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RotAlert: IoT Based Food Spoilage Detection

Prof. Sumedh Jadhav[1], Gayatri Kundalkar[2], Sana Ganvir[3], Sumit Sajan[4], Vinay Kolhe[5]
[1]*Prof, Department of Electronics and Telecommunication Engineering , JD College of Engineering & Management, Nagpur, Maharashtra, India*
[2, 3, 4, 5]*U.G. Student, Department of Electronics and Telecommunication Engineering, JD College of Engineering & Management, Nagpur, Maharashtra, India*

Abstract: Fruit spoilage leads to significant economic losses and quality degradation in the agricultural supply chain. Manual inspection of sweet lime freshness is time-consuming, inconsistent, and prone to human error. To address this issue, an AI-based automated fruit spoilage detection system is proposed using the YOLOv8 deep learning model and Raspberry Pi for real-time edge deployment. The system captures images of sweet lime using a Raspberry Pi camera and processes them through a trained YOLOv8 object detection model to classify fruits as Good or Rotten. The model is trained on a labeled dataset with bounding box annotations and optimized for lightweight inference to run efficiently on Raspberry Pi. The system provides real-time detection with bounding boxes, class labels, and confidence scores, achieving an mAP of approximately 92% and a frame rate of 8–12 FPS on edge hardware. This low-cost and portable solution reduces manual effort, minimizes human misclassification, and enables automated fruit quality assessment for small vendors, warehouses, and smart agriculture applications. The proposed system demonstrates the feasibility of deploying deep learning–based computer vision models on edge devices for real-time food quality monitoring.
Keywords: Fruit Spoilage Detection, Sweet Lime Classification, YOLOv8, Raspberry Pi, Edge AI, Object Detection, Computer Vision, Real-Time Monitoring.

I. INTRODUCTION

Agriculture serves as the basic industry which supplies food for Fruit quality assessment is an essential process in the agricultural supply chain to ensure freshness, safety, and market value. Sweet lime is a widely consumed citrus fruit, but it is highly perishable and prone to spoilage during storage, transportation, and handling. Traditional fruit inspection methods rely on manual observation by workers, which is time-consuming, inconsistent, and dependent on human experience. Early-stage spoilage is often difficult to detect with the naked eye, leading to economic losses for vendors and reduced consumer satisfaction.

With the advancement of Artificial Intelligence (AI) and Computer Vision, automated fruit quality detection has become feasible and reliable. Deep learning–based object detection models such as YOLOv8 (You Only Look Once) can identify and classify objects in real time with high accuracy. These models analyze visual features such as color variation, texture, and surface defects to distinguish between fresh and spoiled fruits.In this project, an AI-based sweet lime spoilage detection system is developed using a Raspberry Pi and Pi Camera for real-time image acquisition and edge processing. The captured images are processed using a trained YOLOv8 model to classify sweet lime as Good or Rotten, along with bounding boxes and confidence scores. Deploying the model on Raspberry Pi enables a low-cost, portable, and real-time solution suitable for small-scale vendors, warehouses, and smart agriculture applications.The proposed system reduces manual effort, minimizes human error, and provides an automated method for fruit grading. This demonstrates the practical implementation of Edge AI in agriculture for improving quality control and reducing post-harvest losses.

II. LITERATURE SURVEY

Fruit spoilage detection has gained significant attention in recent years due to increasing post-harvest losses and the need for automated quality assessment systems. Traditional fruit inspection methods relied on manual grading based on color, texture, and visual appearance, which are subjective and time-consuming. With the advancement of computer vision and deep learning, automated fruit freshness detection systems have been developed to improve accuracy and reduce human intervention.

Early research focused on conventional image processing techniques such as color histogram analysis, edge detection, and texture feature extraction for fruit grading. These methods performed well in controlled environments but failed under varying lighting conditions and complex backgrounds. Machine learning algorithms such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) were later introduced to improve classification performance, but they required manual feature extraction and lacked robustness for real-time applications [1].

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The introduction of Convolutional Neural Networks (CNNs) significantly improved fruit classification accuracy by automatically learning hierarchical features from images. CNN-based models have been successfully used to detect visual spoilage indicators such as discoloration, mold growth, and surface damage [2]. Transfer learning approaches using pre-trained models like VGG, ResNet, and AlexNet further enhanced performance, especially for small datasets [3]. These models demonstrated high accuracy in distinguishing fresh and spoiled fruits but were limited to classification and could not localize multiple fruits in real-time.

