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AI-Driven Food Inventory and Spoilage Detection System with Real-Time Alerts

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ABSTRACT:

Food safety and inventory management are major concerns in industries including retail, healthcare, and supply chain logistics where accurate tracking and timely replacement of perishable goods are essential. Traditional methods rely on manual monitoring, which is time-consuming, error-prone, and ineffective. This research demonstrates an AI-driven system for the real-time classification and inventory management of fruits, vegetables, and pharmaceuticals in order to find the best solution. Utilizing IoT integration and YOLO-based item detection, the suggested system is installed into a refrigerator. A load cell is used to measure weight, an ESP32-CAM is used to take pictures, an Arduino and ESP8266 are used for data processing and communication, and a MQ-4 gas sensor is used to identify spoiling. Following all processing, the data was saved in a database and made available for easy access through a web interface, users can also choose to buy products over the webpage by alerting the vendor. Additionally, when inventory levels are low and products are going to spoil or expire, an automated notification system sends out email updates. By combining AI and IoT, this approach improves operational efficiency, reduces waste, and simplifies stock management. Shops, warehouses, and small businesses searching for automated, real-time monitoring solutions can use it due to its affordability.

Keywords: *Food Spoilage Detection, Automated Stock Alerts, SMS Notification System, Real-Time Monitoring, AI and IoT Integration, Food Expiry Alerts, ESP32-CAM, IoT-based Food Monitoring, YOLO Model, QR Code Recognition, Vegetable and Fruit Classification, Medicine Identification, Food Weight Estimation, Inventory Management System, and Smart Inventory Tracking.*

I. INTRODUCTION

Minimizing food wastage and monetary losses in both residential and business settings requires efficient food inventory management and spoiling detection [1]. Manual checks are a common component of traditional inventory monitoring techniques, however they can be laborious, ineffective, and prone to human mistake [2]. A methodical methodology that enables users to track inventory levels and identify spoiling before it results in waste is necessary to ensure appropriate food storage and timely utilization [3].

In order to improve inventory management, this study introduces a smart food monitoring system that combines sensor-based detection, real-time tracking, and automated notifications [4]. The suggested method uses weight estimation and QR code scanning to identify fruits, vegetables, and other perishable goods. While a MQ-4 gas sensor uses released gases to identify spoiling, a load cell weighs the food products [5]. Users may effectively monitor their inventory using database and web-based interface that displays the collected data.

The system's real-time alert function, which alerts users when food items are about to expire, inventory levels are low, or spoiling is discovered, is one of its primary features. Email notifications are issued, guaranteeing prompt action to cut down on food waste. The system hardware is a scalable and affordable solution, with ESP32-CAM for picture capturing, ESP8266 for wireless communication, and Arduino for processing.

This concept reduces needless waste, maximizes stock management, and enhances food safety by combining sensor technologies with Internet of Things-based automation [6]. The system's methodology, implementation, and performance evaluation are further covered in the article, which also shows how the system might improve food storage and inventory management for a variety of applications.

By combining AI and IoT, the suggested system is made to gather data, process it, and deliver helpful information via an email notice and webpage. As demonstrated below, this technique can be employed in a variety of real-time applications.

