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Ai-Based Multi-Parameter Food Spoilage Prediction System

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Abstract: *Food spoilage is a major challenge in the food supply chain, resulting in significant economic losses, food waste, and potential health risks. Conventional methods of assessing food freshness rely on manual inspection, which is subjective, time-consuming, and unsuitable for continuous monitoring. This paper presents an* ***AI-based Multi-Parameter Food Spoilage Prediction System*** *that integrates Internet of Things (IoT) technology with machine learning for real-time food quality assessment. The proposed system employs multiple sensors, including an MQ135 gas sensor, DS18B20 temperature sensor, DHT22 humidity sensor, soil moisture sensor, and load cell with an HX711 amplifier, to monitor critical environmental and physical parameters associated with food spoilage. An ESP32 microcontroller acquires and transmits sensor data, while a* ***Random Forest*** *classifier analyzes the fused sensor inputs to classify food into four freshness levels:* ***Fresh, Early Spoilage, Unsafe, and Spoiled****, with an estimation of the remaining shelf life. The system also performs cold-chain monitoring by continuously tracking storage temperature and generating alerts when unsafe conditions are detected. Experimental evaluation demonstrates that the integration of multi-sensor data and machine learning improves prediction reliability compared with single-parameter approaches, enabling early spoilage detection and real-time monitoring. The proposed solution offers a scalable, cost-effective, and intelligent framework for enhancing food safety, minimizing wastage, and supporting efficient storage and transportation management in modern food supply chains.*

Keywords: *Food Spoilage Prediction, Internet of Things (IoT), Machine Learning, Random Forest, ESP32, Sensor Fusion, Food Safety, Cold Chain Monitoring, Multi-Parameter Sensing, Smart Food Monitoring.*

I. INTRODUCTION

Food spoilage is a significant global concern that affects food safety, public health, and the efficiency of supply chain management. According to the Food and Agriculture Organization (FAO), a substantial portion of food produced worldwide is lost or wasted annually due to improper storage, transportation, and delayed detection of spoilage. Perishable food products such as fruits, vegetables, dairy products, meat, and seafood are highly sensitive to environmental conditions including temperature, humidity, microbial activity, and gas emissions. Failure to monitor these parameters can lead to rapid deterioration of food quality, resulting in economic losses and increased risks of foodborne diseases.

Traditional food freshness assessment methods primarily rely on visual inspection, odor evaluation, and manual testing. Although widely practiced, these techniques are subjective, inconsistent, labor-intensive, and unsuitable for continuous or large-scale monitoring applications. As modern food supply chains demand real-time quality assessment, there is an increasing need for intelligent systems capable of accurately predicting spoilage before visible signs appear.

Recent advancements in the Internet of Things (IoT) and Artificial Intelligence (AI) have enabled the development of smart food monitoring systems that integrate sensor networks with machine learning algorithms. IoT-based sensing devices continuously collect environmental and physical parameters, while machine learning techniques analyze complex relationships among multiple variables to predict food quality with improved accuracy. Such intelligent monitoring systems facilitate early spoilage detection, optimize storage conditions, and reduce unnecessary food waste.

This paper presents an **AI-Based Multi-Parameter Food Spoilage Prediction System** that combines IoT-enabled sensing with a Random Forest machine learning classifier for real-time food freshness prediction. The proposed system integrates an MQ135 gas sensor, DS18B20 temperature sensor, DHT22 humidity sensor, soil moisture sensor, and a load cell with an HX711 amplifier to monitor critical spoilage-related parameters. An ESP32 microcontroller acquires and transmits sensor data, while the machine learning model classifies food into four freshness categories: **Fresh, Early Spoilage, Unsafe, and Spoiled**. The system also performs cold-chain monitoring by continuously tracking storage temperature and generating alerts when predefined safety limits are exceeded. By employing sensor fusion and predictive analytics, the proposed approach improves the reliability and accuracy of spoilage detection compared with conventional single-parameter methods. The developed system provides a low-cost, scalable, and intelligent solution for real-time food quality monitoring, helping to minimize food wastage, enhance consumer safety, and support efficient storage and transportation in modern food supply chains.

