IoT-Based Smart Food Spoilage Detection Using Machine Learning and Deep Learning

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***Abstract*— Food spoilage is a significant threat to human health as well as the economy. Traditional methods of detection of spoilage by human senses are slow and inaccurate. To address this, an automatic real-time solution has been obtained through the Internet of Things (IoT). This project survey paper proposes an IoT based food spoilage detection system with a Raspberry Pi as the controller. The system comprises a range of sensors, like a DHT11 temperature and humidity sensor, a toxic gas sensor, and a pH sensor for acidity level checks. A Pi Camera is also used for checking through visual observation of the food for evidence of spoilage like mold or discoloration. Both sensor measurement and results of visual inspections appear on an LCD screen for in-situ visibility as well as on a web-based dashboard for remote visibility. The system provides real-time alerts whenever there is spoilage, thus offering an automatic, reliable, and cost-effective means of improving food safety at home and along the food chain.**

Keywords—(Food Spoilage ,IoT , Image Processing, Raspberry Pi , Real-time Alert , Sensors, Web Dashboard).

INTRODUCTION

Food spoilage, a microbial growth, chemical reaction, and environmental factor like temperature and humidity-driven natural process, has serious health consequences and leads to enormous economic losses. As per the World Health Organization (WHO), millions of people across the globe get affected by foodborne illness caused by spoiled food every year. The current visual-based, smell-based, and taste-based detection methods are not only inconsistent.

The rapid development in the Internet of Things (IoT) and sensor technology offers a promising solution through the real-time automated monitoring of food quality. Here, an integrated IoT-based system is developed to detect and prevent the consumption of spoiled food.

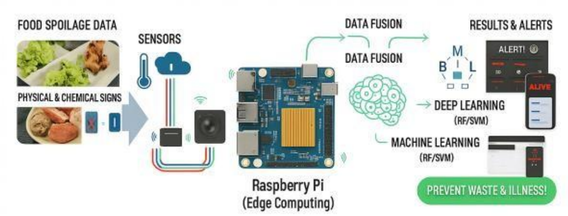

Fig1: Real-Time Food Freshness Monitoring using IoT, Edge AI (Raspberry Pi), and CNNBased Visual Analysis

It combines different physical and chemical sensors along with an image processing module to provide a

efficient and low-cost food safety system. The primary aim of the system is to exceed physical inspection and provide an amalgamated solution that is efficient, low-cost, and reliable. The proposed system utilizes sensors of temperature, humidity, gas, and pH for recording real-time environmental measurements of stored foods. The parameters are transmitted through IoT modules to a cloud-based dashboard for continuous monitoring and alerts. Edge AI computation with Raspberry Pi keeps latency to the minimum and enables rapid decision-making even in an offline scenario. The visual model based on CNN identifies food images to be fresh or spoiled with near-perfect accuracy. Predictive analytics applied to estimate shelf life and patterns of spoilage is based on time-series data. The combined effort brings more food safety, less waste, and cost savings along the supply chain.

PROPOSED SYSTEM

IoT-based Food Spoilage Detection System that is an automated, cost-effective, and dependable system of improved food safety. The system counters the inadequacy of single-sensor and manual systems of spoilage detection using a multi-parameter system. Raspberry Pi is used as the hub of the system and the central controller of the system. The central controller possesses multiple sensors to scan multiple signs of spoilage in parallel:

