Smart Iot & ML System for Food Monitoring

Surya HA
Amrita School of Artificial Intelligence
Amrita Vishwa Vidyapeetham
Coimbatore, India
cb.sc.u4aie23267@cb.students.amrita.edu

K S Venkatram
Amrita School of Artificial Intelligence
Amrita Vishwa Vidyapeetham
Coimbatore, India
cb.sc.u4aie23236@cb.students.amrita.edu

Vishal Seshadri B
Amrita School of Artificial Intelligence
Amrita Vishwa Vidyapeetham
Coimbatore, India
cb.sc.u4aie23260@cb.students.amrita.edu

Sanggit Saaran K C S
Amrita School of Artificial Intelligence
Amrita Vishwa Vidyapeetham
Coimbatore, India
cb.sc.u4aie23247@cb.students.amrita.edu

***Abstract*—Food wastage and poor storage management are worldwide problems, with a third of food wasted because of poor monitoring. This paper introduces an IoT and ML system that solves these problems through automated monitoring of food. Our solution integrates ESP32 microcontrollers, RFID sensors, and DHT22 sensors with MobileNetV2 and SVM algorithms to facilitate real-time inventory tracking and freshness evaluation. A Random Forest model predicts expiration dates, whereas the LLM creates recipes based on ingredients available. Success- ful integration and optimal performance of the system is verified through testing. By adopting this method food wastage can be reduced and enhances efficiency through smart automation.**

***Index Terms*—Internet of Things (IoT), Machine Learning, Food Monitoring, Computer Vision, Support Vector Machine, Random Forest, Large Language Models, RFID Technology**

I. Introduction

Maintaining the quality of perishable food products has always been a challenge, with traditional solutions relying significantly on manual logging and time sensitive tracking. Even with advances in refrigerator technology, the core problem of tracking freshness of food and stock continues to remain inadequately solved. Our work explores the integration of IoT and artificial intelligence to develop an end-to-end solution that not only tracks food conditions but also actively assists users in effective usage of their food products.

Mallikarjun et al. [1] developed a smart model of refrigeration that combines seamlessly IoT sensors with a machine learning-based recipe suggestion capability to boost kitchen automation. It allows the real-time monitoring of food products by using sensors like IR, ultrasonic, and load cells connected to a Raspberry Pi controller. There is ongoing data updating and storage within Firebase, and an Android app shows inventory levels as well as enables users to order groceries. A camera module built into the fridge takes vegetable photos on user demand through MQTT protocol. With the help of OpenCV and K-means clustering, vegetables are detected by color and edges in order to recommend appropriate recipes.

Jessica Velasco et al. [2] developed a system that combines a conventional refrigerator, microcontrollers and a smart phone to create an inventory monitoring that can monitor the stocks inside the refrigerator wirelessly by accessing an Android application.The developed refrigerator used a sensor network system that is installed in a respective compartment inside the refrigerator. Kiran B et al. [3] has developed a user-friendly IoT-based smart refrigerator system using Raspberry Pi as the central control unit. It integrates a Pi Camera for real-time visual monitoring and egg counting through image processing. Load cells are employed to track the weight and quantity of items, while a gas sensor detects spoiled vegetables. The NodeMCU module ensures wireless connectivity, and the DHT sensor monitors internal temperature and humidity. A GSM modem enables SMS alerts in the absence of internet.

Avinash N.J et al. [4] presented a IOT- based smart refrigerator using Raspberry Pi. The system integrated camera modules, load cells, gas sensors, and CNN algorithms for food classification and spoilage detection. The system monitored weight, expiry date, and quality of stored items to reduce food wastage. Object detection and classification was achieved through CNN.Devanath B et al. [5] presented a smart refrigerator system using IoT and machine learning. Raspberry Pi 5 acted as the core processor, connecting sensors and maaging data flow. The fridge contents images are captured using the cameras and object detection performed using a CNN model.

