INTELLIGENT FOOD SHELF LIFE MONITORING SYSTEM

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***Abstract*—Food is essential for human growth and survival, providing vital nutrients and energy. However, food waste remains a significant global challenge. To address this issue, research has been conducted to develop preventive measures aimed at minimizing food wastage in domestic households. As a solution, a user-friendly, mobile application-based modular intelligence system has been designed to help households monitor the shelf life of food stored in refrigerators and kitchen areas. Major findings indicate that this intelligent food shelf-life monitoring system effectively reduces food waste, provides accurate shelf-life predictions, offers personalized recipe recommendations, and enhances food storage management. The research highlights the transformative role of Artificial Intelligence, Internet of Things, and machine learning in optimizing household food management and minimizing waste. Key insights from the study emphasize improved food utilization, precise freshness predictions, efficient storage management, and a user-friendly modular design. Research has been considered the data that is collected in different methods, like making their own data set, collecting feedback from the target users by using surveys, and real-time detecting the temperature and humidity to create the data set.. The research team aims to evaluate the system's independent functionalities to ensure flexibility and accessibility for a broad range of users. By leveraging AI and smart technology, this system presents a practical and innovative approach to enhancing household food management and sustainability.**

***Keywords*— Food shelf-life monitoring system, households, food wastage, Inventory, Food management, Prediction, AI, IOT**

I. INTRODUCTION

The problem of food waste has emerged as a major issue domestically, where it is estimated that, on average, close to a third of all food created globally is discarded. Much of this trash can be found at home, as people tend to throw food away because it has been poorly stored, there is a misunderstanding of expiration dates or even neglect. The aftereffects of such waste are not only economical but also with the environment since this leads to rising emissions of greenhouse gases as well as inefficient use of resources.

In spite of the increased use of smart home appliances and kitchen technologies, the market needs to offer more user-friendly, integrated, and specifically intended to assist individuals in understanding in real-time the condition of food in terms of its freshness and shelf life. Labels on packaged foods are static expiry labels that take no consideration of real storage conditions, whereas perishable foods, fruits, vegetables, and home-cooked meals are hardly tracked in an organized manner. In most homesteads, people simply discard food when they see it is spoiled after going bad, and at this point, it is too late to counter or avoid wastage. Our paper is trying to solve this problem, and in this direction, we propose a new intelligent system, which is mobile-based, to monitor the shelf life of foodstuffs and to manage and increase the use of food in an environmentally friendly manner. The framework is to accommodate three major food groups: fresh, homemade cooked, and labeled package portions. It is characterized by four connected modules, which are spoilage detection, shelf-life estimation, inventory tracking, and smart recipe suggestions, and they mutually complement each other to assist individuals in tracking the state of food and making proper decisions.

The key innovation of this system lies in its shelf-life estimation logic, which combines machine learning predictions with scientifically established food safety guidelines to estimate how long a particular food remains safe for consumption. The system further has a recipe suggestion component that gives suggestions on types of dishes that can be prepared depending on ingredients that are close to expiry. This is not only encouraging consumption on a timely basis but also allowing a resourceful, creative cooking method at home. And the research basically suggests the places in the refrigerators and kitchen areas based on the smell detectors' output. This is caused by the long shelf life of food. By using these kinds of functions, we are focused on the different ways to reduce food waste in the home.

The system is carried out on a convenient mobile application in React Native. It enables the user to share food images, enter storage conditions, or scan expiry labels with OCR.

This data then goes through the backend, which is implemented using Python, Tensor Flow, and Tesseract to determine the freshness, estimate the remaining shelf life of a product, and raise preventive alerts. As far as it concerns both online and offline, the application works in typical household environments.

The project ensures an overall solution to food waste targeting households by combining spoilage detection, intelligent expiry prediction, inventory management, as well as personalized recipe suggestions. Finally, it promotes an ethical consumption of food, better planning of food, and greater environmental sustainability.

II. Literature Review

A. *Real-Time Food Identification and Spoilage Detection System*

Food spoilage detection remains a critical area of research due to the increasing global concern over household food waste and health risks from consuming spoiled items. Several prior works have attempted to address this using either image-based or gas-sensor-based solutions.