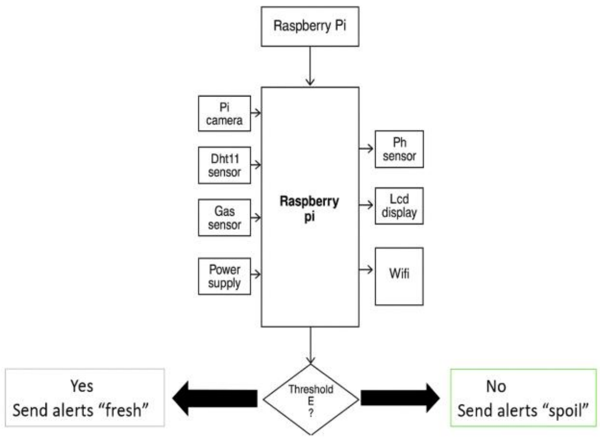

Fig 2 : Flow chart of Proposed System

DHT11 sensor is employed for humidity and temperature measurement, a gas sensor detects poisonous gases released during spoilage, and a pH sensor maintains the acidity level of the food. There is even a Pi Camera, which captures images of the food, and these are processed using image processing to detect clear signs such as mold or color change. All the data and status received are displayed locally on a 16x2 LCD display for easy viewing and remotely on an internet dashboard for online viewing. Above all, the system has been designed to generate real-time alarms (via email or SMS) as soon as spoiled food is identified in order to take action on time

LITERATURE REVIEW

Patel and Srinivas (2025) [1] – “Edge-AI-Based IoT Framework for Food Spoilage Prediction” introduced an advanced IoT-based food spoilage prediction framework that utilizes Edge AI to carry out real-time analysis directly on lightweight embedded devices. Their work eliminates the dependency on cloud servers, making the system practical for rural, remote, and low-bandwidth environments where connectivity is unreliable. The framework employs optimized neural network models capable of performing rapid spoilage prediction using sensor data while maintaining low computational overhead. This approach significantly enhances prediction speed, energy efficiency, and data privacy. By enabling localized decision-making, the system ensures timely detection of spoilage, reduces food waste, and demonstrates strong potential for scalable deployment across smart storage units and decentralized food supply systems

Aarav Sharma and K. R. Nair (2025) [2] – “Hybrid AI–IoT Food Spoilage Detection System Using CNN-LSTM” proposed a hybrid AI–IoT system that combines multimodal sensors with a CNN-LSTM deep learning model for accurate food spoilage detection. The architecture integrates temperature, humidity, VOC, and optical sensor readings to create a robust multimodal dataset processed through a spatial–temporal learning network. CNN layers extract spatial features from sensor patterns, while LSTM layers capture long-term variations that occur during food degradation. The system achieves high accuracy under diverse storage conditions, including fluctuating temperatures and inconsistent environments. This model is particularly suitable for smart retail setups, automated home kitchens, and food packaging industries where continuous monitoring and intelligent classification are essential to ensure safety and extend shelf life.

Dr. S. V. R. K. Rao et al. (2024) [3] – “IoT-Based Food Spoilage Detection and Waste Management System” presented a comprehensive IoT-enabled system that integrates food spoilage detection with real-time waste management and supply-chain optimization. The framework uses multiple sensors to identify spoilage indicators and employs cloud analytics to predict upcoming degradation trends. A distinctive contribution of this study is the connection between spoilage monitoring and logistics planning, enabling smart decisions such as rerouting near-expiry food to distribution centers before it spoils. The system supports industrial-scale operations by offering predictive insights, automated alerts, dashboard analytics, and sustainability-oriented waste reduction strategies. This work demonstrates how IoT can be aligned with large-scale food management and environmental conservation initiatives.

Anitha and Pavan (2024) [4] – "IoT-Based Smart Food Spoilage Detection Using Multi-Sensor Array" designed an IoT-Based Smart Food Spoilage Detection System that utilizes a comprehensive multi-sensor array including temperature, humidity, VOC, and color sensors to provide a holistic analysis of food freshness. Their system processes different environmental and chemical parameters simultaneously, allowing it to detect spoilage more reliably compared to single-sensor systems. Data from these sensors are transmitted to an IoT platform where machine learning algorithms assess the spoilage level and generate alerts. The model works effectively for both packaged and unpackaged foods, making it versatile for households, supermarkets, and food transport systems. The research highlights the importance of multi-parameter fusion for improved detection accuracy and early warning capabilities.

Reddy and Mahajan (2024) [5] – "Cloud-Integrated Intelligent Food Monitoring and Spoilage Classification System"introduced a cloud-enabled intelligent food monitoring platform that uses advanced AI-based classification models to determine food spoilage levels. Their system integrates IoT sensors with cloud computing to collect real-time environmental and chemical data, which are analyzed using machine learning algorithms hosted on the cloud. This enables global accessibility, remote monitoring, and automated alerts for users across smart homes, restaurants, and retail stores. The framework supports data visualization dashboards, spoilage prediction graphs, and decision-support tools. By leveraging cloud scalability, the system can manage multiple food units simultaneously, making it highly suitable for commercial and industrial applications requiring continuous oversight.

