more difficult.

Finally, image analysis accuracy depended heavily on image quality. Factors such as limited lighting, restricted camera angles, reflections, and depth constraints inside the refrigerator affected the reliability of computer vision analysis. These findings demonstrated that while the prototype successfully detected environmental spoilage indicators, further optimization in lighting design, sensor placement, and image acquisition would be necessary for reliable real-world deployment.

Figure 9: Refrigerator shelf image captured under normal lighting conditions during deployment testing.

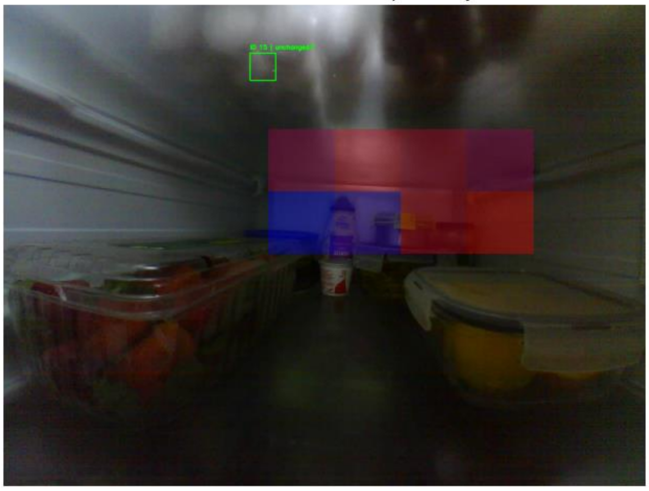
9. Computer Vision Pipeline

The limitations during real-world testing motivated the development of a lightweight behavioral shelf-monitoring pipeline based on sequential image analysis.

Instead of attempting to directly classify food freshness from individual images, the proposed approach analyzes refrigerator shelf interaction patterns over time. Sequential shelf images captured during refrigerator door-open events are compared to identify spatial regions exhibiting varying levels of movement and interaction activity.

Image differencing and spatial change-detection techniques were used to measure shelf-state variation across time intervals. Regions with frequent visual changes were classified as high-interaction zones, while regions with minimal visual changes over extended durations were identified as low-interaction zones. A spatial heatmap representation of refrigerator activity was generated to visualize shelf usage behavior.

The underlying assumption of this approach is that food items located in low-interaction regions are more likely to remain forgotten and therefore have an increased probability of spoilage. By monitoring behavioral shelf activity rather than relying solely on direct spoilage classification, the system provides a more robust method for identifying potentially neglected food items in practical household environments.
Figure 10: Output of the container detection and stability analysis algorithm applied to the refrigerator shelf image. Regions exhibiting minimal visual change over sequential refrigerator events are flagged as potential low-interaction storage zones.



10. Dataset Summary

The experimental dataset consisted of gas sensor telemetry and sequential refrigerator shelf images collected during both controlled ice-box experiments and real-world refrigerator deployment.
Gas sensor data was collected from fresh, caution, and warning-stage fruits and vegetables over multiple experimental sessions. Each telemetry sample included ammonia (NH_3), hydrogen sulfide (H_2S), ethanol (EtOH), and carbon dioxide (CO_2) sensor readings, along with temporal delta features representing changes in gas concentration over time.

The final machine learning dataset consisted of 255 labeled telemetry samples. An 80/20 train-test split was used, resulting in 204 training samples and 51 testing samples. Samples were labeled into spoilage categories including fresh, caution, and warning conditions based on observed food decomposition states. The computer vision experiments were conducted as exploratory feasibility studies for evaluating behavioral shelf-monitoring using sequential image analysis. The computer vision experiments were conducted using approximately 20–30 sequential refrigerator shelf images collected during multiple refrigerator interaction events. The dataset size was sufficient for exploratory feasibility evaluation of behavioral shelf-monitoring using sequential image analysis.

Despite the relatively small dataset size, the experiments successfully demonstrated that sequential image differencing could identify shelf interaction patterns and detect low-movement regions associated with potentially forgotten food items. Future work would require significantly larger image datasets collected across longer time periods, multiple households, and more diverse refrigerator configurations in order to validate generalizability and improve robustness.

