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An Integrated Approach to Spoiled Food Detection in IoT: Combining Gas Sensor Technology and Machine Learning

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Abstract - This research presents a hybrid solution for the timely and accurate detection of spoiled food in an Internet of Things (IoT) environment. The proposed system integrates hardware-based sensing with a machine learning (ML) model to enhance the efficiency and reliability of food quality assessment. The hardware component utilizes an MQ3 gas sensor interfaced with a Raspberry Pi, designed to detect specific gases emitted by spoiled food items. The real-time gas concentration data is transmitted to the ThingSpeak server, providing a continuous monitoring system for potential spoilage indicators. In parallel, a robust ML model is developed using a diverse dataset of annotated images featuring both spoiled and fresh fruits. The model, trained on a convolutional neural network (CNN), is adept at classifying the visual attributes associated with food spoilage. The ML model is implemented for on-device processing, enabling rapid and accurate assessment of food quality based on images captured by an embedded camera.

Key Words: Food spoilage detection, IOT, MQ3, Raspberry Pi, Machine Learning.

1. INTRODUCTION

In an era marked by rapid technological advancements, the convergence of hardware-based sensing and machine learning has paved the way for transformative innovations across various domains. One critical application that stands to benefit significantly is the detection of spoiled food, an essential aspect of ensuring food safety and quality in a globalized supply chain. This research introduces a pioneering hybrid approach that synergizes Internet of Things (IoT) technology [1,2]., gas sensor hardware, and machine learning to create a robust system for real-time spoiled food detection.

The escalating demand for efficient and reliable methods of monitoring food freshness has spurred the development of diverse technologies. In this context, our approach integrates MQ3 gas sensors with a Raspberry Pi, providing a hardware-centric solution to detect specific gases emitted by deteriorating food items. Simultaneously, we harness the power of machine learning by developing a convolutional neural network (CNN) [3] trained on a comprehensive dataset of annotated images depicting both fresh and spoiled fruits.

This fusion of hardware and software creates a dynamic system capable of capturing multi-modal indicators of food spoilage. The gas sensor component offers real-time monitoring of volatile compounds, while the machine learning model leverages visual cues to assess the quality of fruits. The seamless integration of these technologies not only enhances the accuracy of detection but also enables a timely response to potential spoilage events. As we delve into the intricacies of our hybrid approach, this research aims to contribute not only to the field of IoT-enabled food monitoring but also to the broader landscape of sensor integration and machine learning applications. The subsequent sections detail the methodology, experiments, and results, highlighting the effectiveness and versatility of our proposed system in addressing the challenges of modern food quality assurance.

2. METHODOLOGY

The methodology for this study encompasses a multi-faceted approach to advance the field of spoiled food detection within an Internet of Things (IoT) framework. Fig 1 shows the circuit diagram of the project.

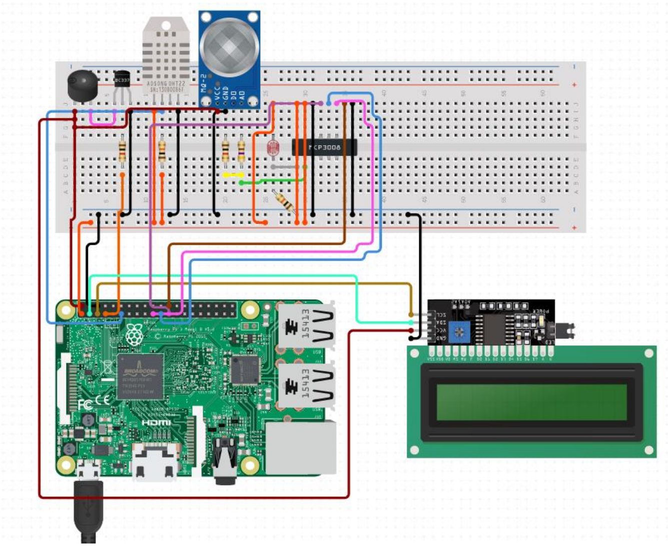

Fig -1: Circuit diagram of the system

The hardware components utilized in this study include a Raspberry Pi 3 - Model B, featuring an ARMv8 processor with 1GB of RAM, which serves as the central processing unit for seamless data acquisition, real-time processing, and system control. A Piezo Buzzer is incorporated into the system to provide audible alerts, enhancing the user experience by offering immediate feedback during operation or in case of system events. A 1K Ohm Resistor is integrated into the circuit for precise impedance matching and signal conditioning, ensuring accurate data transmission and stable circuit performance. Additionally, a 16x2 LCD Display Screen with I2C interface is included as a visual output device, delivering real-time system information through an efficient two-wire communication protocol, thereby minimizing wiring complexity and enhancing the system's overall reliability and usability.