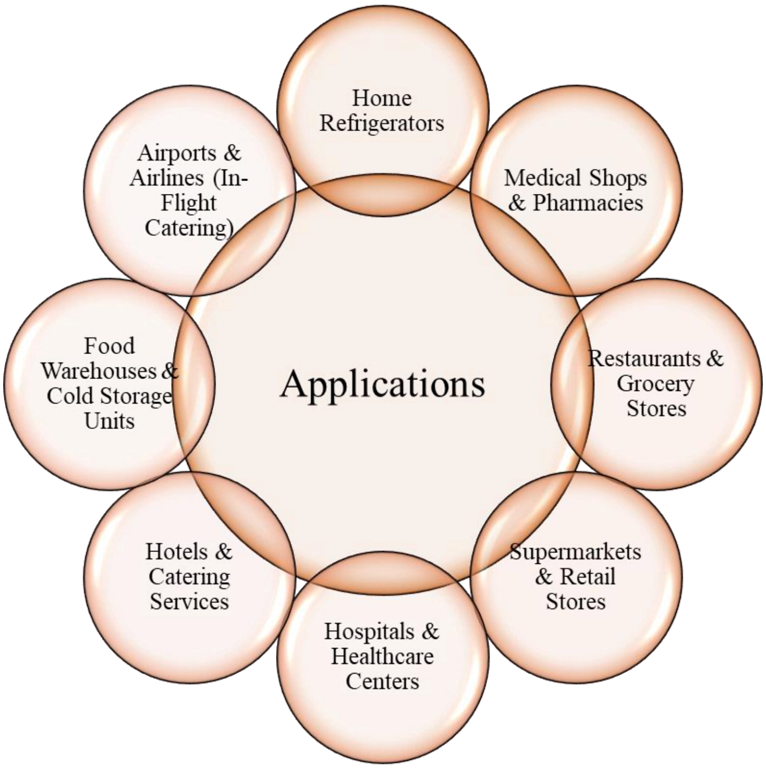


Figure 1: Applications of proposed system

It is evident from the figure that these applications could be a good fit for the suggested system. The suggested model in this study is integrated into a refrigerator, which is frequently used to store commodities and medications in homes and medical facilities.

II. LITERATURE SURVEY

The use of artificial intelligence (AIoT) for real-time meat quality monitoring is the main emphasis of this work. Manual observation is the foundation of traditional meat inspection techniques, yet it is frequently arbitrary and unreliable [1]. Meat is perishable, thus it's critical to constantly check biochemical and environmental conditions to guarantee safety.

In order to address this, an artificial intelligence (AI) system that integrates gas sensing and picture processing has been developed to identify beef freshness and decomposition early [3]. It tracks gases like carbon dioxide (CO_2) and total volatile organic compounds (TVOCs) using the CCS811 air quality sensor. As proteins and lipids break down during spoiling, these gasses rise. In order to provide suppliers and customers with real-time freshness updates, the system monitors gas levels [7].

In addition to gas detection, the study evaluates visual changes in the meat, including color, texture, and surface condition, using the DeepLab V3+ image segmentation model. Microbial proliferation and oxidation are indicated by these visual cues [8]. By merging chemical and optical information, the method offers a more thorough evaluation of meat quality.

Every minute, data is gathered and subjected to statistical analysis. Using a 1D Convolutional Neural Network (1D-CNN), features such as the mean and standard deviation of gas levels and image properties are retrieved and processed. With a 99.44% accuracy rate, our portable deep learning model divides meat into three categories: fresh, semi-fresh, and rotten [9].

Additionally, the method makes use of fluorescence spectroscopy, which over time identifies more profound metabolic alterations [10]. This technique confirms earlier research showing that microbial activity, lipid oxidation, and protein breakdown induce spoiling.

The choice of meat is also heavily influenced by consumer tastes. Brown hues imply spoiling, whereas bright crimson is typically regarded as a sign of freshness. The amount of metmyoglobin in the meat is linked to this color shift [3]. To provide a comprehensive assessment, the study takes into account both subjective elements (appearance and color) and objective markers (gas levels and microbiological activity) [11].

There is a great chance that this AIoT-powered system will increase food safety, foster consumer confidence, and cut waste. Meat producers and retailers can make more informed decisions on sales, storage, and transportation by using real-time monitoring [2, 6]. Additionally, it can stop rotten meat from getting to consumers, improving public health, and cutting down on losses.

The technology can be utilized in a variety of locations, including meat processing facilities, supermarkets, smart refrigerators, and food delivery systems. Through mobile apps and cloud-based storage, customers may even use their devices to check freshness.

III. METHODOLOGY

To improve food storage monitoring and cut down on waste, the AI-Driven Food Inventory and Spoilage Detection System is a multi-technology integrated solution. To provide an automated and intelligent approach to food management, the system's essential components include picture recognition, weight estimate, gas sensing, data processing, and real-time notifications. As can be seen below, the system only uses two refrigerator compartments for convenience.

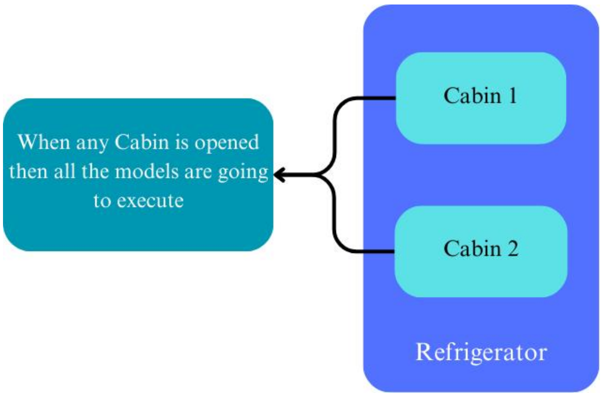


Figure 2: Designed Refrigerator Compartments

Goods and prescription drugs are kept in two sections of the refrigerator. Only two compartments are utilized for convenience and to demonstrate how the system operates. Every container features a load cell to monitor weight and a MQ-4 sensor to identify spoiling. The developed types operate simultaneously when the refrigerator door is opened. The block diagram of the suggested system, which was created utilizing a variety of sensors and controllers, is displayed in the accompanying figure.