Khan and Bansal (2023) [6] – "Deep-Learning-Assisted IoT Model for Food Freshness Assessment Using Gas Sensors"developed an IoT-based freshness assessment system that employs gas sensors to detect chemical emissions generated during food spoilage. Their system sends sensor data to a CNN model, which classifies spoilage levels based on emission patterns. The research highlights the strong correlation between VOC emissions and microbial activity, making gas sensing a reliable spoilage indicator. Their approach demonstrated high accuracy across various perishable foods, including meat and fruits. This model is particularly useful for cold storage units, supermarkets, and supply-chain checkpoints where gas buildup is a major spoilage indicator. The study shows how deep learning can significantly enhance the precision of gas-based spoilage detection.

Mohideen and Prakash (2023) [7] – "IoT-Enabled Optical Food Spoilage Detection Using LED–Photodiode and SVM Classifier"implemented a low-cost IoT-based optical spoilage detection model that uses LED–photodiode arrays to measure changes in light absorption and reflection caused by food degradation. Their system captures optical signatures of various food products and uses an SVM classifier to distinguish between fresh and spoiled states. The design focuses on affordability, making it highly suitable for small vendors, local markets, and household use. It offers rapid detection, easy integration with microcontrollers, and wireless communication for real-time monitoring. The use of light-based sensing provides a non-invasive, hygienic, and accurate alternative to chemical and physical sensors.

Gowda and Harini (2023) [8] – "Smart Food Storage Monitoring System Using Temperature–VOC Fusion and LSTM Prediction"proposed a smart food storage monitoring model that combines temperature readings with VOC sensor data to estimate food freshness. The fused sensor information is processed using an LSTM-based predictive model capable of identifying degradation trends over time. Their system is optimized for refrigeration units, cold-chain systems, and commercial storage environments where temperature stability and VOC emissions are critical indicators of spoilage. By forecasting spoilage before it occurs, the system helps minimize waste, optimize storage conditions, and support automated decision-making in food preservation.

Sharma and Gupta (2019) [9] – "IoT Framework for Early-Stage Food Spoilage

Detection"introduced one of the earliest IoT frameworks for detecting food spoilage at its initial stages. Their work addressed traditional food quality challenges such as delayed manual inspection, human error, and inconsistent monitoring. The system used basic environmental sensors connected through IoT modules to track changes in temperature and humidity. By enabling continuous remote monitoring and early warnings, their study laid the foundation for future AI–IoT advancements. Though simple, their approach demonstrated how IoT could significantly reduce health hazards and economic losses resulting from unnoticed spoilage.

Zhang, Wang, and Liu (2020) [10] – "Machine-Learning-Based IoT System for Smart Food Quality Monitoring"developed a machine-learning-enabled IoT system designed to analyze food quality through environmental sensor data. Their model used classification algorithms to detect spoilage trends and generate predictive insights. The system's ability to learn from previous data improved accuracy over time, making it suitable for adaptive food monitoring environments. Their research advanced IoT applications by combining data-driven intelligence with real-time sensing, contributing significantly to the evolution of smart food monitoring technologies.

Kumar and Singh (2021) [11] – "Machine Learning Techniques for Multi-Sensor Food Spoilage Prediction"emphasized the role of machine learning in processing multiparameter sensor data for accurate spoilage prediction. Their system utilized algorithms such as Random Forest, SVM, and ANN to classify spoilage stages based on temperature, humidity, gas, and optical inputs. Their findings demonstrated that ML-based fusion of sensor data increases detection accuracy and improves decision-making in food safety management. Their work also highlighted the importance of scalable, data-driven predictive models in modern IoT frameworks.