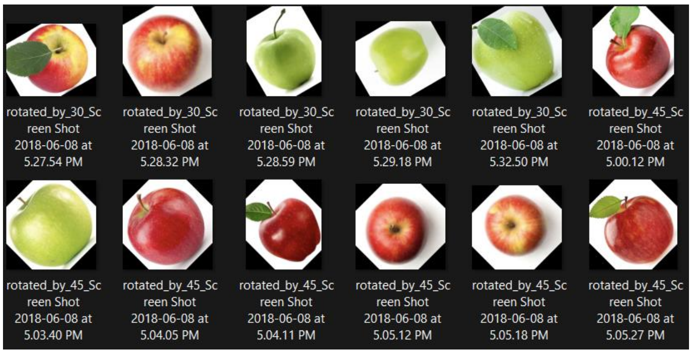

Fig-1: Sample images used for ML model creation: Fresh fruits

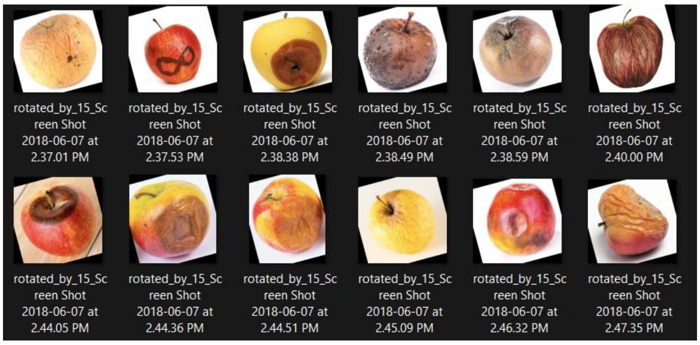

Fig- 2: Sample images used for ML model creation: Spoiled fruit

For gas sensing capabilities, the Methane, Butane, and Smoke Gas Sensor (MQ-3) is employed to detect specific volatile organic compounds (VOCs) emitted by deteriorating food items. The MQ-3 operates on a tin dioxide (SnO_2) sensing layer, which exhibits low conductivity in clean air but significantly increases in the presence of target gases. Its high sensitivity and fast response time make it an ideal choice for identifying gases indicative of food spoilage.

An LDR (Light Dependent Resistor) is integrated into the system to monitor ambient light conditions, which play a crucial role in controlling the exposure of food items to light, a factor known to accelerate spoilage in certain cases. The LDR's resistance variation with light intensity allows the system to adapt dynamically by adjusting operational parameters based on environmental lighting. To ensure precise processing of sensor outputs, the MCP3008 - 8-Channel 10-Bit ADC with SPI Interface is utilized. This ADC converts the analog signals from sensors like the MQ-3 and LDR into digital signals that the Raspberry Pi can interpret. Its 10-bit resolution enables high accuracy, translating sensor voltages into a digital format with a resolution of up to 2^{10}=1024 levels. The SPI (Serial Peripheral Interface) communication ensures rapid and efficient data transfer, allowing real-time monitoring and decision-making.

The DHT22 (AM2302) further enhances the system's sensing capabilities by serving as a temperature and humidity sensor. With a wide operating range of -40°C to 80°C for temperature and 0–100% for relative humidity, along with a high precision of ±0.5°C for temperature and ±2% for humidity, the DHT22 [4] provides accurate environmental data critical for assessing food storage conditions. Its ability to output calibrated digital signals simplifies integration with the Raspberry Pi, reducing computation overhead while maintaining reliability. This combination of hardware components is carefully selected to provide an integrated and effective solution within the Internet of Things (IoT) framework. The synergy between the MQ-3 for gas detection, the LDR for light monitoring, the MCP3008 for precise ADC functionality, and the DHT22 for environmental data collection ensures comprehensive monitoring of factors influencing food freshness.