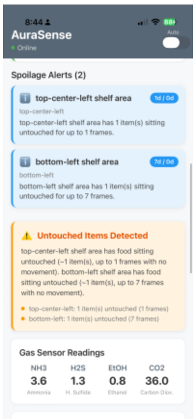
11. Results and Experimental Evaluation

The experimental results demonstrate that the proposed embedded monitoring system can successfully combine gas sensing and behavioral computer vision for household food monitoring applications. Unlike traditional smart refrigerator systems that rely heavily on direct food recognition or manual user input, the proposed approach focuses on refrigerator shelf interaction behavior using sequential image analysis.

Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

Experimental deployment showed that low shelf-interaction regions could be identified and visualized through spatial heatmaps, enabling the system to detect potentially forgotten food items over time. The integrated AuraSense mobile application further demonstrated how behavioral shelf analysis and environmental telemetry could be presented to users through real-time alerts and monitoring interfaces.

Figure 11: Screenshot of AuraSense mobile app showing the shelf zones with low activity and untouched items.



The Decision Tree classifier was evaluated using an 80/20 train-test split on the collected gas sensor dataset. The model achieved an overall classification accuracy of **88%** across 51 testing samples, demonstrating that gas concentration patterns can be effectively used to distinguish between fresh, caution and warning-stage environmental conditions.
The confusion matrix results are shown below:

Actual Class	**Predicted Fresh**	**Predicted Caution**	**Predicted Warning**
Fresh	38	0	0
Caution	0	1	5
Warning	1	0	6

The classifier achieved very strong performance for detecting fresh food conditions, with a precision of 0.97, recall of 1.00, and F1-score of 0.99. No fresh samples were incorrectly classified as warning, indicating high reliability in identifying non-spoiled food conditions.

Performance for warning-stage spoilage risk conditions was also relatively strong, with the warning category achieving a recall of 0.86 and an F1-score of 0.67. Most warning samples were correctly identified based on elevated gas concentration patterns.

However, the intermediate “caution” spoilage stage achieved significantly lower recall performance (0.17). This suggests that transitional spoilage conditions produce overlapping gas signatures that are more difficult to distinguish consistently. During decomposition, gas concentrations fluctuate gradually rather than changing abruptly between discrete spoilage stages, resulting in ambiguity between partially spoiled and warning samples.

The weighted average F1-score of 0.86 indicates strong overall model performance despite class imbalance and environmental variability. The results support the hypothesis that MQ-series gas sensor telemetry correlates with food spoilage progression under controlled conditions.

At the same time, environmental mixing, airflow variation, and low-temperature conditions reduced sensor stability and increased ambiguity in practical household environments. These observations motivated the integration of behavioral computer vision analysis as an additional monitoring modality within the overall system architecture.

Figure 12: Confusion matrix of gas readings model

```
[[38  0  0]
 [ 0  1  5]
 [ 1  0  6]]
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        38
           1       1.00      0.17      0.29         6
           2       0.55      0.86      0.67         7

    accuracy                           0.88        51
   macro avg       0.84      0.67      0.65        51
weighted avg       0.92      0.88      0.86        51
```

There is confusion between caution-stage and warning-stage states, which is common because gas patterns overlap during decomposition stages.

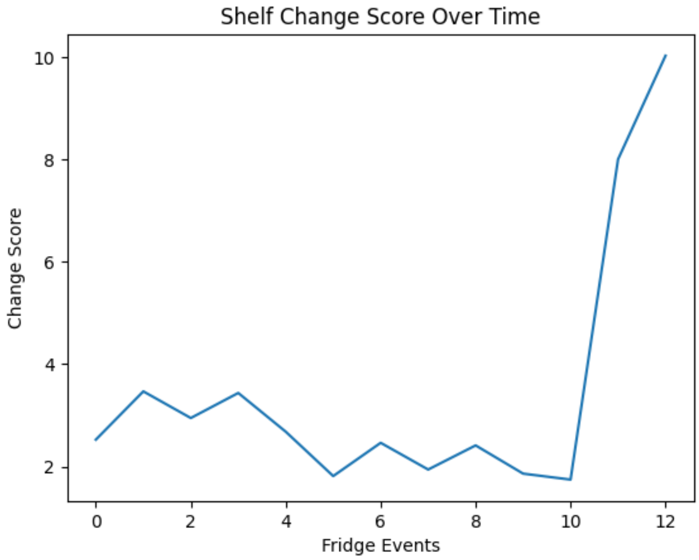
The gas sensor model achieved strong classification performance (88% accuracy), confirming that chemical emissions increase as food deteriorates. However, gas readings alone were inconsistent inside the refrigerator due to low temperatures and airflow variation.