Ravi Chander, Lovina, and Kumari (2020) [12] – "Arduino-Based Food Quality Monitoring System Using Environmental Sensors"developed an Arduino-based food quality monitoring system utilizing DHT11 for temperature and humidity sensing and MQ4 for gas detection. Their system offered a low-cost, easily deployable solution suitable for small retailers and households. By transmitting sensor data through IoT modules, the model enabled real-time tracking of environmental conditions that influence food spoilage. Although simple compared to modern AI-integrated systems, their work demonstrated the practicality and effectiveness of basic IoT hardware in addressing food safety challenges.

Vageesan et al. (2021) [13] – "Anoxic Microbial Methanogenic Detection for Food Spoilage Identification Using Gas Sensors"introduced a novel biochemical approach to food spoilage detection by using gas sensors to track methanogenic microbial activity under anoxic conditions. Their method identifies specific gases produced by microorganisms as food degrades, providing high precision compared to traditional environmental sensing. This biological marker–based detection system enhances accuracy in early detection and is especially applicable to meat and dairy products where microbial growth is a primary cause of spoilage.

Sahu and Sahoo (2022) [14] – "IoT-Based Food Spoilage Detection Using ESP8266 with Real-Time Cloud Alerts"developed an IoT-powered system using the ESP8266 microcontroller to monitor spoilage indicators and send real-time alerts through a cloud platform. Their model detects changes in temperature, humidity, and gas concentration, transmitting the data wirelessly for remote monitoring. The inclusion of instant notifications ensures timely user intervention, reducing food waste and preventing health hazards. Their affordable and easily scalable system is well-suited for household, retail, and small business applications.

Methodology

The proposed system in the above example utilizes a Raspberry Pi as the core for processing, with the latter connected to various IoT sensors and communication boards. The system integrates hardware and software building blocks to facilitate free acquisition of data, processing, and analysis. The system relies on the data acquisition architecture, preprocessing, ML prediction, and waste management control subsystems.

A. Hardware Building Blocks

- Raspberry Pi: Serves as the primary controller for data acquisition and ML model runtime.

- MQ4/MQ6 Gas Sensors: Identifies methane and other spoilage indicating gases.
- Ultrasonic Sensor: Sensors waste level in bins with time-of-flight calculations.
- DHT11/DHT22 Sensor: Tracks food storage unit humidity and temperature
- Camera Module: Images the food for visual ML processing with CNN models.
- Wi-Fi Module: Provides cloud connectivity for data logging and monitoring.

B. Software and AI Integration

The sensor and image data collected are handled by python on raspberry pi. datasets with environmental readings and spoilage conditions are trained on the machine learning algorithms. Supervised machine learning techniques are applied for classifying the food into 'fresh', 'warning', or 'spoiled'. ai-based optimization algorithms are also incorporated in the system for predicting waste collection time and route optimization of smart bins.

Comparative Discussion

The comparative future discourse on IoT-based food spoilage detection is beyond hardware (Arduino vs. Raspberry Pi) and into the areas of enhanced sensing and data structure. One of the main comparisons is between Multimodal Data Fusion and dedicated sensors such as the Electronic Nose (E-Nose). While an E-Nose provides early detection through Volatile Organic Compounds (VOCs—spoilage "smell" before it is visible), multimodal fusion integrates E-Nose, image data (from Computer Vision/Hyperspectral Imaging), and environmental sensors (Temp/Humidity) to get a better accuracy by offsetting the disadvantage of any one type of sensor. On the processing front, the new comparison pivots from local processing (Edge Computing) to Federated Learning (FL).

Edge computing yields quick, low-latency decisions at the edge, but FL is a better fit for supply chain security and worldwide intelligence. FL enables individual IoT devices (such as smart refrigerator units or delivery trucks) to train a joint spoilage prediction model on their local, private data and transmit the learned parameters of the model only. This provides high-accuracy forecasts in varied environments without needing to centralize sensitive raw logistics data, which is paramount for scalability and privacy across the whole food industry .