Almassar K.M et al. [6] presented a systematic review using PRISMA guidelines to expore how IOT and AI are applied in smart refrigerators and food storage systems. The authors analysed key componenets like sensors, cloud platforms, and image processing units used in these systems. A decision tree model was used to identify patterns in component use and system design. Gupta S et al. [7] proposed a smart refrigerator system that utilised IoT to monitor both weight and temperature of food items.A load cell with HX711 measured food weight, while a thermistor senses temperature using voltage divider logic.An Android application was made for processing and displaying the data. Users can monitor contents remotely and control temperature manually. The system enhances convenience and food management, with potential for future features like freshness detection. Md. Johirul Islam Tutul et al. [8] developed a smart food monitoring system using IoT and machine learning models to improve food safety, reduce wastage of food due to spoilage. Their system integrates temperature, humidity and gas sensors with microcontrollers to monitor food freshness in real time. All of their sensor data is analyzed using machine learning algorithms to predict spoilage. They developed a mobile based dashboard which displays environmental conditions of the storage unit and sends alerts when threshold temperature value is crossed. Their system was evaluated on various food items and showed high accuracy in freshness prediction. Additionally, the use of methane gas detection and cloud-based data visualization improved it's reliability and usability in both personal and industrial food storage applications. Mrs. R. Vasanthi et al. [9] developed an IoT-based food quality monitoring system using sensors like temperature, humidity, pH, and gas sensors to track food conditions in real-time. Their system uses machine learning algorithms such as Logistic Regression, SVM, Decision Tree, and Random Forest for quality prediction. Among those models, Logistic Regression achieved the highest accuracy of all resulting in 82% while classifying food as fresh or spoiled. Their data where collected via Arduino and ESP8266 modules which are then processed, and displayed on an LCD interface with alerts provided through buzzer sounds. Their system effectively reduces food waste and enhances food safety through real time monitoring. Prabhakar Krishnan et al. [10] developed an AI-powered intelligent IoT system for real-time food quality monitoring across a supply chain. Their system uses smart sensors and a CNN algorithm to evaluate freshness based on environmental factors like temperature and humidity. Their model achieved an accuracy of 95.2% and had a precision across transportation of (96.3%), storage (94.7%) and processing (92.1%) stages. Their approach demonstrates strong adaptability under varying conditions and enables secure monitoring. This solution offers a robust method to improve food safety, reduce spoilage and ensures quality throughout the supply chain.

1) Key Contributions:

- **Feature Extraction:** MobileNetV2 (CNN) extracts meaningful features from food images for effective classification.
- **Data Processing:** IoT devices like the ESP32, RFID, and DHT22 sensors collect and transmit real-time data for accurate monitoring.
- **Food Classification:** Support Vector Machine (SVM) is used to classify food freshness (fresh vs. rotten) and identify food types.
- **Expiry Prediction:** Random Forest model predicts food spoilage based on environmental data like temperature and humidity.
- **Smart Recipe Suggestions:** LLM generates recipes using available and expiring ingredients to minimize food waste.

II. METHODOLOGY

A. Proposed System

The proposed system integrates IoT and ML techniques to monitor classify the food items efficiently. It uses RFID sensor and DHT22 sensor and the ESP32 module to collect real-time data from appliances. MobileNetV2 (CNN) is used for lightweight and fast feature extraction from the sensor data. These features are then classified using Support Vector Machine (SVM) to recognize food items accurately.

Our workflow of smart food monitoring system integrates IoT and Machine Learning to enhance food safety and reduce food wastage as presented in Figure I. Our system uses an IP webcam and RFID sensors to capture food details and manage stock updates in real time. MobileNetV2 is used for deep feature extraction from food images, and Support Vector Machine (SVM) classifiers are applied to determine freshness and classify food types. Temperature and humidity sensor(DHT22) assures proper storage conditions, while a Random Forest model predicts food expiration. Furthermore, a recipe generation module powered by LLM suggests meal ideas based on the available ingredients, prioritizing items nearing expiration to minimize food wastage.

In the proposed smart food classification system that identifies both the freshness and type of food items using deep feature extraction with MobileNetV2 and classification through Support Vector Machines (SVM).

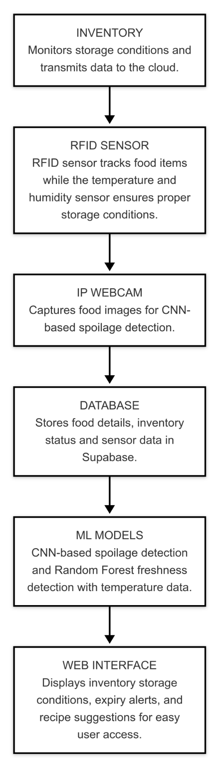

Fig. 1. Workflow of the Proposed Architecture

B. Dataset Organization and Preprocessing

The dataset used is ”Fruits and Vegetables Dataset” consists of 120000 overall images of fruits and vegetables divided into two broad classes— Fruits and Vegetables, with subfolders representing freshness.(FreshApple, RottenApple..,etc).

- **Image Selection:** To ensure balanced representation and computational efficiency, 400 images per class were loaded.
- **Labeling:** A binary label was assigned for freshness detection: 0 for fresh and 1 for rotten. A multi-class label was used for identifying the food type (e.g., Apple, Tomato), using the index of the subfolder.
- **Preprocessing:** Images were resized to 224×224 pixels to match the input dimensions of MobileNetV2.

C. Feature Extraction Using MobileNetV2

To extract complex features from input images, we employed a pre-trained MobileNetV2 model as our feature extractor. MobileNetV2 is a lightweight convolutional neural network architecture optimized for deployment in resource-constrained environments. It is particularly well-suited for real-time applications—such as those in the IoT domain—due to its use of depthwise separable convolutions and inverted residual connections.