12. Computer Vision Results and Shelf Movement Analysis

The behavioral computer vision model analyzed sequential refrigerator shelf images to measure how much the shelf state changed between refrigerator interaction events. Each image was cropped to focus on the shelf region, converted to grayscale, and blurred using a Gaussian filter to reduce noise. The model then compared each image with the previous image using pixel-level absolute difference analysis. The mean difference value was recorded as the shelf change score.

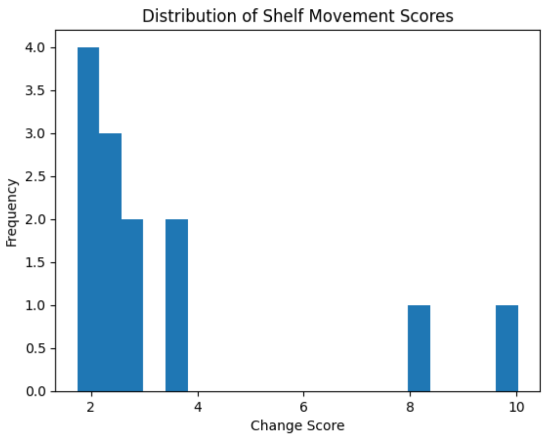
The shelf movement analysis produced a mean change score of **3.49**, with a standard deviation of **2.45**. The minimum observed change score was **1.74**, while the maximum observed change score was **10.03**. Most refrigerator events produced low change scores, indicating that large portions of the shelf remained stable across multiple openings.

Figure 13: Sequential shelf change scores generated using image differencing analysis.



The histogram of shelf movement scores showed that most image pairs had change scores between approximately 1.7 and 3.6. This suggests that the refrigerator shelf often experienced minimal rearrangement during normal usage. Only a small number of events produced much higher change scores, including values near 8 and 10, which likely corresponded to major shelf interactions such as removing, adding, or repositioning food items.

Figure 14: Distribution of shelf movement scores on the shelf image.



The shelf change score over time further showed a long period of low-to-moderate shelf activity followed by a sharp increase near the final refrigerator events. This pattern suggests that most food items remained relatively stationary for several events, while later events involved more significant shelf movement.

Using a low-movement threshold of 5, most events were classified as low-movement events. These low-movement periods indicate shelf stability and may help identify regions as persistent low-interaction regions. In contrast, high change scores represent active interaction with the shelf and suggest that food items in those regions were recently accessed or moved.

Figure 15: Spatial shelf stability heatmap generated from sequential image differencing. Blue indicates stable low-movement zones, while red indicates higher-activity regions.