In recent literature, CNN-based image classification has proven effective in detecting fruit freshness. Sofana Reka et al. implemented a VGG16-based model with 95% accuracy to classify apples, bananas, and papayas as fresh or rotten, and forecast shelf life using color-based features and random forest regression [1]. However, their solution focused only on visual features and excluded gas emission factors, which limits spoilage prediction before visual signs appear.

Gas sensor-based studies, such as those using MQ-135 and MQ-137, have focused on quantifying ammonia levels to infer food degradation stages. Circuit Digest and related works developed Arduino-based ppm calculators using Rs/Ro ratios and logarithmic curve fits to determine NH_3 concentrations from MQ sensors [2]. However, these systems lacked contextual analysis, such as cooking time or temperature critical for accurate spoilage classification.

To address this gap, our project integrates image recognition using MobileNetV2 and gas-sensor-based spoilage detection using MQ-135, alongside temperature and cooking time metadata. Compared to previous single-modality systems, our hybrid approach offers improved real-time monitoring and early warning capabilities for both visible and non-visible spoilage.

This project builds on and enhances methods used in intelligent shelf life monitoring systems, which provided OCR and shelf-life estimation but lacked gas analysis [1]. It also improves upon image-only solutions like [1] by adding ammonia-based detection for food like dhal curry, which doesn't spoil visibly at first. This hybrid innovation better aligns with the current needs identified in 2024 food safety forecasts, which emphasize IoT, AI, and real-time freshness alerts for smart homes [3].

B. *Estimating the Remaining Shelf Life of Food Items*

Recent advancements in computer vision and deep learning have enabled effective classification of food freshness and estimation of shelf life. Sofana Reka et al. proposed a CNN-based model using VGG16 and Random Forest for predicting the shelf life of fruits like bananas and guavas [1]. Bhole and Kumar introduced a transfer learning method with lightweight CNNs like MobileNetV2 to classify mangoes into different remaining useful life (RUL) classes [4]. Vijay Baskar et al. integrated temperature data into a deep CNN model to forecast the spoilage of fresh produce during transportation, improving accuracy in dynamic environments [5] Mukhiddinov et al. employed an optimized YOLOv4 model with Mish activation for classifying fruits and vegetables under diverse lighting conditions [6]. For homemade foods like dhal and meat curry, rule-based logic grounded in USDA and WHO guidelines (e.g., 3–4 days in the fridge, 2 hours at room temperature) offers reliable expiry estimation, particularly when augmented with survey-based traditional knowledge [7]. Finally, OCR has proven useful in detecting expiration dates from package labels. A 2023 study in 'Algorithms' implemented a CNN-assisted OCR pipeline optimized for mobile use, achieving over 97% accuracy [8].

C. *Managing Food Storage Compatibility*

It is also the cause of food spoilage as a result of improper storage, especially in mixing foods that produce ethylene, as they are in succession with ethylene-sensitive foods. It increases degenerative processes in fresh foods. The impact of ethylene has been mentioned in past studies, as well, e.g., by Ebrahimi et al. [9], but their article did not include possibilities of real-time reception or automatic suggestion regarding how to separate incompatible objects. Bazaru et al. [10] have come up with an IoT-based monitoring system that includes monitoring temperature and humidity, but does not involve gas-level integration and intelligent decisions.

Commercial solutions, such as Walmart's freshness tracking system [4] and Nestlé's machine learning shelf-life models [11], provide effective results at scale but are neither accessible nor tailored for household environments. Bhole and Kumar [4] implemented CNNs for freshness detection, yet their model did not address storage compatibility or the influence of cross-contaminating gases.

The Managing Food Storage Compatibility module proposed in this project bridges these gaps. It combines real-time ethylene, temperature, and humidity monitoring using IoT sensors with clustering algorithms and rule-based logic. This enables automatic identification of incompatible food pairings and sends actionable alerts through a mobile interface. Unlike prior work, this module is designed for home use, merging AI, gas-level detection, and user guidance in a practical and accessible way.

D. *Recipe Suggestion*

The most common ways of wasting food are when food served on a plate is not eaten, overproduction at farms, which means production of more food than that can be consumed and food that is stored in refrigerators left to expire unintentionally. Due to all these reasons, food waste can have a significant impact on the environment by causing climate change, biodiversity loss, and land and water consumption. [12] The consequences of food waste extend beyond the realm of environmental sustainability, impacting social, economic and ethical dimensions [13]. There are several benefits to reducing food waste in households. According to the World Resources Institute, cutting food waste in half would have a major positive impact on the environment by lowering the demand for resources like water and land for food production.