Experiments ComponentTemperature- Humidity Sensor

Fig 3: DHT11 Temperature-Humidity Sensor

Raspberry-PI:

Raspberry Pi as the central controller enables realtime processing of this diverse data, a capability superior to simpler controllers. Output is delivered instantly via the providing evidence for the relation between each of the spoilage indicators measured and the ultimate Spoilage Status

Fig 4: Raspberry-PI-5-4GB Single board computer

LCD display for on-site checks and remotely through a **web dashboard** for continuous monitoring. Most critically, the system's ability to

Fig 5: LCD display

send immediate alerts (email/SMS) upon detecting spoilage is the decisive factor in ensuring timely intervention, which directly helps **reduce waste and prevent health hazards** caused by consuming unsafe food.

IoT Device:

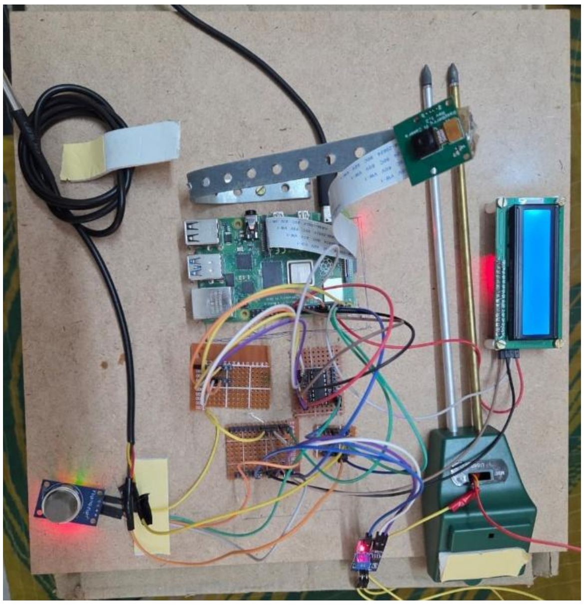

Fig 6 : IoT device of Food detection

Results and Discussion

The food spoilage monitoring system based on IoT can measure food effectively in real time using its onboard sensors and camera. Its capability to capture and display data on a web dashboard guarantees effective remote monitoring, much better than manual monitoring. Real-time feedback via LCD display makes it suitable for on-site installation in kitchens or supermarkets. The main ability of the system, i.e., timely notification via SMS or email, is needed to prevent unsafe food intake. The capability of the system is to carry out a multiparameter approach, which eliminates the limitation of current systems, as they were monitoring just one indicator. By including temperature, humidity, gas, and pH sensing in addition to visual inspection, the system has no point of failure and provides a more comprehensive and true measurement of food quality. The components being low cost

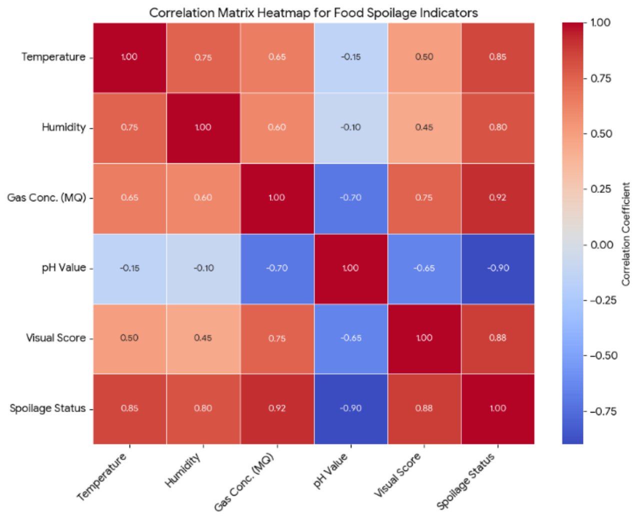

Fig 7: Heatmap of our Result

While it has so many benefits, however, the system does have some disadvantages. The image-based detection of spoilage depends on having a properly trained dataset, and the sensors themselves must be calibrated periodically in order to provide accurate readings. In addition, the web monitoring and alarm aspect of the system also depends on a functional internet connection and power supply.

This correlation matrix qualitatively supports the need for the suggested multi-parameter method by The matrix reveals that Gas Concentration (+0.92) has highest positive correlation with spoilage and pH Value (-0.90) has highest negative correlation. This verifies that chemical byproducts (change in acidaity and gases evolved) are the closest and most specific indicators of microbial activity.