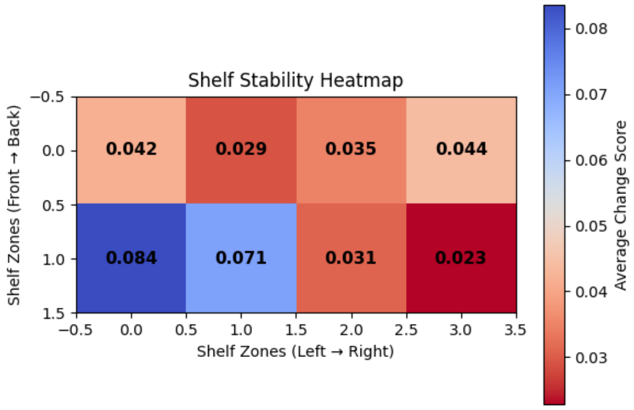
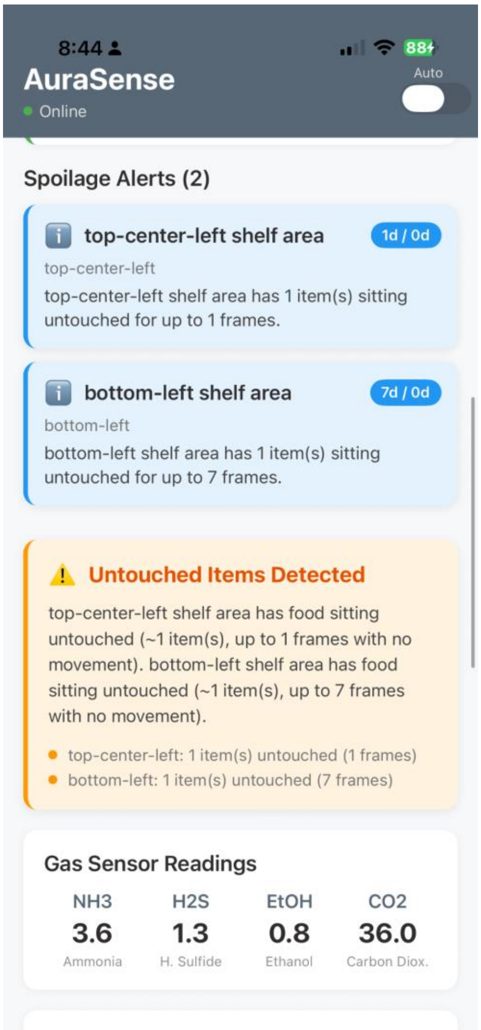


Figure 16: Shelf interaction heatmap overlaid on a refrigerator shelf image, showing regions of higher and lower visual change over time.

These results support the hypothesis that sequential image analysis can detect refrigerator shelf interaction patterns over time. Rather than attempting to directly identify spoilage from a single image, the system uses shelf movement behavior as an indirect indicator of potential forgotten food.

The computer vision system successfully identified shelf regions and containers that remained visually stable across multiple refrigerator openings. The stability heatmap showed that regions with minimal visual change corresponded to food items that were rarely accessed. This indicates that user interaction patterns can be used as an early indicator of potential food waste before spoilage becomes visually obvious.

Figure 17: Screenshot of AuraSense mobile app showing the shelf zones with low activity and untouched items.



13. Discussion and Future Work

The results of this research demonstrate both the potential and the practical limitations of low-cost embedded food monitoring systems deployed in household refrigerator environments. While controlled experiments showed measurable differences in gas sensor readings between fresh, caution and warning-stage food samples, real-world deployment revealed that environmental complexity significantly impacts sensing reliability. Mixed food storage conditions, variable lighting, reflections, occlusion, and constrained camera placement introduced challenges that reduced the effectiveness of direct spoilage detection methods.

One of the most important outcomes of this project was the unexpected evolution of the research toward behavioral shelf monitoring. Instead of relying solely on direct spoilage recognition, the developed system analyzes shelf interaction patterns over time to identify potentially forgotten food items. This approach proved to be more practical and robust under realistic household conditions and represents a promising direction for future smart kitchen systems.

The current implementation was intentionally designed with privacy preservation in mind. All image analysis was performed locally within the system infrastructure, minimizing the need for external cloud-based image processing. The camera was positioned exclusively toward refrigerator shelves and food storage areas, ensuring that no facial data or personal biometric information was intentionally collected during operation. The system was therefore limited to shelf-only monitoring rather than general household surveillance.

Despite these precautions, future deployments of intelligent household monitoring systems should carefully consider user consent, transparency, and data governance policies. Users should be clearly informed regarding what data is collected, how long it is stored, and how it is processed. Data retention policies should minimize long-term storage of unnecessary image data while still allowing sufficient historical analysis for spoilage detection and behavioral monitoring. Providing users with configurable privacy settings and local-only processing options could further improve trust and adoption.

Future work could focus on improving sensing reliability and expanding the system’s capabilities. Additional environmental sensors, improved low-light imaging hardware, infrared illumination, and edge embedded processing could significantly enhance detection accuracy. More advanced machine learning models, including temporal deep-learning architectures, could also improve behavioral prediction and spoilage forecasting.