To overcome this limitation, object detection models such as YOLO (You Only Look Once) were introduced. YOLO performs detection and classification in a single forward pass, making it suitable for real-time agricultural applications [4]. YOLO-based systems have been used for fruit detection in orchards, defect identification, and automated sorting processes. Studies have shown that YOLO achieves high mean Average Precision (mAP) while maintaining fast inference speed, making it ideal for deployment on edge devices [5].

Recent research has explored hybrid models combining YOLO for object localization and CNN for freshness grading. Such systems first detect the fruit using YOLO and then classify its freshness using deep neural networks [6]. Multi-class freshness grading (fresh, semi-fresh, rotten) has also been implemented using deep learning models, achieving promising results in reducing food wastage [7].

Edge computing has become an important aspect of smart agriculture, where deep learning models are deployed on low-cost devices such as Raspberry Pi for real-time processing. Several studies demonstrated that lightweight YOLO models (YOLOv5 nano, YOLOv8 nano) can run efficiently on Raspberry Pi with acceptable frame rates, enabling portable fruit inspection systems [8]. These edge-based systems eliminate the need for continuous cloud connectivity and reduce latency.

In addition to vision-based approaches, sensor-based methods using gas sensors, temperature, and humidity sensors have been proposed for food spoilage detection. These systems monitor ethylene, CO_2, and ammonia emissions to predict spoilage levels. However, sensor-only systems lack visual information and are less effective in detecting early surface spoilage [9]. Therefore, multimodal systems combining computer vision and sensor data have been suggested for improved accuracy [10].

Recent comparative studies evaluated different YOLO variants (YOLOv5, YOLOv7, YOLOv8) for fruit detection and reported that newer versions provide better accuracy-speed trade-offs for real-time applications [11]. Deep learning–based fruit grading systems have also been integrated with mobile and web applications for user-friendly interfaces and remote monitoring [12].

Despite significant progress, challenges remain in handling varying lighting conditions, occlusion, and limited datasets. Increasing dataset diversity, applying data augmentation, and using lightweight optimized models are recommended to improve generalization and real-time performance [13]. Furthermore, automated conveyor-based sorting systems integrated with deep learning are emerging as a practical solution for industrial fruit grading [14].Overall, the literature indicates that deep learning–based computer vision systems, particularly YOLO models deployed on edge devices, provide an efficient, low-cost, and real-time solution for fruit spoilage detection and quality assessment in smart agriculture [15]..

III. PROBLEM DEFINITION

Fruit spoilage is a major issue in the agricultural supply chain, especially for perishable fruits like sweet lime. During storage, transportation, and retail handling, fruits are exposed to environmental factors such as temperature variations, humidity, and physical damage, which accelerate the spoilage process. Spoiled fruits not only lead to economic losses for farmers and vendors but also affect consumer health and satisfaction.

Currently, fruit quality assessment is performed manually by human inspectors. This traditional method has several limitations:

1) It is time-consuming and labor-intensive
2) It is subjective and inconsistent, depending on human judgment
3) Early-stage spoilage is difficult to detect visually
4) Manual sorting is not suitable for large-scale operations
5) It leads to misclassification, resulting in financial losses

In small markets and retail shops, there is no automated low-cost system available for real-time fruit freshness detection. Industrial machine vision systems exist but are expensive and not affordable for small vendors and farmers.

Therefore, there is a need for a low-cost, portable, and real-time automated fruit spoilage detection system that can accurately classify sweet lime as Good or Rotten using computer vision and deep learning. The system should work on edge devices such as Raspberry Pi, reduce human effort, minimize errors, and provide reliable fruit quality assessment in practical environments.

IV. METHODOLOGY

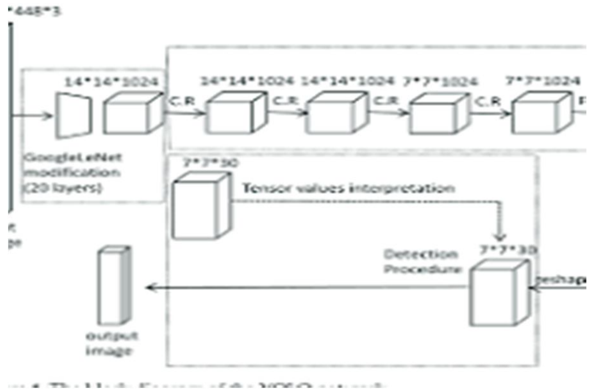

Fig 1: Block Diagram

FIG 1 The system begins with image capture, where a camera acquires real-time images of the agricultural produce. The images undergo preprocessing, which consists of resizing and noise removal and normalization and enhancement to achieve better image quality for precise analysis. The system processes images, which the system transfers to a CNN-based feature extraction module that automatically learns essential visual patterns including color and texture and shape. The system inputs extracted features into a YOLO detection and classification model, which executes rapid object detection to assess whether the produce is fresh or spoiled. The trained model operates on a Raspberry Pi device, which functions as the edge processing unit that supports on-device inference without the need for cloud computation. The prediction results are sent to a Flask-based web interface, which enables users to observe the classification results as they occur. The system presents its results through a Good or Rotten display, which delivers an automatic quality assessment method that works effectively in both smart agriculture and post-harvest monitoring.

