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Supporting Harvest Optimization: Ripeness Detection System Using YOLOv11 and LoRaWAN

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Abstract. The requirement of accurately determining the levels of ripeness of fruits has always been an important issue when it comes to maximizing the efficiency of fruit harvesting. However, current methods for determining the ripeness level of fruits are highly dependent on the experience of farmers, leading to inconsistent post-harvest quality. This study presents an automated four-level ripeness detection system that integrates deep learning and IoT technology. The system uses YOLOv11 to classify fruits by color and characteristics in real time and applies LoRaWAN transmission technology to transmit image data from farm sensors to a central processing unit. FRiMan system has been tested in a pilot field and has achieved very positive results, also demonstrating the accuracy and effectiveness of the system in classifying the ripeness of fruits even under complex environmental conditions. This method provides a cost-effective solution and ensures that the equipment runs at low energy levels, suitable for agriculture, but still ensures accuracy while optimizing efficiency during harvesting and reducing post-harvest losses.

1 Introduction

Accurately determining fruit ripeness is essential for improving quality, reducing post-harvest losses, and enhancing productivity. However, many farms still rely on subjective visual assessment based on color, shape, and texture—methods prone to error. Early harvesting can lower market value, while late harvesting increases spoilage risk during transport and storage [1,2].

1.1 Related Technologies

Computer vision and machine learning have been widely applied to automate ripeness detection. Traditional methods like color thresholding and texture analysis [3,5] struggle under variable lighting and outdoor conditions. Deep learning, particularly models like

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YOLO, has significantly improved detection accuracy by learning visual features directly from images [6,7,10]. Among them, YOLOv11 offers superior speed and accuracy in complex scenes with multiple fruits [11].

Transmitting data from the field to central servers is another challenge. High-energy methods such as Wi-Fi and 4G are unsuitable for remote or large-scale farms. In contrast, LoRaWAN provides low-power, long-range communication, making it well-suited for agricultural use [12]. Despite this, few systems effectively combine LoRaWAN with deep learning for real-time, multi-fruit ripeness monitoring.

1.2 Motivation and Proposed Approach

Although significant progress has been made, current solutions often support only a single fruit type or binary classification. Few integrate deep learning with energy-efficient transmission like LoRaWAN, and even fewer are evaluated under real-world agricultural conditions. To address these gaps, we propose FRiMan, a four-stage ripeness detection system (Unripe, Partially Ripe, Fully Ripe, Overripe) built on a customized YOLOv11-FRiMan model. STM32-based edge devices capture images and transmit them via LoRa RA-02 to a cloud server for inference. FRiMan demonstrates reliable performance across diverse fruits and environments [5], with evaluations confirming its accuracy and practicality [8]. The system is cost-effective and suitable for tropical farming contexts [6].

1.3 Key Contributions

This work introduces a full-stack fruit monitoring system combining YOLOv11 and LoRaWAN for efficient, real-time ripeness classification. A dataset of 20 fruit types and four ripeness stages was developed to train and evaluate the model. Field deployment in Vietnam achieved an F1-score of 0.833. Additionally, real-time alerts sent to farmers' smartphones highlight the practical potential of integrating deep learning with low-power IoT in remote agriculture [3].

2 System Architecture

The FRiMan system follows a three-stage pipeline architecture for fruit ripeness monitoring, as illustrated in Fig. 1. It includes: (1) FieldCam Network for data acquisition, (2) Central Server for processing and classification, and (3) High-Level Module for visualization and user interaction.

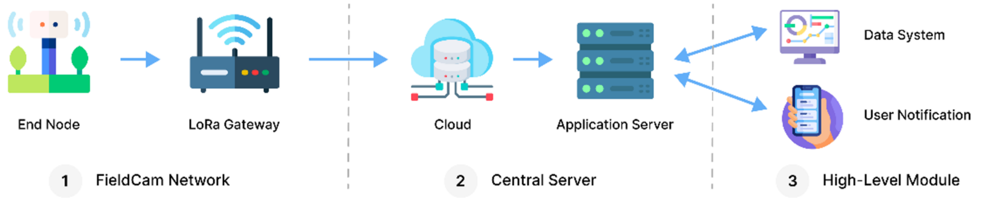

Fig. 1. The proposed model of fruit ripeness on farms in real-time.

Figure 1 provides a general overview of an IoT system utilizing LoRaWAN and YOLOv11 to predict the ripening stage of crops. The entire system is structured into three key blocks:

2.1 FieldCam Network

At the edge of the FRiMan system, End Nodes are deployed in fruit plantations to continuously monitor the ripening process. Each node is built on an STM32F103C8 32-bit microcontroller, which interfaces with an OV7670 camera, SD card module, and LoRa RA-02 module via SPI and GPIO. A dedicated PCB enhances signal routing and hardware stability while supporting future upgrades.