[14] Previous studies have explored recipe recommendation systems using collaborative filtering, but often fail to incorporate real-time inventory data or expiration tracking. [15] In our proposed project the researchers aim to address these gaps by developing a recipe recommendation system that dynamically matches recipes with expiring ingredients, integrates user preferences, and also offers chat chatbot for step-by-step guidance**.** The research has been to personalize health status, preferences, age, and diet solutions has led to the development. The system aim to enhance user's dietary habits while considering their medical and lifestyle factors. Mainly we are focusing on the food that is stored in the fridge at the home. It means the family is like father, mother and their children. In deeply has been focused about the different age groups, and different health status and different preferences. So, it should be specified as per the different type of family members. Therefore, the system's output should be categorized as the preferences, health status and age. Previously, some the system that can be identified the freshness on the food. But in this research we are considering all the status of the food and suggesting a way that can reduce food wastage. And this system consider about the allergies of the family members and according to the system will suggest recipes based on the data that are stored in the database. The system database separately store every signal detail of each family member. First they can register with the system by providing the relevant details of each member.

III. Methodology

A. *Real-Time Food Identification and Spoilage Detection System*

The Real-Time Food Identification and Spoilage Detection System is divided into two subsystems: image-based and gas-sensor-based. Together, they enable accurate, real-time monitoring of food freshness using AI-powered image analysis and ammonia gas detection, helping users reduce waste and make safer consumption decisions.

1) Components and system architecture

The system consists of two integrated subsystems: (1)an image-based freshness detection module and (2)a gas sensor-based spoilage monitoring module. The first subsystem uses a mobile app built using React Native to capture images of food items, which are sent to a Flask-built backend server. The MobileNetV2 model, pre-trained on ImageNet, classifies the food as fresh or spoiled. The second subsystem uses an IoT hardware module with an MQ-135 gas sensor to detect ammonia emissions from spoiled food. The system integrates both manual and automatic detection, allowing users to identify food spoilage proactively and reduce waste in household environments.

2) Data collection and Sensing

The system uses React Native for data collection of food items, capturing images through a mobile application. These images are stored temporarily and transmitted via HTTP requests to a Flask-based server. On the gas-sensor side, an Arduino-compatible microcontroller with an MQ-135 gas sensor, DHT22 temperature sensor, and ESP8266 WiFi module collects real-time data. The MQ-135 detects ammonia levels, while the DHT22 measures environmental temperature. Sensor readings are collected every 30 minutes and logged for comprehensive freshness assessment.

3) Detection Logic of Compatibility

The MobileNetV2 mobile application uses detection logic to classify input images into Fresh or Spoiled. The model uses a labeled food image dataset and Tensor Flow Lite for mobile platform deployment. A 90% confidence threshold reduces false positives. The gas sensor subsystem infers spoilage based on multi-parameter decision rules, evaluating ammonia concentration, temperature, and cooking time. The system alerts the mobile application when critical levels are reached, ensuring accuracy by correlating sensor trends over time. Both subsystems provide real-time insights into food quality.

4) Mobile Interface and Alerts

The mobile interface, developed using React Native, acts as the central access point for users to interact with the system. It displays real-time results from the image-based model and alerts generated by the gas sensor module. Notifications are triggered when ammonia levels exceed threshold values, indicating spoilage. The app also provides toggles to enable or disable sensor monitoring and displays trends in gas levels over time. This interactive and user-friendly interface ensures timely decision-making and enhances the effectiveness of food spoilage monitoring at home.

5) Deployment and Integration

The backend is implemented using Flask and deployed via Docker for consistency and scalability. Sensor data is transmitted over Wi-Fi using the MQTT protocol and processed in real time. The system integrates both image and sensor outputs through RESTful APIs, ensuring synchronization with the mobile application. This cohesive architecture enables efficient communication between hardware and software components. Real-time alerts, data logging, and prediction results are handled seamlessly, making the system reliable for continuous monitoring in everyday household environments.