Together, these elements enable a robust, scalable, and adaptable platform for real-time food quality assessment and environmental monitoring. Initial efforts involve the compilation of a diverse dataset comprising high-resolution images depicting various fruits at different stages of spoilage, subsequently annotated to create a ground truth for machine learning model training. Preprocessing steps standardize and augment the dataset, enhancing the robustness of the convolutional neural network (CNN) model selected for image classification. Fig-2 and Fig-3 show the screenshots of the image dataset of fresh and spoiled food respectively.

The CNN model and gas sensor system are harmoniously merged to form a cohesive solution. A control system on the Raspberry Pi coordinates data transmission to the ThingSpeak server, facilitating centralized monitoring. Real-time monitoring in a controlled environment is undertaken to assess system performance, with continuous optimization and calibration iterating upon the integrated solution. Validation and comparative analyses against traditional methods, along with a comprehensive results analysis, form the basis for the evaluation of the proposed methodology's efficacy in detecting spoiled food, thereby

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contributing to the evolution of IoT-enabled food quality monitoring systems.

3. RESULTS AND DISCUSSION

The data uploaded to the IoT server reveals a strong alignment with the testing conditions, affirming the reliability of the system in capturing and transmitting real-time information. Fig-4 specifically illustrates the data obtained from the MQ sensor, indicating its responsiveness to variations in the presence of both good and spoiled food.

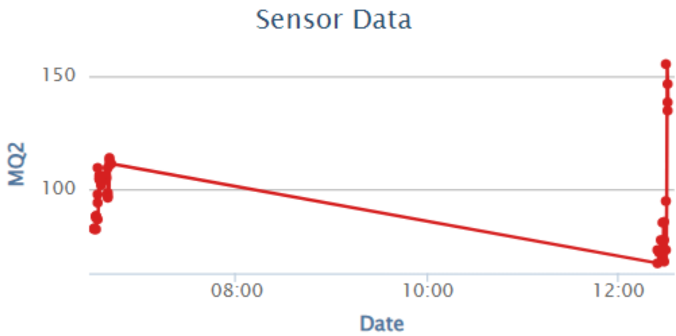

Fig- 3: MQ Sensor data recorded in the IOT server

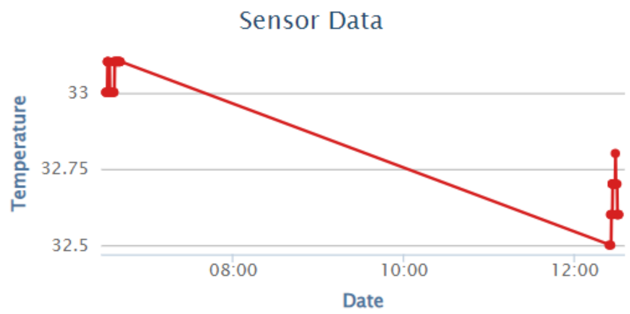

Fig- 4: Temperature sensor data recorded in the IOT server

The sensor's sensitivity to changes in gas concentrations serves as a valuable indicator for the detection of potential food spoilage events. The distinct patterns observed in the sensor readings during different test scenarios underscore the system's ability to discriminate between the presence of good and spoiled food based on the emitted gases. The DHT22 temperature data was validated with the help of a digital thermometer, a good accuracy was obtained. Fig- 5 and Fig-6 show the measured temperature and humidity data respectively.