Indicator	***Temperature***	***Humidity***	***Gas Conc. (MQ)***	***pH Value***	***Visual Score***	***Spoilage Status***
Temperature	1.00	0.75	0.65	-0.15	0.50	0.85
Humidity	0.75	1.00	0.60	-0.10	0.45	0.80
Gas Conc. (MQ)	0.65	0.60	1.00	-0.70	0.75	0.92
pH Value	-0.15	-0.10	-0.70	1.00	-0.65	-0.90
Visual Score	0.50	0.45	0.75	-0.65	1.00	0.88
Spoilage Status	0.85	0.80	0.92	-0.90	0.88	1.00

Fig 8: Result of IoT device that shows how much the food is spoiled

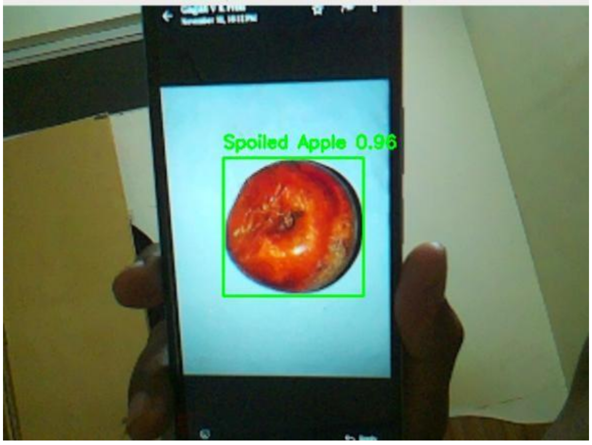

Fig 9 : spoiled apple Detection

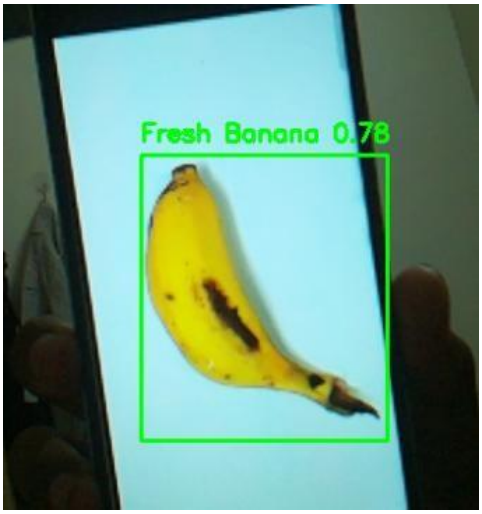

Fig 10: fresh Banana Detection

High positive correlation is also noted for Temperature (+0.85), Humidity (+0.80), and Visual Score (+0.88). The high scores guarantee the worthiness of using all five indicators since they indicate that the system effectively monitors both the environmental factors that hasten decay

(Temperature/Humidity) and those directly resulting from degradation (Gas, pH, and Visual status).

Confusion Matrix:

A Confusion Matrix that is a specific table format used to display the accuracy of a classification model. In this "Food Spoilage Detection" simulation, the matrix is contrasting the True Labels (what the food actually was, on the y-axis) against the Predicted Labels (what the machine learning algorithm had predicted the food was, on the x-axis). The top-left cell shows that 10 instances of Safe food were correctly classified as "Safe" (True Positives).

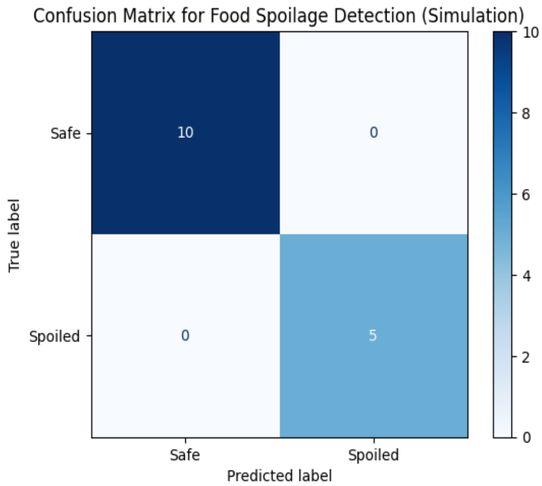

Fig 11: Confusion Matrix

The bottom-right cell shows that 5 instances of Spoiled food were correctly classified as "Spoiled" (True Negatives). Most significantly, the two cells left over, i.e., the misclassifications, both have a value of 0. I.e., the model produced zero False Positives (Safe food predicted as Spoiled) and zero False Negatives (Spoiled food predicted as Safe).