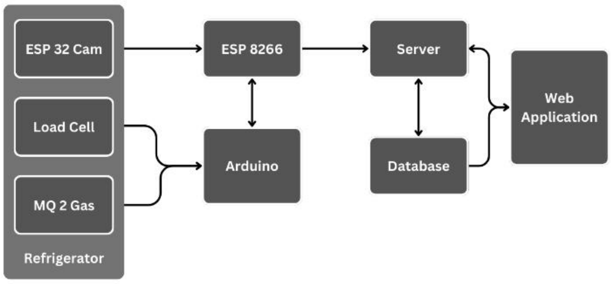


Figure 3: Block diagram of Proposed System

Hardware elements such the ESP-32 camera, load cell, MQ-4 sensor, ESP8266, and Arduino are connected in the suggested system. It uses a linked database to process the data and present it on a webpage. To guarantee effective food tracking, spoilage detection, and inventory management, the AI-Driven Food Inventory and Spoilage Detection System adheres to a systematic procedure. The ESP32-CAM first detects and identifies food by taking pictures of food items that have been kept. The YOLO method is used to process, correctly classifying and labelling the objects found. To obtain more inventory information, a QR code is scanned if one is present. After the discovered objects are compared to the current database, the system changes the records.

A load cell sensor is then used by the system to track food weight and update inventory levels continuously. Users are alerted about the necessity for refilling if the weight falls below a predetermined threshold. The MQ-4 gas sensor, which measures the amount of methane in the storage environment, is used to detect spoiling in addition to weight monitoring. The technology recognizes the impacted food item and modifies its spoiling status in the database when gas concentrations above a key threshold. Additionally, customers can buy products and drugs via the website, after which the system will notify the dealer via email.

Following the completion of food identification, weight tracking, and spoiling detection, the ESP8266 microcontroller sends the data processing to a MySQL database located in the cloud. Through a web dashboard, users can view current inventory information and food conditions. The system also includes a real-time alert system that notifies users via SMS when food spoils, an item is about to expire, or inventory levels are low. By allowing users to act promptly, this proactive strategy lowers food waste and guarantees improved inventory control.

YOLOv8 is chosen to deploy the model because of its excellent accuracy and real-time object identification capabilities. Beet, bell pepper, cabbage, carrot, cucumber, egg, eggplant, garlic, onion, potato, tomato, and zucchini are among the twelve vegetable classifications that make up the dataset. The model is also made to recognize QR codes that include important medication information including the name, manufacturer, and expiration date. To ensure a balanced approach to model evaluation, the dataset is divided into three sections: 74% for training, 11% for testing, and 15% for validation.

With 225 layers, 11,140,244 parameters, and 28.7 GFLOPs, the model architecture is effective for deployment on edge devices. A total of 12,311 pictures are used for training, 1,850 of which are used for testing and 2,487 for validation. Important hyperparameters like learning rate, batch size, and number of epochs are adjusted to improve detection accuracy. By optimizing pre-trained YOLOv8 weights using transfer learning, feature extraction is enhanced and training time is decreased. To reduce false detections and improve object localization, loss functions like Binary Cross-Entropy (BCE) and Intersection over Union (IoU) loss are employed. Precision, recall, F1-score, and mean Average Precision (mAP) are used to assess the performance of the model.