II. MATERIAL AND METHODS

The proposed **AI-Based Multi-Parameter Food Spoilage Prediction System** was developed using IoT hardware components integrated with a machine learning framework to enable real-time monitoring and prediction of food freshness. The system combines multiple sensors with an ESP32 microcontroller to acquire environmental and physical parameters associated with food spoilage. The collected data is processed using a Random Forest classifier to determine the freshness status of food.

The hardware components used in the proposed system are summarized below:

ESP32 Microcontroller:

The ESP32 serves as the central processing unit of the system. It acquires data from all connected sensors, performs preliminary data processing, and transmits the sensor readings to the machine learning model through serial communication. Its built-in Wi-Fi capability also enables future cloud-based monitoring and IoT applications.

MQ135 Gas Sensor:

The MQ135 sensor detects gases such as ammonia (NH_3), carbon dioxide (CO_2), and volatile organic compounds (VOCs) released during food decomposition. Gas concentration is one of the primary indicators of microbial spoilage and is used as an important input feature for prediction.

DS18B20 Temperature Sensor:

The DS18B20 digital sensor continuously measures the storage temperature with high accuracy. Temperature plays a crucial role in preserving food quality and maintaining cold-chain conditions.

DHT22 Humidity Sensor:

The DHT22 sensor measures relative humidity around the stored food. High humidity accelerates microbial growth and influences the rate of spoilage. The sensor provides stable and accurate digital measurements for real-time monitoring.

Soil Moisture Sensor:

A soil moisture sensor is repurposed to detect surface moisture changes in food. Increased moisture due to microbial activity serves as an early indicator of spoilage and enhances prediction accuracy when combined with other sensor parameters.

Load Cell with HX711 Amplifier:

The load cell measures changes in food weight during storage, while the HX711 module amplifies and digitizes the load cell output. Weight variation resulting from moisture loss and decomposition provides additional information regarding spoilage progression.

Buzzer:

A buzzer is incorporated as an alert mechanism to notify users whenever the predicted spoilage level reaches unsafe conditions or abnormal environmental parameters are detected.

Software Requirements

The software platform consists of **Arduino IDE** for programming the ESP32 and **Python** for machine learning implementation. The Random Forest classifier is developed using the **Scikit-learn** library, while **Pandas** is used for data preprocessing and **Joblib** is employed to save and load the trained model. Real-time communication between the ESP32 and the prediction model is established through serial communication (UART).

Machine Learning Dataset

A labeled dataset containing sensor readings for **temperature, humidity, gas concentration, surface moisture, and food weight** was used to train the Random Forest classifier. Each dataset instance was assigned one of four freshness labels: **Fresh, Early Spoilage, Unsafe,** or **Spoiled**. The trained model was subsequently used to classify real-time sensor data collected from the hardware prototype.

Procedure methodology

The proposed AI-Based Multi-Parameter Food Spoilage Prediction System integrates Internet of Things (IoT) technology with machine learning to enable real-time monitoring and prediction of food freshness. The overall methodology consists of sensor data acquisition, data preprocessing, machine learning-based classification, and real-time monitoring with alert generation.

2.1 System Architecture

The system comprises an ESP32 microcontroller interfaced with an MQ135 gas sensor, DS18B20 temperature sensor, DHT22 humidity sensor, soil moisture sensor, and a load cell coupled with an HX711 amplifier. Each sensor continuously monitors a specific parameter associated with food spoilage, including gas concentration, temperature, humidity, surface moisture, and weight. The ESP32 collects sensor readings at regular intervals and transmits the processed data to the machine learning module through serial communication.

2.2 Sensor Data Acquisition

Real-time sensor data are collected simultaneously from all sensing devices. The MQ135 sensor detects gases generated during microbial decomposition, while the DS18B20 and DHT22 sensors monitor storage temperature and relative humidity, respectively. The soil moisture sensor measures changes in surface moisture caused by spoilage, and the load cell records weight variations due to moisture loss and decomposition. These parameters provide complementary information for comprehensive spoilage assessment.