The feature extraction process was conducted as follows:

- The MobileNetV2 model was initialized with ImageNet-pretrained weights, excluding the top classification layers by setting `include_top=False`. This ensured the use of only the convolutional base for feature extraction.
- Input images were passed through the convolutional layers of the network. The output from the final convolutional block was then flattened into a one-dimensional vector, producing a compact and discriminative feature representation.
- These feature vectors, capturing abstract visual characteristics such as texture, shape, and color, were subsequently used as input for classical machine learning classifiers.

The feature vector $\mathbf{x}$ is computed from the input image using the MobileNetV2 model as follows:
Mathematically, let $I \in \mathbb{R}^{224\times224\times3}$ denote an input image. The corresponding feature vector $\mathbf{x} \in \mathbb{R}^d$ is computed as:

$$\mathbf{x} = \text{Flatten}(f(I)) \in \mathbb{R}^d \tag{1}$$

where:

- f denotes the MobileNetV2 model used for feature extraction,
- d represents the dimensionality of the resulting feature vector.

D. Classification Using Support Vector Machine (SVM)

Two SVM classifiers were trained on the extracted features for different classification tasks:

- **Freshness Detection (Binary Classification):** This task was framed as a binary classification problem, where the SVM model with an RBF (Radial Basis Function) kernel was used to classify food samples into two categories:
  - 0 = Fresh
  - 1 = Rotten
- **Food Type Classification (Multi-Class Classification):** In this task, an SVM model with an RBF kernel was trained using the same set of feature vectors but with multi-class labels corresponding to specific food types (e.g., apple, tomato, carrot, etc.).

The SVM decision function for classification is defined as:

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b\right) \tag{2}$$

where:

- $K(\mathbf{x}_i, \mathbf{x}) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}\|^2)$ is the RBF (Radial Basis Function) kernel,
- α_i are the learned coefficients,
- y_i are the class labels,
- b is the bias term.

E. Environmental Monitoring and Inventory Tracking

The IOT framework forms the physical layer of the system, enabling continuous and automated data acquisition for food monitoring.

- **Sensing and Data Acquisition:** The system employs the DHT22 sensor for continuous monitoring of temperature and humidity, and the RC522 RFID reader for unique food items indentification. These sensors serve as the edge nodes.
- **Communication:** Hardware component ESP32 communicate with the backend server using serial protocols over COM ports. This dual mode communication ensures flexibility in connecting physical devices to digital platforms.
- **Real-Time Data Exchange using HTTP Protocols:** The backend shows RESTful API endpoints which are continuously accessed by the frontend to retrieve sensor readings and RFID data. This makes sure real-time data synchronization and seamless communication between hardware and user interface.
- **Visual Communication via IP Webcam:**An IP webcam was integrated with the system which streams live footage of the food storage compartment to the frontend. This enhances visibility and supports remote monitoring adding a visual component to the sensory data for a comprehensive environmental awareness.

Hardware Components:

- **ESP32 Microcontroller:**
  It serves as the central control for the system logic and peripheral devices.

- **DHT22 (Temperature and Humidity Sensor):**
  The DHT22 sensor captures the environmental parameters at regular intervals. This data serves for the freshness detection.
- **MFRC522 RFID Module:**
  Detects the presence and removal of the food items. Each food item is mapped with a passive RFID tag, once it senses the tag it constantly gets updated in the web application.
- **IP Webcam:**
  It captures images of contents inside the fridge periodically for ML-Based freshness and categorical classification.

The condition of the storage environment is evaluated using temperature (T) and relative humidity (RH) based on the following logic:

$$\text{Condition}(T, RH) = \begin{cases} 0, & \text{if } 18 \leq T \leq 40 \text{ and } 30 \leq RH \leq 60 \\ 1, & \text{otherwise} \end{cases}$$

Where:

- T is the temperature in degrees Celsius.
- RH is the relative humidity (percentage).
- $\text{Condition}(T, RH)$ returns 0 if the environment is safe and 1 if it is unsafe.

III. RESULTS AND DISCUSSION

TABLE I
PERFORMANCE METRICS OF CLASSIFICATION MODELS

Model	Accuracy	Precision	Recall	F1 Score
Fresh vs. Rotten Classification	0.8833	0.8833	0.8833	0.8833
Food Type Classification	0.6333	0.6930	0.6333	0.6319

Table I presents the performance comparison of two machine learning models integrated into the system. The first model classifies food as either fresh or rotten using image inputs and achieves a balanced performance with an accuracy, precision, recall, and F1 score of 88.33%. This consistency underscores the model's robustness in spoilage detection and highlights its reliability for real-time quality monitoring.