Images are captured at scheduled intervals, temporarily stored on the SD card, and compressed using the TinyJPEG algorithm. They are then segmented into small packets suitable for LoRa transmission. This design reduces bandwidth usage and ensures compatibility with long-range, low-power LoRaWAN communication. The LoRa Gateway collects image packets from multiple nodes and forwards them to the FRiMan Cloud for centralized processing. Thanks to its energy efficiency and extensive coverage, LoRaWAN is particularly suited for remote and large-scale agricultural deployments [12].

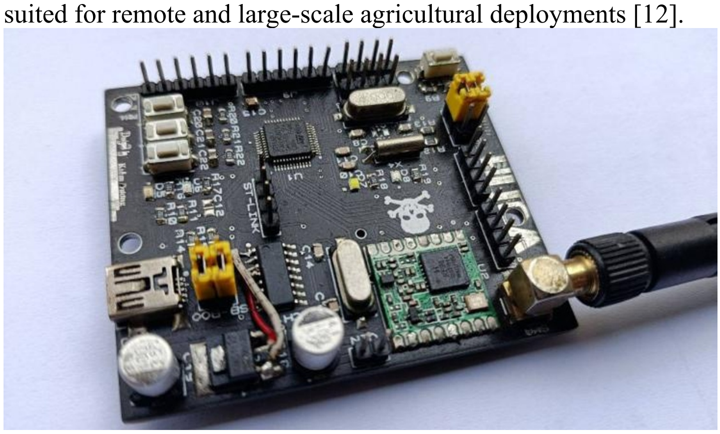

Fig. 2. The proposed model of fruit ripeness on farms in real-time.

2.2 FRiMan Central Server

The FRiMan Central Server hosts both the Cloud Infrastructure and the Application Server on a single physical machine, streamlining deployment during the system's initial phase. Built on the ChirpStack framework, the FRiMan Cloud manages communication between LoRaWAN gateways and field devices, receiving image packets via MQTT. It verifies packet integrity, reassembles image files, and ensures protocol compliance before analysis.

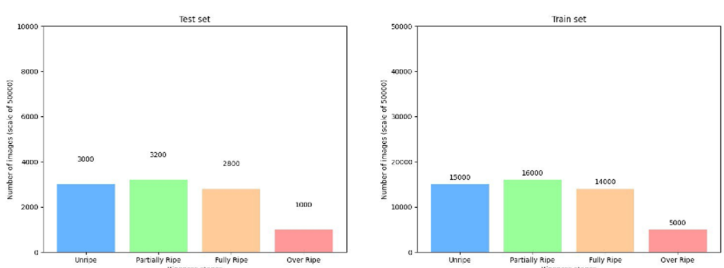

Fig. 3. Train Set and Test Set for model train.

Reconstructed images are then processed by the Application Server, which runs the YOLOv11-FRiMan model. This model detects fruits and classifies them into four ripeness stages : Unripe, Partially Ripe, Fully Ripe, and Overripe [10, 11]. Heavy computation is offloaded to the server, enabling real-time or near-real-time inference without overloading edge devices.

To train YOLOv11-FRiMan, the research team compiled a dataset of 50,000 images between 2023 and 2024, covering 20 tropical fruit types with an average of 2,500 images each. Images were captured under diverse conditions—lighting, angles, weather, and devices—to enhance robustness [7]. Label Studio was used to support high-quality annotation, resulting in a curated test set of 10,000 accurately labeled images.

Fig. 5. Labeling process and object bounding box using Label-Studio.

Following 30,000 training iterations, the model achieved a mean Average Precision (mAP) above 0.80, demonstrating consistent accuracy across varying scenarios. This pretrained model (see Figure 5) now serves as the core of the FRiMan platform, ensuring reliable and scalable classification for real-world deployment [7, 8].

The cloud-based server architecture ensures that heavy computation is offloaded from the edge devices while allowing real-time or near-real-time inference with scalable performance.

2.3 High-Level Module

The final output is managed by the High-Level Module, which is divided into two functions:
- Data System: Provides a visual dashboard for farm managers to monitor the ripeness status of crops, track historical trends, and make decisions based on aggregated insights .
- User Notification: Sends periodic or threshold-based alerts through Firebase Cloud Messaging (FCM) to mobile devices. Farmers are notified of the current ripeness stage and optimal harvest time without needing to manually inspect the crops

Notifications are generated at fixed intervals or when specific ripeness thresholds are met. This enables timely intervention and decision-making, even in the absence of direct field inspection. This layered approach aligns with hybrid deep learning frameworks used in livestock tracking systems [13], further confirming the feasibility of deploying AI models in uncontrolled environments.