2.3 Data Preprocessing

The acquired sensor readings are preprocessed before being supplied to the machine learning model. Analog sensor outputs are converted into digital values using the ESP32's analog-to-digital converter (ADC). Gas sensor readings are normalized, moisture values are calibrated, and noisy weight measurements are filtered to improve data quality. Temperature and humidity values are validated before transmission. The processed data are organized into a structured feature vector containing temperature, humidity, gas concentration, moisture level, and weight.

2.4 Machine Learning Model

A **Random Forest** classifier was selected because of its robustness, high classification accuracy, and ability to model nonlinear relationships among multiple input features. A labeled dataset containing sensor measurements corresponding to four food freshness categories—**Fresh, Early Spoilage, Unsafe,** and **Spoiled**—was used to train the model. The dataset was divided into training and testing subsets, and the classifier learned decision boundaries from the sensor patterns. After training, the model was saved and deployed for real-time prediction using the Scikit-learn library.

2.5 Real-Time Prediction

During system operation, the ESP32 continuously transmits sensor readings to the trained Random Forest model. The model processes the incoming feature vector and predicts the current freshness stage of the food sample. In addition to classification, the system estimates a spoilage index and the remaining shelf life using the collected sensor parameters. The prediction results are immediately transmitted back to the ESP32 for user notification.

2.6 Alert Generation and Monitoring

The predicted spoilage status is displayed through the monitoring interface, and a buzzer is activated whenever unsafe storage conditions or advanced spoilage stages are detected. The system also performs continuous cold-chain monitoring by tracking storage temperature and generating alerts when predefined temperature thresholds are exceeded. This enables early intervention to maintain food quality during storage and transportation.

2.7 Overall Workflow

The proposed methodology follows the sequence:

1. Acquisition of multi-parameter sensor data.
2. Data preprocessing and normalization.
3. Transmission of processed data to the machine learning model.
4. Classification of food freshness using the Random Forest algorithm.
5. Estimation of spoilage level and shelf life.
6. Display of prediction results and activation of alerts for unsafe conditions.

This integrated methodology enables accurate, real-time food spoilage prediction by combining IoT-based sensing, sensor fusion, and machine learning, thereby improving food safety while reducing food wastage

III. RESULT

The proposed AI-Based Multi-Parameter Food Spoilage Prediction System was successfully implemented and evaluated using an ESP32-based hardware prototype integrated with multiple sensors and a Random Forest machine learning classifier. The system continuously monitored temperature, humidity, gas concentration, surface moisture, and weight to determine the freshness status of food in real time.

The experimental results demonstrated that each sensor contributed valuable information for spoilage detection. The MQ135 gas sensor recorded a gradual increase in volatile gas concentration as decomposition progressed, while the DHT22 humidity sensor detected increasing humidity levels associated with microbial growth. The DS18B20 temperature sensor effectively monitored storage conditions, confirming that elevated temperatures accelerated food spoilage. Similarly, the soil moisture sensor identified increasing surface moisture during decomposition, and the load cell measured gradual weight loss caused by moisture evaporation and structural degradation.

The Random Forest classifier successfully processed the fused sensor data and classified food samples into four freshness categories: **Fresh, Early Spoilage, Unsafe,** and **Spoiled**. Compared with single-parameter monitoring approaches, the proposed multi-sensor fusion strategy produced more reliable predictions by simultaneously analyzing environmental and physical characteristics of food. The system was able to identify early spoilage conditions before obvious visual deterioration occurred, enabling timely intervention.

Real-time communication between the ESP32 microcontroller and the machine learning model was achieved through serial communication, allowing continuous prediction without noticeable delay. The monitoring interface displayed live sensor readings, predicted spoilage status, spoilage index, and estimated shelf life. Whenever unsafe conditions or advanced spoilage stages were detected, the buzzer generated immediate alerts to notify the user.

Representative experimental observations are summarized in Table 1.

Temperature (°C)	Humidity (%)	Gas Level	Moisture	Weight Condition	Predicted Status
25	60	Low	Low	Stable	Fresh
28	65	Medium	Medium	Slight Weight Loss	Early Spoilage
32	70	High	High	Moderate Weight Loss	Unsafe
35	80	Very High	Very High	Significant Weight Loss	Spoiled

Table 1. Sample Sensor Readings and Predicted Food Condition

The experimental evaluation confirms that integrating multiple sensing parameters with a Random Forest classifier significantly improves the reliability of food spoilage prediction. The proposed system enables continuous monitoring, early spoilage detection, and intelligent decision-making, making it suitable for applications in food storage facilities, cold-chain logistics, supermarkets, and household food monitoring systems.