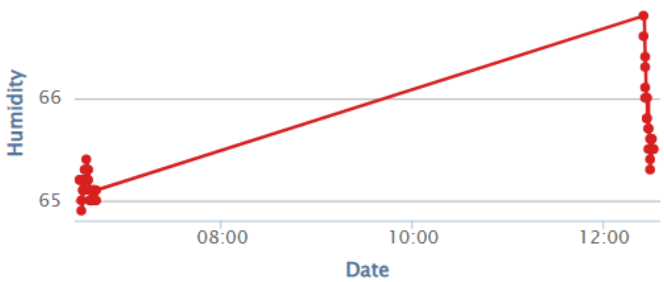

Fig- 5: In situ Humidity data recorded at IOT server

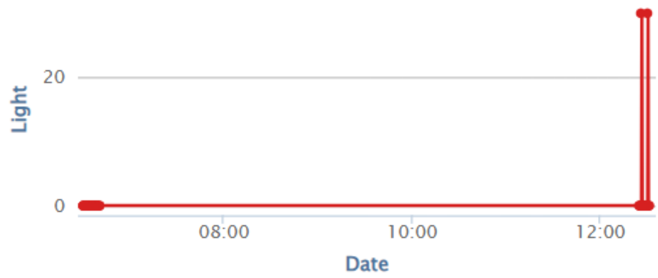

Fig- 6: Light sensor data recorded in the IOT server

To ensure the tests are carried out inside a dark chamber, we used an LDR sensor. In dark conditions, its values are around 0 and in light conditions, it is around 30 as shown in Fig- 7. The overall recorded data is shown in Table 1. This data also can be used for Machine learning prediction purposes which is a future objective of this work.

For the machine learning (ML) component, we demonstrated the effectiveness of a Convolutional Neural Network (CNN) implemented using TensorFlow and Keras for this application [5–8]. The CNN architecture consisted of sequential convolutional layers, each followed by ReLU (Rectified Linear Unit) activation functions and max-pooling layers, which were then connected to fully connected (dense) layers. This architecture showcased robustness in learning hierarchical features from the input images, critical for distinguishing between fresh and rotten food.

CNN Mathematical Formulation

1. Convolutional Layer

The convolutional layer extracts spatial features from the input using a set of learnable filters (kernels). Each filter slides over the input image to compute feature maps using

$$Z_{ij}^{k} = (X * W^{k})_{ij} + b^{k}$$

Where

X is the input matrix (image or feature map).

W^k is the kernel for the k-th filter.

b^k is the bias term.

* denotes the convolution operation.

Z_{ij}^{k} is the resulting feature map value at position (i,j)

2. ReLUActivation

To introduce non-linearity, the ReLU activation is applied:

$$A_{ij}^{k} = \max(0, Z_{ij}^{k})$$

Where A_{ij}^{k} is the activated feature map.

3. Max-Pooling Layer

Max-pooling reduces the spatial dimensions of the feature maps, helping to down-sample and make the model translation-invariant

$$P_{ij}^{k} = \max\{A_{m,n}^{k} \mid (m,n) \in \text{pooling window}\}$$

Where P_{ij}^{k} represents the pooled feature map.

4. **Fully Connected (Dense) Layer**

Flattened feature maps are fed into dense layers for classification. The output is computed as

$$Y = \sigma(W^T X + b)$$

where

W is the weight matrix.

b is the bias vector.

σ is the activation function

To improve generalization and prevent overfitting, data augmentation was applied using the ImageDataGenerator. This method exposed the model to a diverse set of transformations, including rotations, translations, flips, and zooms, effectively expanding the variability of the training dataset. The model was trained for 10 epochs on a dataset stored in the 'train/' directory, which consisted of two subdirectories: 'freshfood' and 'rottenfood.' The training process was validated using a separate dataset located in the 'test/' directory. During training, the model demonstrated consistent improvement in both training and validation accuracy over the epochs. The learning process achieved a final accuracy of 97%

The results indicate that the implemented CNN, trained on a dataset of food images, can effectively detect and classify spoiled food items. The combination of visual cues and potential environmental factors positions the project as a promising step toward the development of a robust food spoilage detection system with applications in food safety and quality assurance. These results showcase its potential applications in smart agriculture, supply chain management, and food safety industries. The adaptability of the proposed solution positions it as a versatile tool for diverse IoT applications requiring both hardware-based sensing and machine-learning capabilities. As technology continues to advance, our hybrid approach serves as a model for addressing complex challenges in real-world scenarios, offering a scalable and efficient solution to enhance the quality and safety of perishable goods throughout the supply chain.

4. CONCLUSION

In conclusion, our hybrid approach to spoiled food detection, combining hardware-based gas sensing with machine learning, presents a robust and versatile solution for real-time food quality assessment in an Internet of Things (IoT) environment. The integration of MQ3 gas sensors with a Raspberry Pi, coupled with the development of a convolutional neural network (CNN) based on a diverse dataset of fruit images, demonstrates the effectiveness of a multi-modal approach. The hardware component provides a reliable mechanism for detecting volatile gases emitted by spoiled food items, offering an immediate and continuous monitoring system. Simultaneously, the ML model enhances the system's adaptability by providing an image-based classification of food quality. The synergy between these methods ensures a comprehensive and timely assessment of food freshness.

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