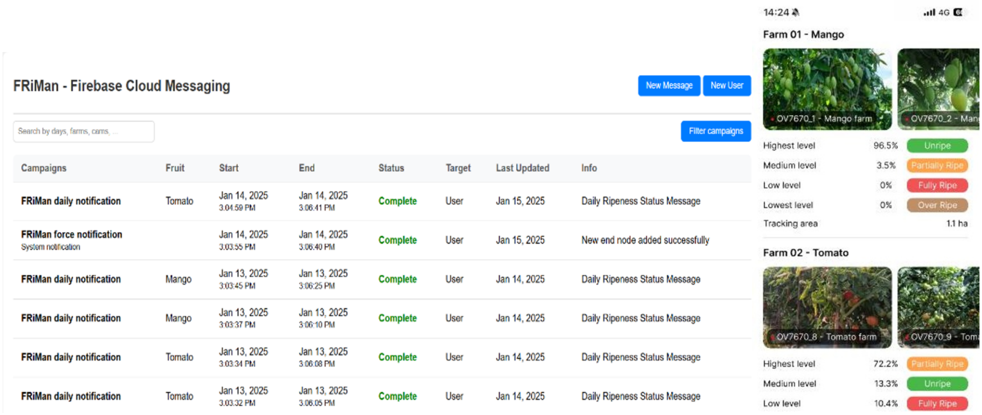

Fig. 6. FRiMan monitoring mobile application.

The system will automatically send periodic notifications providing ripeness updates via mobile notifications every 12 hours as in Figure 6.

3 Experimental setup and results

3.1 Evaluation Method

Since the main goal of FRiMan is to determine the ripeness levels of the fruit through the YOLO-FRiMan model, these levels are determined through the following machine learning model evaluation indexes [9, 10]:

Precision (P) Precision - The rate of correctly identifying the ripeness level classified over the total number of times the model predicts. In which TP is the number of correct predictions, FP is the number of incorrect predictions. Precision is calculated as follows:

$$\text{Precision (P)} = \frac{TP}{TP+FP} \tag{1}$$

where TP (True Positives) are correctly classified fruit ripeness levels, and FP (False Positives) are incorrect classifications.

Recall (R) - The rate of correctly identifying by the model, recall is calculated as follows. It refers to the model's ability to identify all relevant ripeness instances. It is calculated as:

$$\text{Recall (R)} = \frac{TP}{TP + FN}$$

- FN (False Negatives) where FN (False Negatives) are misclassified fruit ripeness stages.

After determining the two Precision and Recall indexes, the model can be accurately evaluated through the F1-score which is synthesized from the above two indexes. F1-score is an important index in the pilot, because it is synthesized from Precision and Recall, so it can calculate the accuracy and error through each experiment. After many times of training the model, it can be seen that the higher the F1-score, the more accurate the model is. The F1-score is calculated as follows:

$$\text{F1} - \text{score} = \frac{2 \times P \times R}{P + R}$$

The F1-score is a critical metric in this study because it accounts for both false positives and false negatives, ensuring that the system performs well in real-world agricultural settings.

The higher the F1-score, the better the model. When F1-score higher than 60\% (0.6), the model is considered to have acceptable accuracy.

3.2 Experimental setup

The experimental study was conducted at the Tropical Fruit and Vegetable Research Center in Phu Tho Province, Vietnam (21°25’53”N, 105°15’29”E). The center specializes in research and improvement of the genetics of tropical fruits. The total experimental area is about 12 hectares, growing a variety of fruits. The research area has a tropical climate, characterized by high humidity (75% to 85%), seasonal rainfall (1,500 mm to 2,500 mm) and relatively stable temperature (25°C to 30°C). The soil in this area is alluvial with rich organic matter content, good water retention and drainage capacity. These climatic factors need to be studied because they affect the ripening rate of the fruit, change the skin texture and change the color [1, 2].

This pilot was tested with 20 different fruit species, each with its own growth period, ripening characteristics and appearance. The selection was based on similarities in economic importance, physical characteristics and complexity of the ripening process. The growth cycles of the fruits ranged from three to twelve months, allowing the ability of the model to detect both short- and long-term crops to be evaluated. The diversity of fruit types ensures that the detection system is not biased towards a particular category but can be generalized to many species.