IV. DISCUSSION

The experimental results demonstrate the effectiveness of the proposed AI-Based Multi-Parameter Food Spoilage Prediction System in accurately assessing food freshness using IoT-based sensing and machine learning. Unlike conventional methods that rely on manual inspection or a single sensing parameter, the proposed system integrates multiple environmental and physical indicators, including gas concentration, temperature, humidity, surface moisture, and weight. This multi-parameter approach provides a more comprehensive understanding of the spoilage process and improves prediction reliability.

Among the monitored parameters, gas concentration measured by the MQ135 sensor showed a strong correlation with microbial decomposition, while temperature and humidity significantly influenced the rate of spoilage. Surface moisture and weight variation provided additional evidence of physical degradation, enabling the system to identify spoilage at an earlier stage. The integration of these complementary parameters through sensor fusion reduced the limitations associated with individual sensors and enhanced the overall robustness of the prediction model.

The Random Forest classifier effectively analyzed the collected sensor data and successfully categorized food samples into four freshness levels: **Fresh, Early Spoilage, Unsafe,** and **Spoiled**. Its ensemble-learning approach allowed the model to capture complex nonlinear relationships among multiple input features, resulting in stable and reliable predictions even when sensor readings exhibited minor fluctuations. The real-time implementation demonstrated efficient communication between the ESP32 microcontroller and the machine learning model, enabling continuous monitoring with minimal processing delay.

The proposed system also supports cold-chain monitoring by continuously observing storage temperature and generating timely alerts when predefined safety thresholds are exceeded. This capability is particularly beneficial for food storage facilities, transportation systems, supermarkets, and warehouse environments, where maintaining proper storage conditions is essential for preserving food quality and reducing economic losses.

Although the developed prototype demonstrated satisfactory performance, certain limitations remain. The prediction model was trained using a limited dataset collected under controlled experimental conditions. Expanding the dataset to include a wider variety of food products and storage environments would improve the model's generalization capability. Furthermore, integrating advanced deep learning techniques, cloud-based analytics, and computer vision for visual inspection could further enhance prediction accuracy and support large-scale deployment.

Overall, the findings indicate that the proposed AI-based multi-parameter monitoring system provides a reliable, scalable, and cost-effective solution for real-time food spoilage prediction. By combining IoT-enabled sensor fusion with machine learning, the system contributes to improved food safety, reduced food wastage, and more efficient management of modern food supply chains.

V. CONCLUSION

This paper presented an **AI-Based Multi-Parameter Food Spoilage Prediction System** that integrates Internet of Things (IoT) technology with machine learning for real-time food freshness assessment. The proposed system utilizes multiple sensors, including the MQ135 gas sensor, DS18B20 temperature sensor, DHT22 humidity sensor, soil moisture sensor, and load cell with an HX711 amplifier, to continuously monitor key environmental and physical parameters associated with food spoilage. A Random Forest classifier analyzes the fused sensor data to classify food into four freshness categories: **Fresh, Early Spoilage, Unsafe,** and **Spoiled**, while also supporting shelf-life estimation and cold-chain monitoring.

The experimental results demonstrate that the proposed multi-parameter approach provides more reliable and accurate spoilage prediction than conventional single-parameter or manual inspection methods. The integration of sensor fusion and machine learning enables early detection of spoilage, continuous monitoring, and timely alert generation, thereby improving food safety and minimizing food wastage. Furthermore, the ESP32-based architecture offers a low-cost, scalable, and energyefficient platform suitable for practical deployment in food storage facilities, transportation systems, supermarkets, and household applications.

Overall, the proposed system successfully combines IoT-enabled sensing and artificial intelligence to provide an intelligent solution for food quality monitoring. Future work may focus on expanding the training dataset, incorporating deep learning and computer vision techniques, deploying cloud-based analytics, and developing mobile applications for remote monitoring. These enhancements have the potential to further improve prediction accuracy, system scalability, and applicability in modern smart food supply chain management.

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