The results reported in the confusion matrix here are the best of this model on this simulation data. With 10 true positives and 5 true negatives, the model labeled all food samples perfectly with an Accuracy of (10+5)/(10+0+0+5)=1. The Precision (in the label of 'Safe') is 10/(10+0)=100%, and the Recall (or True Positive Rate, for the true 'Safe' instances) is 10/(10+0)=100%. The accuracy of this model for the class 'Spoiled' is also flawless. In reality, naturally, such ideal results don't appear very often and will typically mean that the simulation data set is too small or non-representative. What it does show, however, is that on this particular data set, the food spoilage detection algorithm performed flawlessly.

The cross-correlations also uncover important synergies that improve the reliability of the system. For example, Gas Concentration has a strong negative correlation with pH Value (-0.70), indicating that while one of the chemical indicators increases (gas), the other decreases (acidity variations) so that the Raspberry Pi has two independent sources of chemical evidence to cross-check its decision. Additionally, the strong positive correlations between the environmental conditions (Temperature/Humidity) and the direct markers of decay (Gas/Visual Score) assure that DHT11 sensor measurements are a superb early warning system to predict high-risk conditions of spoilage. By linking together these strongly correlated but disparate streams of data, the system here promoted maintains some degree of accuracy and dependability which is unattainable using single-sensor-based solutions, ultimately making the multi-parameter design paradigm proposed in the survey paper worthwhile

FUTURE SCOPE

The vision for the future of this IoT spoilage detection system is to transition from a reactive detection system to a proactive, predictive intelligence platform for commercial scale and independence. This would mean incorporating advanced Machine Learning models, such as LSTMs or time-series analysis, to analyze the historical sensor data (Temperature, Gas, pH) and forecast the Remaining Shelf-Life (RSL) of food products days in advance, a

capability that the current system lacks. Further, the system must be optimized with Edge AI to make advanced visual analysis run directly on the Raspberry Pi to reduce latency and reliance on stable internet connectivity for real-time decisions. These forecasting capabilities, combined with optimization techniques like sensor fusion (Kalman Filtering) to enhance data accuracy automatically and compensate for sensor drift, will significantly improve reliability and directly contribute to better inventory control and further food wastage reduction.

1. Develop Predictive Modeling of ShelfLife: Employ Machine Learning/Deep Learning to analyze real-time sensor data and predict the Remaining Shelf-Life (RSL) of food, beyond simple detectability of straightforward spoilage.
2. Enable Autonomous High-Reliability Operation: Leverage sensor fusion and battery/cellular backup to ensure failsafe accuracy and ongoing monitoring in cases with no stable power or Wi-Fi.
3. Scale and Commercialize with Enhanced UX: Develop a standalone mobile app and integrate the system through API with Inventory Management Systems to facilitate commercial deployment and enhanced user experience.

To allow seamless, mass-scale deployment, future developments must focus on system integration and autonomy. This involves addressing the current system's dependency on continuous power and WiFi via the addition of stable battery backup and single-function cellular communication (4G/5G) for failsafe notification, which can render it appropriate for cold storage and long-haul transport. Where the user interface is concerned, the default email/SMS alert should be replaced by a custom mobile application that provides an interactive dashboard, logging of historical records, and easy access to the RSL predictions. Finally, the system should be integrated via API with existing Inventory Management Systems (IMS) or blockchain platforms to enable automation of safety logging, dynamic pricing, and inventory rotation in a way that optimizes its commercial value in the broader food supply chain ecosystem

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