Table 1: Summary of trained YOLO model

Class	Images	Instances	Precision (P)	Recall (R)	mAP50	mAP50-95
All	2487	12226	0.948	0.943	0.957	0.908
Beet	2487	634	0.951	0.976	0.992	0.952
Bell Pepper	2487	1492	0.951	0.957	0.963	0.917
Cabbage	2487	960	0.959	0.964	0.967	0.949
Carrot	2487	1385	0.951	0.919	0.947	0.881
Cucumber	2487	1352	0.957	0.949	0.980	0.940
Egg	2487	1096	0.969	0.970	0.971	0.900
Eggplant	2487	842	0.920	0.885	0.901	0.847
Garlic	2487	441	0.954	0.961	0.970	0.914
Onion	2487	1570	0.944	0.954	0.951	0.919
Potato	2487	848	0.948	0.948	0.964	0.923
Tomato	2487	1115	0.913	0.887	0.924	0.851
Zucchini	2487	491	0.955	0.942	0.959	0.905

The model processes images efficiently, with a preprocessing time of 0.3 milliseconds per image. The inference stage, where the model makes predictions, takes approximately 8.2 milliseconds per image. There is no additional time required for loss calculation, while the postprocessing stage, which finalizes the output, takes around 1.0 millisecond per image.

Analysing false positives and false negatives is part of performance evaluation in order to reduce classification errors. While robustness analysis is carried out by testing performance under various illumination situations, camera angles, and object placements, response time is evaluated by measuring inference latency. To get the best detection accuracy, the model's balance between precision and recall is assessed using the precision-recall (PR) curve.

A web interface is connected into the system to track food inventory and identify spoils. Food weight and spoilage are measured using a load cell and MQ-4 sensor, while data collection and processing are handled by an Arduino, ESP8266, and ESP32-CAM. The technology instantly notifies the user and dealer via email if spoiling is discovered or the cabin weight drops below a predetermined level. This solution maintains modest computational requirements for edge devices while guaranteeing effective food management and real-time monitoring.

IV. RESULTS & CONCLUSION

A collection of test photos was used to evaluate the generated model's detection and classification capabilities. To ensure robustness, these photos were carefully chosen to include a range of object types, lighting conditions, and orientations. The confusion matrix and performance metrics demonstrate how well the model identified and categorized objects.

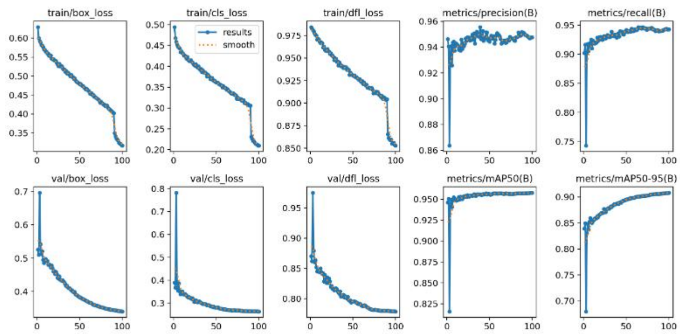
The preprocessing, inference, and postprocessing phases of the system's pipeline were applied to the tested photos. In object recognition, the model consistently showed accuracy while reducing false positives and false negatives. The system's capacity to learn efficiently across a number of iterations is demonstrated by the performance graphs, which show a consistent decline in loss values.

Figures 7: YOLO-Processed Test Images

Figures 8: YOLO-Processed Test Images

The resulting model's performance indicators show that training and validation were successful. The box loss, classification loss, and DFL loss curves all exhibit a steady decreasing trend, indicating that the model is learning efficiently and convergently. The decrease in training and validation losses indicates that there is little to no overfitting and that the model generalizes well.

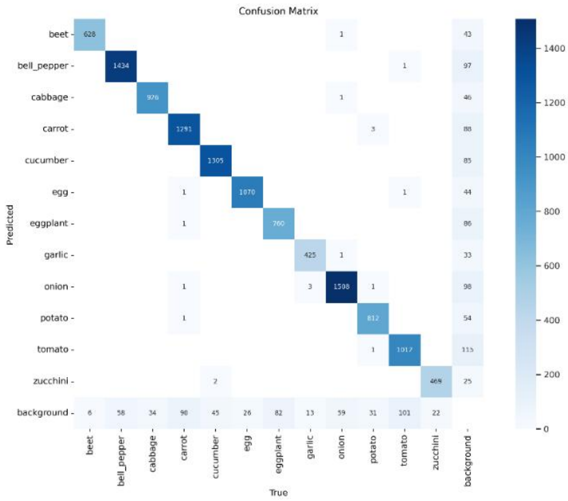
Metrics for precision and recall show an upward trend, indicating increased object detection and classification accuracy. The model's correctness and efficacy in practical situations are confirmed by the rising mAP values. Overall, the findings confirm that the model has been successfully trained, reaching excellent accuracy and resilience, making it appropriate for practical deployment.