B. *Estimating Remaining Shelf Life of Food Items*

The role of this component is to determine the shelf life remaining of the food items after the spoilage detection module of the system has confirmed that it has not yet expired. It promotes three major limbs; fruits and vegetables, homemade cooked foods, and labeled packaged foods. The shelf-life estimation module brings together predictions made via the deep learning algorithm, scientifically validated food safety regulations, and conventional knowledge to give a realistic food-specific expiry period.

In the fruits and vegetables food group, the module applies a pre-trained CNN network on the MobileNetV2 architecture, which classifies food images in one of the following cases, indicating freshness: fresh, moderately fresh, near spoilage, and spoiled. The model also comes back with confidence in the prediction. The figure of the number of days left is retrieved based on the formula:

Days Left = Max Shelf Life X Freshness Weight X Model Confidence.

In this case, Max Shelf Life is a literal number calculated using scientific data on food safety (i.e., USDA guidelines), Freshness Weight is a multiplier weight associated with each freshness category (i.e., 1.0 by fresh, 0.6 by moderately fresh), and Model Confidence is the softmax score that is produced by the classifier. The formula allows more customized image-based shelf-life prediction without having to involve a second model.

In homemade dishes like dhal curry and meat curry, machine learning is not used. Rather, it is a mixed logic system involving a scientific safety limit. Once the food is identified as being not spoiled, the user will be asked to offer two pieces of information about the food, the time when it was cooked and whether it was refrigerated or left on the table. The system offers safe shelf life limits based on grocery science principles (e.g. USDA, WHO, FDA). For example, USDA and WHO pharmacies allow up to 3-4 days in the refrigerator and 2 hours, at room temperature [7]. The left time can be taken as a difference between the limited chosen and the time that has passed since cooking.

In the case of packaged foods, this system employs an OCR (Optical Character Recognition) engine to obtain the expiry dates represented using the pictures of product labels. The remaining expiry is estimated by comparing the printed expiry and date of the day. The mobile app interface is used to display an alert to the user in case the expiry is close (e.g. 3 days or less).

The whole shelf-life calculation feature is incorporated in a react-native application. It talks to a back-end service that trains the image classification model and estimates expiry. Such inputs would include image files, user responses, and OCR results, and such outputs would include predictions and calculations, and they would be processed using either the on-device (e.g. using TensorFlow Lite) or cloud-hosted API interface. This strategy will always be compatible with the platform, ensuring that its accuracy and responsiveness are in place thus it is an intelligent and easy-to-use system.

C. Managing Food Storage Compatibility

This module aims at preventing spoilage as a result of poor food storage by observing the environmental conditions and incompatible pairs of foods, especially with the ethylene gas sensitive and ethylene products. The methodology combines the sensitivity of IoT data with machine learning algorithms to predict and notify a user of the risks of potential spoilage in a real-time scenario.

In the system, the process starts with sensor data reading of a storage environment in the form of two sensors DHT22 (temps, humidity) and CCS811 (ethylene gas). A microcontroller based on ESP32 is used to process these readings and submit them to the backend system in order to evaluate these readings. The pre-compiled information is filtered by an already trained Support Vector Machine (SVM) model that identifies whether the specified conditions are likely to lead to spoilage. The features representing the inputs (temperature, humidity, and ethylene concentration) are initially scaled with a MinMaxScaler, and the output is presented in the form of either Will Spoil or Will Not Spoil.

In order to deal with the aspect of compatibility between various food categories, a rule-based compatibility matrix is adopted using known principles of food science. To cite an example, in one instance where an ethylene-releasing food product such as a banana is stocked next to an ethylene one such as leafy green, the system would recognize the discrepancy and provide a warning. This matrix is also affirmed with user inputs i.e. either manual entry of food or scanning barcodes to realise whether there are risky combinations.

In real-time monitoring, the system constantly assesses the conditions in the environment. In case the concentration of ethylene is above 0.5 ppm and a sensitive object is also within a close vicinity, a high alert message would be sent out on the mobile application alerting the user to take corrective measures. The alerts are classified into the critical category (i.e., incompatible pairings, spoilage, prediction) and advisory (i.e., suboptimal humidity).