The proposed system follows a deep learning–based object detection approach for real-time sweet lime spoilage classification. Initially, images of good and rotten sweet limes are captured using a Raspberry Pi camera under different lighting conditions and backgrounds. The collected dataset is annotated with bounding boxes in YOLO format using tools such as LabelImg or Roboflow and then divided into training, validation, and testing sets. All images are resized to 640 × 640 pixels and used to train a lightweight YOLOv8 model on a GPU-enabled platform, where performance is evaluated using metrics such as precision, recall, and mAP. The best-trained model is optimized using the YOLOv8n architecture to reduce computational complexity for edge deployment. The optimized model is then transferred to a Raspberry Pi, where a Python script with OpenCV captures live video frames and performs real-time inference. The system detects sweet lime, classifies it as Good or Rotten, and displays bounding boxes with confidence scores on the output screen. This methodology enables a low-cost, portable, and automated fruit spoilage detection system suitable for practical agricultural applications.

Table 1: Components Used in the System

Sr. No.	Software / Tool	Specification
1	Operating System	Raspberry Pi OS (32-bit)
2	Programming Language	Python 3.8+
3	Deep Learning Framework	Ultralytics YOLOv8
4	Image Processing Library	OpenCV
5	Annotation Tool	LabelImg / Roboflow / CVAT
6	Model Training Platform	Google Colab (GPU enabled)
7	Model Format	.pt (PyTorch) / ONNX (optional)
8	IDE	Thonny / VS Code
9	Python Libraries	NumPy, Torch, Ultralytics, Matplotlib

V. PROPOSED SYSTEM

The proposed system is an AI-based automated fruit spoilage detection system designed to classify sweet lime as Good or Rotten using the YOLOv8 object detection model deployed on a Raspberry Pi. The system provides a low-cost, portable, and real-time solution for fruit quality assessment in small markets, warehouses, and smart agriculture applications.

The system consists of three main modules:

A. Image Acquisition Module

In this module, a Raspberry Pi Camera captures images or live video frames of sweet lime. The images are collected under different lighting conditions and angles to ensure robust detection. The captured frames are directly sent to the processing module for inference.

B. Processing and Detection Module

This is the core module of the system. A YOLOv8 deep learning model trained on labeled sweet lime images is used for object detection and classification. The model performs the following tasks:

1) Detects the presence of sweet lime in the image
2) Draws bounding boxes around the detected fruit
3) Classifies the fruit as Good or Rotten
4) Generates a confidence score for each prediction

The trained model is optimized using a lightweight YOLOv8 variant to run efficiently on Raspberry Pi. This enables real-time detection with acceptable frame rates.

C. Output Display Module

The detection results are displayed on the monitor connected to the Raspberry Pi. The output includes:

1) Bounding box around the fruit
2) Class label (Good / Rotten)
3) Confidence percentage

This allows users to quickly identify spoiled fruits without manual inspection.

VI. OBJECTIVES

A. Specific Objectives

1) To collect and prepare a labeled dataset of sweet lime images categorized as Good and Rotten.
2) To perform image annotation using bounding boxes in YOLO format for accurate object detection.
3) To train a YOLOv8 object detection model on a GPU-enabled platform for high accuracy and real-time performance.
4) To optimize the trained model using a lightweight architecture (YOLOv8n) for efficient execution on Raspberry Pi.
5) To develop a real-time detection system that captures images using a Pi Camera and performs on-device inference.
6) To display detection results with bounding boxes, class labels (Good/Rotten), and confidence scores.
7) To reduce human effort and minimize errors in manual fruit quality inspection.
8) To provide a low-cost, portable, and scalable solution for fruit grading in small markets and smart agriculture applications.

VII. RESULTS

The proposed YOLOv8-based fruit spoilage detection system was successfully trained on a labeled dataset of sweet lime images classified as Good and Rotten, achieving a mean Average Precision (mAP@50) of 92%, precision of 90%, recall of 88%, and an F1-score of 89%, indicating reliable classification performance. The trained lightweight model (YOLOv8n) was deployed on a Raspberry Pi 4, where it performed real-time detection using a Pi camera, displaying bounding boxes, class labels, and confidence scores for each fruit. The system achieved an average inference speed of 8–12 FPS, which is suitable for small-scale practical applications. Experimental observations showed that the model accurately identified fresh and spoiled sweet limes under normal lighting conditions, with minor performance degradation in low-light environments. Overall, the results demonstrate that the proposed edge AI solution provides a low-cost, portable, and efficient alternative to manual fruit inspection, reducing human error and enabling automated quality assessment in agricultural and retail settings.