The current prototype monitors a single refrigerator shelf; however, future versions could support multi-shelf monitoring, automated food inventory tracking, expiration-date integration, and personalized consumption recommendations. Integration with mobile applications and smart home ecosystems may further improve usability and encourage sustainable household food management practices.

Overall, this research demonstrates that low-cost embedded monitoring systems have strong potential to reduce preventable household food waste while simultaneously highlighting the technical, environmental, and ethical considerations necessary for practical real-world deployment.

14. Limitations

Several limitations were identified during the development and evaluation of the Food Waste Monitoring System. While the prototype demonstrated promising results for household food monitoring, real-world refrigerator environments introduced multiple technical and environmental challenges that impacted sensing reliability and system accuracy.

One major limitation involved environmental gas mixing inside refrigerators. Unlike controlled laboratory experiments where food samples were isolated, household refrigerators contain multiple food items, containers, packaging materials, and airflow sources simultaneously. As a result, MQ-series gas sensor readings represented aggregate environmental conditions rather than spoilage signals from individual food items. This reduced the precision of direct spoilage attribution and introduced variability in sensor measurements.

The computer vision subsystem also faced significant operational challenges. Refrigerator environments typically contain inconsistent lighting conditions, reflections from plastic containers, shelf occlusion, varying object arrangements, and restricted camera viewpoints. Image quality was especially degraded when refrigerator doors remained closed and internal lighting was unavailable. These factors reduced the reliability of direct image-based spoilage classification.

Another limitation involved hardware deployment constraints. The rechargeable battery powering the embedded system experienced rapid cooling inside low-temperature refrigerator environments, negatively affecting long-term operational stability. Future implementations would require improved thermal insulation or external power integration for continuous deployment.

The behavioral shelf-monitoring algorithm additionally relies on indirect inference rather than direct spoilage verification. The system assumes that food items remaining stationary for extended durations are more likely to be forgotten and therefore at increased risk of spoilage. However, low shelf interaction does not always guarantee that a food item is spoiled, and some frequently accessed items may still deteriorate rapidly depending on food type and storage conditions.

The experimental dataset used for machine learning training was also limited in scale. Experiments were conducted using a relatively small set of fruits and vegetables under controlled and household conditions. Additional testing across larger datasets, more households, diverse refrigerator configurations, and broader food categories would be necessary to validate generalizability and improve model robustness.

Finally, the current prototype monitors only a single refrigerator shelf and performs relatively lightweight embedded analysis. The system does not currently maintain full food inventory tracking, expiration-date recognition, or advanced object identification capabilities. Future versions could integrate additional sensors, larger datasets, edge AI acceleration, and more advanced temporal machine learning models to improve detection reliability and real-world scalability.

15. Conclusion

This research investigated the feasibility of using an embedded system to detect food spoilage and potentially forgotten food items inside household refrigerator environments. The proposed Food Waste Monitoring System combined MQ-series gas sensors, computer vision, machine learning, and embedded IoT infrastructure to continuously monitor refrigerator shelf conditions and analyze spoilage-related environmental patterns.

Controlled experiments demonstrated that gas sensor readings correlate with food decomposition and can be used to classify spoilage-related environmental conditions with measurable classification performance under isolated conditions. However, real-world refrigerator deployment revealed important practical limitations affecting both gas sensing and direct image-based spoilage detection. Environmental gas mixing, inconsistent lighting, reflections, occlusion, airflow variation, and constrained camera positioning reduced the reliability of direct spoilage recognition approaches in household conditions.

These findings led to one of the key contributions of this research: the development of a behavioral shelf-monitoring approach based on sequential image analysis. Instead of relying solely on direct spoilage detection, the system analyzes shelf interaction patterns over time to identify low-activity regions associated with potentially forgotten food items. Experimental observations demonstrated that behavioral interaction monitoring provides a more practical and robust strategy for identifying potential food neglect and elevated spoilage risk in real household environments.