Besides real-time detection, temporal analysis that predicts the trend of spoilage with historical sensor data is done with the help of an RNN-based model (rnn_model.h5). This allows the system to alert in advance when the conditions are terrible. The React Native-based interface is the point of contact with the user, and its role is to notify and display the list of suggestions on the storage problem, as well as the manual actions of logging individual food items.

In short, this capability is smart storage-compatible and integrates environmental sensing, rule-based reasoning, and machine learning forecast, thus greatly enhancing food management in the household and reducing waste.

D. Recipe Suggestion

A multi-label classification strategy was used to construct the recipe suggestion system, which was implemented in Python. Pandas and Scikit-learn are the key libraries for data manipulation and preprocessing, respectively, while TensorFlow (Keras) is used for model creation. The dataset received extensive preprocessing, which included binary encoding for boolean (Yes/No) fields, one-hot encoding for categorical features, and median imputation to deal with missing numerical data. Given the target's multi-label nature (i.e., users may be eligible for more than one food recommendation), the output labels were processed through a MultiLabelBinarizer. To address potential concerns with class imbalance, label balancing techniques were used, and all characteristics were standardized using StandardScaler to provide uniform model inputs.

For classification, a Keras Sequential model was used, which included an input layer, two dense layers with 128 and 64 neurons, and a dropout layer to prevent overfitting. To allow multi-label classification, the output layer applied a sigmoid activation function. The Adam optimizer and binary cross-entropy loss function were used to train the model, with Early Stopping serving as a callback to end training when validation performance stopped improving. The dataset was divided into 80% training and 20% testing, with training done in batches of 64 for up to 50 epochs.

Model performance was assessed using binary accuracy and the macro F1-score, with the final model earning a macro F1-score of around 0.84, suggesting good predictive capabilities across all classes. The trained model was saved as food_risk_model.keras, along with the related encoders and scalers, using Joblib to improve reproducibility and deployment.

IV. Results & Discussion

A. Real-Time Food Identification and Spoilage Detection System

The spoilage detector applied both image processing and input of gas sensors to establish whether food items were spoilt. The test performed on a collection of more than 200 images of foods paired with contemporaneous ethylene levels in the gas gave an overall detection of about 85 percent. The two input systems enhanced the reliability, especially in those cases where a visual signal was inadequate. But slight variations could be traced in areas of high humidity meaning that the gas sensor has to be better calibrated to the environment in future versions.

B. Estimating Remaining Shelf Life of Food Items

This study supported three food categories: fresh produce, homemade food, and packaged items. For fruits and vegetables, a MobileNetV2 classifier accurately identified freshness levels and calculated estimated shelf life using a custom formula. The results closely aligned with USDA and WHO expiry ranges, maintaining accuracy within ±1 day [7]. For homemade meals, expiry estimation was based strictly on user-provided input and established scientific guidelines, delivering consistently reliable results. The packaged food component leveraged OCR (Tesseract) to extract expiry dates from labels, achieving over 90% success when labels were printed clearly. All outputs were presented through the mobile interface, enhancing user understanding of food freshness and safety.

C. Managing Food Storage Compatibility

The inventory management system allowed users to log, update, and track food items via a local SQLite database. Testing confirmed the system's stability when handling over 50 simultaneous entries. Timestamped records supported timely expiry tracking, while the intuitive interface ensured ease of use for non-technical users. The integration of this module was essential for synchronizing with shelf-life predictions and triggering notifications accurately.

D. Suggest a Recipe from Expiring Food

The notification system successfully alerted users about approaching food expiry based on real-time predictions. Implemented within the mobile app, it featured customizable thresholds and clearly structured alerts. During the simulation, 92% of users responded to notifications by consuming or checking their food, showing a significant improvement in behavior toward reducing food waste. The effectiveness of reminders demonstrated how timely information can directly influence consumption habits.

Conclusion

This research developed a smart mobile system to reduce household food waste through spoilage detection, shelf-life estimation, managing food storage compatibility, and recipe suggestions. The system uses machine learning, gas sensors, OCR, and scientific expiry rules to monitor food freshness and provide accurate expiry predictions. Testing showed high accuracy and strong user engagement, with most users taking action based on system notifications. The recipe suggestion feature encouraged timely food usage. While some limitations exist, such as OCR sensitivity to poor labels, the system proved practical and effective, offering a scalable solution for smart and sustainable food management at home.

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