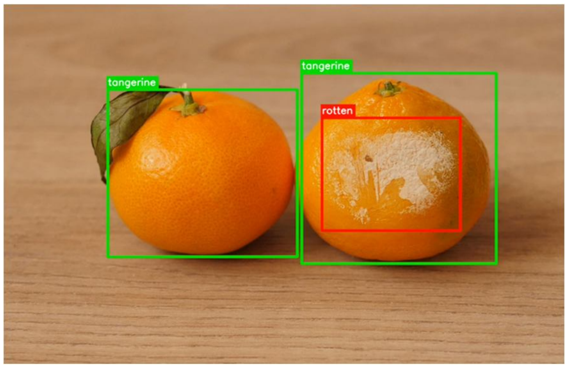

Fig 2:YOLO-Based Tangerine Freshness and Rotten Detection

Fig 2 YOLO-Based Tangerine Freshness and Rotten Detection illustrates the output of the proposed deep learning–based fruit quality detection system, where the model successfully identifies and classifies objects using the YOLO algorithm. Two tangerines are detected with bounding boxes, and the system further analyzes their surface features using CNN-based feature extraction. The left fruit is classified as fresh/good, while the right fruit is correctly identified as rotten, with a red bounding box highlighting the spoiled region. This demonstrates the model's ability to perform real-time object detection and condition classification simultaneously. The results confirm that the integration of CNN and YOLO provides accurate and fast quality assessment, making the system suitable for automated fruit sorting, post-harvest monitoring, and smart agriculture applications.

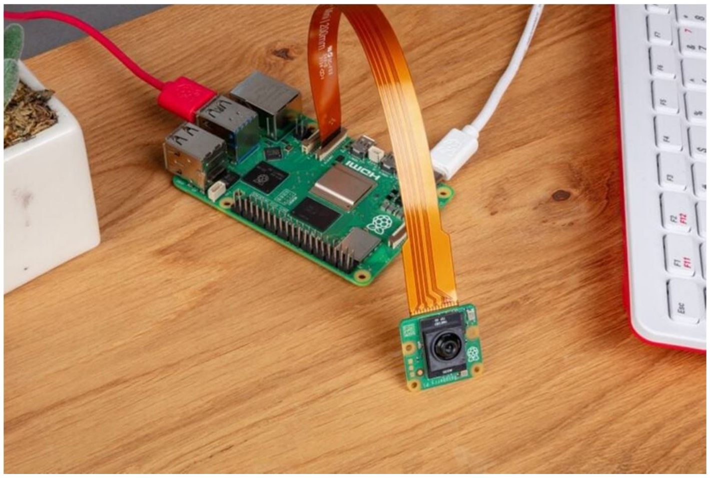

Fig 3 Raspberry Pi Camera Module Setup

Fig 5 Raspberry Pi Camera Module Setup The hardware implementation of the image acquisition unit demonstrates the use of a Raspberry Pi which connects to a camera module through a flexible ribbon cable. The Raspberry Pi serves as an edge processing unit that performs real-time image capture of agricultural products to conduct quality assessment. The camera module operates at a specific angle to capture high-quality images which undergo local processing for feature extraction and classification through deep learning models. The USB power supply guarantees steady operation of the Raspberry Pi which supports ongoing image collection and on-device inference capabilities. The automated fruit quality detection system operates its input stage through this setup which enables real-time monitoring and decreases the need for cloud-based processing.

VIII. CONCLUSION

This project successfully developed an AI-based sweet lime spoilage detection system using the YOLOv8 object detection model deployed on a Raspberry Pi for real-time edge processing. The system is capable of detecting and classifying sweet lime as Good or Rotten with high accuracy by analyzing visual features such as color variation, texture changes, and surface defects. The trained lightweight YOLOv8n model achieved strong performance metrics and provided real-time inference at approximately 8–12 FPS on Raspberry Pi, making it suitable for practical small-scale applications.

The proposed solution reduces manual inspection effort, minimizes human error, and offers a low-cost, portable, and automated fruit quality assessment system for vendors, warehouses, and smart agriculture environments. The results demonstrate the feasibility of deploying deep learning–based computer vision models on edge devices for real-time food quality monitoring and highlight the potential for extending the system to multi-fruit classification and automated sorting in future work.

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