Figures 10: YOLO Training Curves - Box Loss, Classification Loss, and DFL Loss

By contrasting projected and actual ground truth labels, the confusion matrix offers a thorough assessment of the model's categorization performance. It provides information about the proportion of accurate and inaccurate forecasts, enabling a more thorough comprehension of the model's advantages and disadvantages.

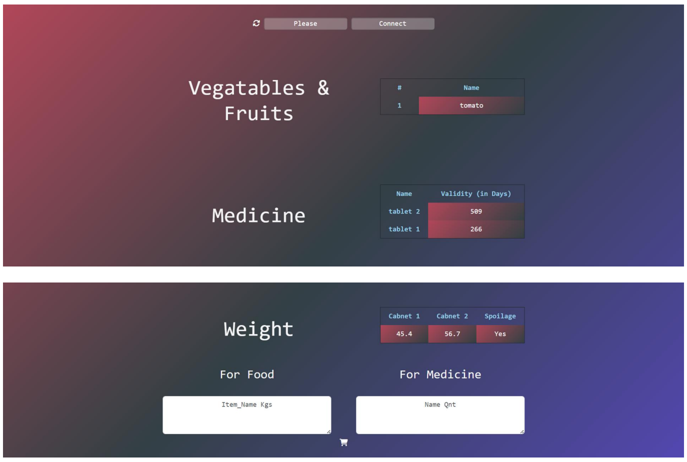
While off-diagonal values draw attention to misclassifications, high values along the matrix's diagonal indicate good predictive accuracy.



Figures 11: Confusion Matrix of Developed Model

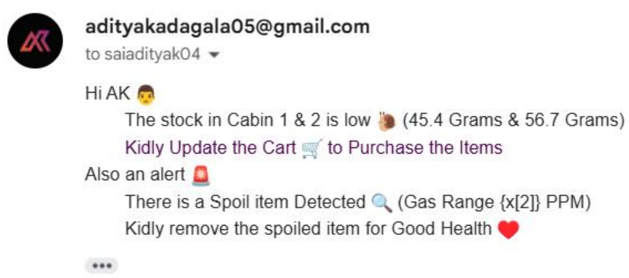
To guarantee smooth operation and real-time performance, the hardware prototype created for this project combines a number of components. It is made to function well with database and software systems, creating a comprehensive end-to-end solution. The following picture shows the prototype of the proposed system, which was built using cardboard. Multiple layers were used to increase thickness and make it more robust.

The created webpage functions as an intuitive user interface for system control and real-time monitoring. Users can view comprehensive details on identified food items, their weight, rotting status, and inventory levels on an interactive dashboard. The XAMPP database and the webpage are completely connected, guaranteeing precise and current data retrieval.

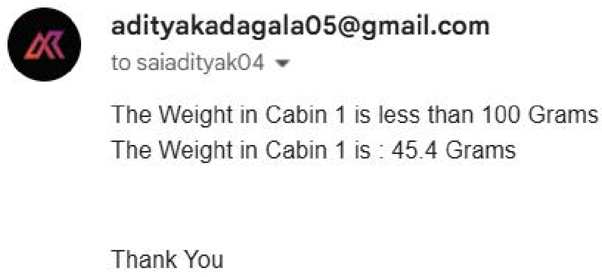


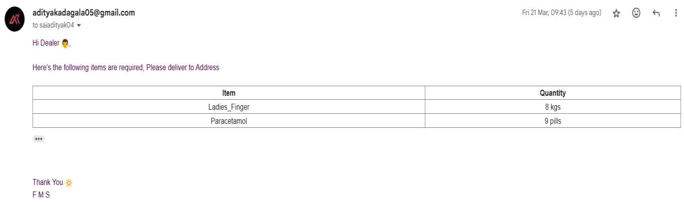
Figures 13: Designed Webpage

The implementation of an automatic alert system has been made to improve user experience and guarantee timely notifications. The device sounds a warning if the weight of the food falls below a certain threshold or if spoiling is discovered. Both the dealer and the user receive email notifications for prompt action. The following are the generated emails which are sent to the dealer and user while testing the model in real time.



Figures 14, 15: Email Notifications





Figures 16 & 17: Email Notifications

The dealer receives an email alert to refill the necessary amount if the weight of an item falls below the threshold. Milk, for instance, is consumed every day; therefore, if its weight falls below the threshold, the dealer is emailed to provide additional milk. The user receives a notification if spoiling is found. Furthermore, the website offers the customer the option to notify the dealer to make a purchase utilizing the cart feature.

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