Future improvements involving larger datasets, multi-shelf deployments, improved low-light imaging, advanced temporal machine learning models, and edge-based inference could further improve system accuracy, scalability, and real-world usability. Overall, this research demonstrates the feasibility of behavioral refrigerator shelf monitoring as a practical direction for future household food waste reduction systems.

References / Bibliography

1. Food and Agriculture Organization of the United Nations (FAO). (2019). The State of Food and Agriculture: Moving Forward on Food Loss and Waste Reduction. https://www.fao.org
2. United Nations Environment Programme (UNEP). (2021). Food Waste Index Report 2021. https://www.unep.org/resources/report/unep-food-waste-index-report-2021
3. Wilson, A. D. (2013). Diverse applications of electronic-nose technologies in agriculture and forestry. Sensors, 13(2), 2295–2348. https://doi.org/10.3390/s130202295
4. Arshak, K., Moore, E., Lyons, G., Harris, J., & Clifford, S. (2004). A review of gas sensors employed in electronic nose applications. Sensor Review, 24(2), 181–198.
5. Ampuero, S., & Bosset, J. O. (2003). The electronic nose applied to dairy products: A review. Sensors and Actuators B: Chemical, 94(1), 1–12.
6. Hanwei Electronics Group. MQ-135 Gas Sensor Technical Datasheet. Available: https://www.handsontec.com/dataspecs/MQ-135.pdf
7. Bradski, G. (2000). The OpenCV Library. Dr. Dobb's Journal of Software Tools. (OpenCV framework used for image processing.)
8. Radke, R. J., et al. (2005). Image Change Detection Algorithms: A Systematic Survey. IEEE Transactions on Image Processing, 14(3), 294–307.
9. Want, R., Schilit, B., & Jenson, S. (2015). Enabling the Internet of Things. IEEE Computer, 48(1), 28–35.
10. Abhari, S., et al. (2019). Smart Refrigerator System Using IoT and Cloud-Based Technologies for Food Monitoring and Management. International Journal of Advanced Computer Science and Applications, 10(5), 179–186.

Appendix A: Sample Gas Sensor Dataset

Table A1 shows a small sample of environmental telemetry collected during controlled food decomposition experiments. The dataset contains gas concentration measurements obtained from MQ-series gas sensors monitoring decomposition-related environmental changes produced by stored food items.

Each sample was labeled according to observed spoilage-related environmental conditions:

- Fresh
- Caution

Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

- Warning

The dataset was later used for exploratory machine learning classification experiments.

Figure A1: representative examples from the experimental telemetry collected during food monitoring trials and are included for illustrative purposes.