The second model focuses on classifying the type of food based on image data. It achieves a moderate accuracy of 63.33% and a precision of 69.30%, suggesting reasonably correct predictions. However, its recall (63.33%) and F1 score (63.19%) indicate occasional misclassifications, potentially due to visual similarity between food items or limited samples per class. Despite this, the model still adds valuable insight for decision-making, such as personalized recipe suggestions and spoilage trend analysis across different categories.

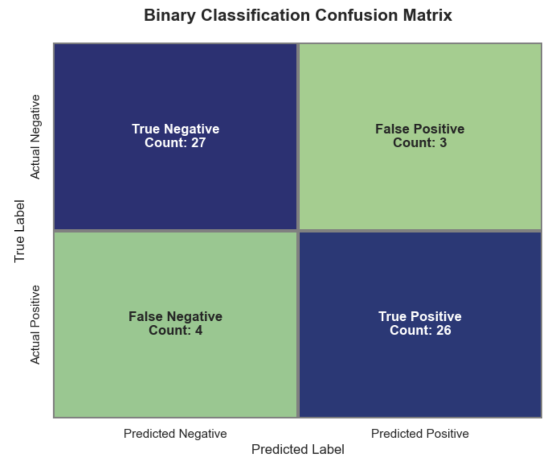

Fig. 2. Confusion Matrix of Model 1

Figure 2 confusion matrix visualizes the performance of the ML model in classifying fresh and rotten items. The model successfully predicted:

- 27 true negatives (correctly identified as rotten),
- 26 true positives (correctly identified as fresh),

with only:

- 3 false positives (rotten predicted as fresh),
- 4 false negatives (fresh predicted as rotten).

This reflects a well-performing model with high reliability in distinguishing between fresh and rotten food items.

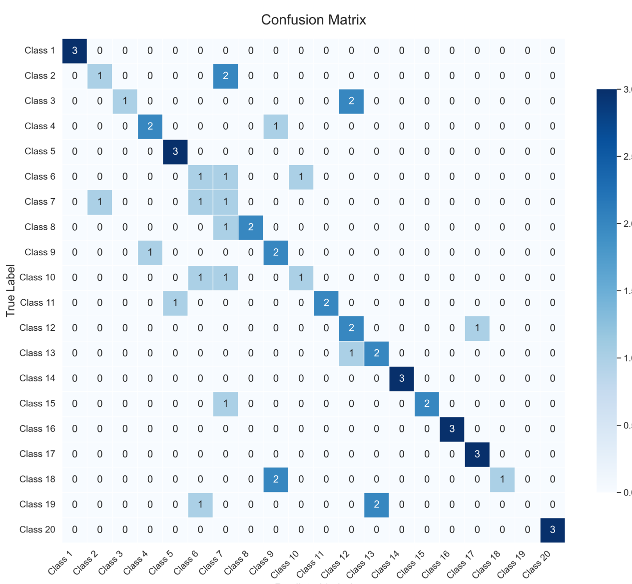

Fig. 3. Confusion Matrix of Model 2

Figure 3 shows the confusion matrix generated by the multi-class classification model used to predict different categories of food freshness and spoilage. The model was evaluated on 20 separate classes, each representing a specific spoilage condition. Correct predictions appear along the diagonal of the matrix, where the predicted class matches the actual class. Off-diagonal values indicate misclassifications between classes.

The model performed well for several classes—such as Class 1, 5, 14, 16, 17, and 20—where all samples were correctly classified. However, some confusion was observed in classes like 2, 7, 10, and 13, where the model sometimes predicted neighboring classes. These results suggest that while the model is generally accurate, it could be improved to better distinguish between similar spoilage categories.

1) Advantages od the proposed Architecture:

- **High Accuracy and Efficiency:** The combination of MobileNetV2 and SVM models ensures precise food classification and freshness detection.
- **Real-Time Inventory Monitoring:** The sensors update about the storage conditions and inventory status via the integration.
- **User-Friendly System:** The web interface displays inventory, spoilage alerts and recipe suggestions for better user interaction.
- **Waste Reduction:** Smart predictions and recipe suggestions helps in reducing food wastage.

IV. CONCLUSION

The proposed system offers a smart, practical solution for everyday food monitoring and management by combining IoT sensors with machine learning and language models. Using MobileNetV2 and SVM, it accurately identifies food items and assesses freshness, while a Random Forest model predicts spoilage ahead of time—helping users reduce waste and make informed decisions.

One of the most helpful features is the intelligent recipe suggestion module powered by LLMs. It suggests creative, personalized recipes based on what's available and what's about to expire, making cooking easier and minimizing waste.

The system has already shown noticeable improvements in how households manage and use food. Its modular, scalable design means it could be just as useful in restaurants, grocery stores, or industrial settings. In short, it's not just about convenience—it's a step toward smarter, more sustainable living. Looking ahead, adding cloud integration and expanding to supply chains could make it even more powerful.

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