timestamp	nh3	h2s	etoh	co2	d_nh3	d_h2s	d_etoh	d_co2	gas_status	food_count	foods_detected	gas_analysis
2026-01-27T22:48:48.186Z	19.6	1.9	4.1	196	-0.86	-0.08	-0.04	-8.6	fresh	1	red onion(90%)	All gas levels are within the fresh category, indicating good overall air quality in the storage environment.
2026-01-27T22:50:49.585Z	23.6	2.1	4.2	236	3.14	0.12	0.06	31.4	warning	1	onion(75%)	NH3 level indicates warning status, others remain in fresh range.
2026-01-27T22:51:38.684Z	22.9	1.8	4.5	229	2.44	-0.18	0.36	24.4	fresh	1	onion(90%)	All gas readings are within the fresh threshold, indicating good air quality and low spoilage risk.
2026-01-27T23:00:04.439Z	20.4	1.9	4.2	204	-0.06	-0.08	0.06	-0.6	fresh	1	onion(90%)	All gas readings are within the 'fresh' category indicating low spoilage risk.
2026-01-27T23:38:26.459Z	25	1.7	4	250	4.54	-0.28	-0.14	45.4	warning	1	apple(90%)	NH3 level indicates a warning status, possibly causing overall freshness concern.
2026-01-27T23:38:47.981Z	21.3	2.2	4.4	213	0.84	0.22	0.26	8.4	fresh	1	apple(90%)	All gas sensor readings within fresh thresholds.
2026-01-27T23:40:25.295Z	23.7	2.3	4.6	237	3.24	0.32	0.46	32.4	warning	1	unidentified item(80%)	NH3 levels are at warning. H2S, EtOH, and CO2 are at fresh levels.
2026-01-27T23:40:41.179Z	23.7	2.3	4.6	237	3.24	0.32	0.46	32.4	warning	1	red bell pepper(75%)	NH3 levels indicate a warning status due to elevated levels, suggesting food might be starting to spoil. Other gases
2026-01-27T23:40:57.090Z	23.1	2	4.5	231	2.64	0.02	0.36	26.4	fresh	1	wrapped meat(85%)	All gas values are within the fresh range.
2026-01-28T00:00:03.419Z	20.5	1.7	4	205	0.04	-0.28	-0.14	0.4	fresh	1	wrapped produce (likely a fruit or vegetable)(75%)	All gas readings are within the fresh range, indicating a good overall air quality in the container.
2026-01-28T00:17:57.401Z	22.3	2.1	4.6	223	1.84	0.12	0.46	18.4	fresh	1	wrapped produce(85%)	All gas readings are within fresh thresholds, indicating no spoilage detected.
2026-01-28T00:18:14.640Z	22.3	2.1	4.6	223	1.84	0.12	0.46	18.4	fresh	1	wrapped food item(70%)	All gas readings are within fresh range, indicating overall freshness.
2026-01-28T01:00:03.989Z	23.1	2.1	4.5	231	2.64	0.12	0.36	26.4	fresh	1	pomegranate(90%)	All gas readings are within fresh thresholds, indicating no significant spoilage.
2026-01-28T02:00:03.944Z	21.7	2.1	4.5	217	1.24	0.12	0.36	12.4	fresh	1	tomato(70%)	All gas levels are within the fresh range.
2026-01-28T03:00:03.639Z	21.3	2	4.2	213	0.84	0.02	0.06	8.4	fresh	1	red cabbage(80%)	All gas sensor deltas indicate a fresh status. No concerning levels detected.
2026-01-28T04:00:03.287Z	24.4	2	4.6	244	3.94	0.02	0.46	39.4	warning	1	tomato(60%)	NH3 levels indicate a warning for spoilage. Other gases are within the fresh range.
2026-01-28T05:00:03.573Z	22.8	2.2	4.9	228	2.34	0.22	0.76	23.4	fresh	1	pomegranate(90%)	All gas readings are within the fresh thresholds, indicating a fresh environment.
2026-01-28T16:00:30.661Z	22.8	2.2	4.9	228	2.34	0.22	0.76	23.4	fresh	1	apple(90%)	All gas readings are within fresh thresholds, with minor increases indicating normal conditions.

Appendix B: Decision Tree Model Configuration

The gas sensor classification experiments were implemented using Python within the Google Colab environment. Sensor telemetry collected from the ESP32-S3 embedded system was stored in tabular form and processed using the Scikit-learn machine learning library.

The following environmental telemetry features were used for model training:

- NH3 (Ammonia concentration)
- H2S (Hydrogen sulfide concentration)
- EtOH (Ethanol concentration)
- CO2 (Carbon dioxide concentration)
- d_NH3 (change in ammonia concentration)
- d_H2S (change in hydrogen sulfide concentration)
- d_EtOH (change in ethanol concentration)
- d_CO2 (change in carbon dioxide concentration)

The collected samples were manually categorized into three spoilage-related environmental condition labels:

- Fresh
- Caution
- Warning

These labels represented progressively increasing decomposition-related environmental changes observed during experimental food monitoring.

A simplified implementation snippet of the machine learning training pipeline is shown below:

Figure B1: Decision Tree Classifier code - model trained with 80/20 train and test split

```
df["label"] = df["overall_status"].map(label_map)

features = [
    "nh3","h2s","etoh","co2",
    "d_nh3","d_h2s","d_etoh","d_co2"
]

X = df[features]
y = df["label"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

model = DecisionTreeClassifier(max_depth=4)
model.fit(X_train, y_train)
```

The dataset used an 80/20 train-test split with random_state=42

Appendix C: Shelf Movement Analysis Algorithm

Sequential shelf interaction analysis code used for region-based movement detection and low-interaction zone identification.

Figure C1: Sequential shelf interaction analysis pipeline showing grid-based spatial zoning used to track refrigerator shelf activity and identify low-interaction regions associated with potentially forgotten food items.

```
# ============================
# AUTO-DETECT SHELF HEIGHT
# ============================

activity_profile = np.mean(diff, axis=1)

threshold = np.percentile(activity_profile, 60)

active_rows = np.where(activity_profile > threshold)[0]

shelf_top = active_rows.min()
shelf_bottom = active_rows.max()

print("Shelf detected between rows:",
      shelf_top, shelf_bottom)


sorted_tracks=sorted(tracks.items(),
                     key=lambda kv:kv[1]["unchanged"],
                     reverse=True)

print("\nLikely stationary containers:")

for tid,t in sorted_tracks:
    w,h = t["bbox"][2], t["bbox"][3]

    # ignore large false regions
    if w*h > 20000:
        continue

    if t["unchanged"] > 0:
        print(tid,t["unchanged"],t["moved"],t["bbox"])
```

Figure C2: Grid calculation to divide shelf into a grid of zones and tracking activity per zone. Movement scores were used to classify shelf regions into low, medium, and high interaction zones.

```
# ============================
# MOTION BOXES
# ============================
for c in contours:
    area=cv2.contourArea(c)
    x,y,w,h=cv2.boundingRect(c)

    if area<MIN_AREA: continue
    if area>0.25*frame_area: continue
    if w>0.6*frame_w or h>0.6*frame_h: continue

    boxes.append((x,y,w,h))

# ============================
# STATIC EDGE BOXES (NEW)
# ============================
for c in edge_contours:

    area=cv2.contourArea(c)

    # larger threshold → ignore noise
    if area < 1500:
        continue

    x,y,w,h=cv2.boundingRect(c)

    if w>0.6*frame_w or h>0.6*frame_h:
        continue

    candidate = (x,y,w,h)

    duplicate = False
    for b in boxes:
        if iou(candidate, b) > 0.4:
            duplicate = True
            break

    if not duplicate:
        boxes.append(candidate)


print("Detected boxes:",len(boxes))
```

Appendix D: AuraSense Mobile Application Screens

Figure D1: AuraSense Welcome Screen

Figure D2: AuraSense displaying detected refrigerator shelf items and freshness estimates

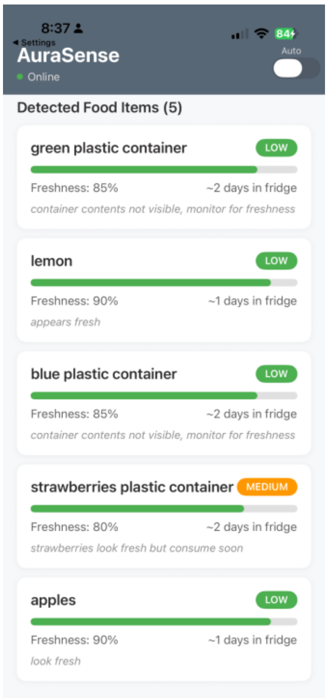
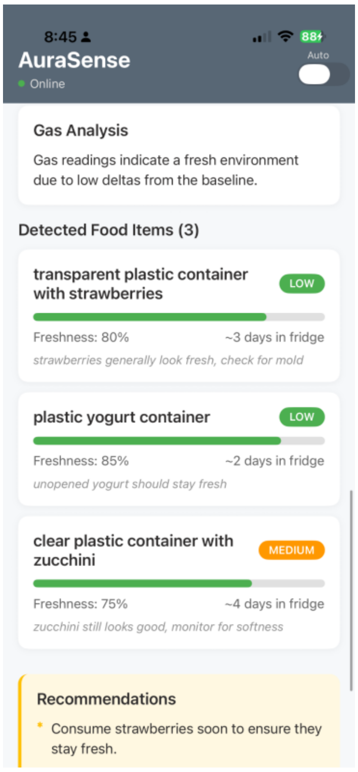


Figure D3: AuraSense environmental gas analysis



Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

Figure D4: AuraSense showing last image taken and overall report