Table 1. F1-scores of Ripeness Detection by Fruit and Ripening Stage

Fruit	Precision	Recall	F1-score	IoU
Mango	0.91	0.78	0.89	0.72
Banana	0.93	0.75	0.90	0.70
Papaya	0.92	0.77	0.88	0.74
Dragon fruit	0.90	0.76	0.89	0.71
Pineapple	0.88	0.72	0.86	0.68
Guava	0.87	0.74	0.85	0.69
Lychee	0.91	0.73	0.90	0.66
Longan	0.89	0.71	0.88	0.67
Starfruit	0.90	0.75	0.87	0.70
Jackfruit	0.92	0.78	0.91	0.73
Rambutan	0.89	0.76	0.88	0.70
Mangosteen	0.88	0.74	0.87	0.69
Orange	0.90	0.73	0.89	0.68
Grapefruit	0.87	0.72	0.85	0.66
Coconut	0.85	0.70	0.83	0.65
Soursop	0.88	0.74	0.86	0.71
Passion fruit	0.91	0.76	0.9	0.72
Sapodilla	0.89	0.73	0.88	0.69
Avocado	0.86	0.72	0.85	0.68
Watermelon	0.92	0.75	0.91	0.7

Table 1 summarizes the F1-scores of 20 selected tropical fruits, chosen for their economic relevance and diverse ripening characteristics. The model performs best on fruits with clear visual ripeness cues, such as banana, mango, and jackfruit. In contrast, fruits like coconut and avocado show lower accuracy in intermediate stages due to subtle visual changes. These results highlight the model’s strong generalization ability while also revealing opportunities for improvement on visually ambiguous fruit types.

4 Result and Discussion

4.1 Overall Model Performances

The FRiMan system was evaluated using a dataset of 10,000 test images covering 20 different tropical fruit types. The classification model achieved a maximum average F1 score of 0.833 at a confidence threshold of 0.82, indicating a strong balance between precision and recall. This performance validates the system's ability to classify fruit ripeness accurately across varied species and environmental conditions.

As shown in Table 1, the model performed best in identifying the Unripe and Fully Ripe stages, with F1-scores consistently exceeding 0.88 for common fruits such as mango, banana, and jackfruit. These stages are visually distinctive and easier to detect due to strong color and texture cues.

4.2 Overall Model Performances

The classification accuracy declined in the partially ripe and overripe stages, with F1 scores typically ranging between 0.68 and 0.75. These stages exhibit more subtle and gradual visual changes, making them harder to detect with RGB images alone. For instance :

- Fruits like coconut and avocado showed minimal surface color variation between stages.
- Natural lighting, shadows, and overlapping leaves also introduced noise into the image data.

This highlights the model's dependence on clear visual cues and indicates that additional sensing technologies-such as multispectral imaging or near-infrared-may help improve detection accuracy in future versions.

4.3 Overall Model Performances

The FRiMan system operated reliably in the pilot deployment at Phu Tho province under real-world farming conditions. It handled high humidity (75-85%), variable lighting, and complex fruit arrangements, demonstrating both robustness and adaptability. Similar to recent animal tracking systems that combine deep learning and field-deployed sensors [13], FRiMan has proven its robustness under fluctuating lighting, partial occlusion, and environmental noise.

Although a formal statistical comparison with human evaluators was not conducted, an informal test was performed with 5 experienced fruit farmers. Each was asked to manually classify a set of 100 fruit images sampled randomly from the field dataset. The average agreement between farmers and the YOLOv11-FRiMan system was 83.4%, while inter-human agreement among the farmers was 77.1%, showing that the system not only maintained consistency but also performed comparably with human perception under challenging conditions. The greatest disagreement occurred in the Partially Ripe category, where visual ambiguity is inherently high.

Farmers were able to receive real-time updates every 12 hours via the mobile app. These notifications were found helpful in scheduling harvests more efficiently, particularly for fruits like banana, papaya, and jackfruit, where ripeness was easily distinguished.

Although a formal comparison with human evaluation was not conducted in this study, informal field observations showed that the system was generally more consistent than manual assessments, especially in borderline cases. Future studies should include a controlled comparison between AI classification and expert farmers' judgment to quantitatively assess added value.

5 Conclusion

This study developed an automated fruit ripeness detection system by integrating deep learning, IoT, and wireless communication technologies. The system uses the YOLOv11-FRiMan model to classify fruits in real time and LoRaWAN transmission technology to transmit data over long distances with low energy consumption.

From the experimental results of the pilot in Phu Tho province, Vietnam, the system has shown the ability to accurately identify four ripening stages of 20 different fruits with F1-scores. However, the accuracy for partially ripe and overripe fruits still needs to be improved. In addition, optimizing the system for each component in each specific stage will enhance the applicability for small and medium-scale pilots.

The integration of YOLOv11-FRiMan and LoRaWAN in smart agriculture has demonstrated high accuracy and scalability through practical pilots. The results show that the End nodes and FRiMan Cloud service are cost-effective and have great potential for large-scale deployment of fruit ripeness monitoring. The combination of IoT sensor modules and LoRaWAN communication technology reduces operating costs, making the system accessible even to farms in areas with complex terrain. This study confirms that deep learning-based solutions can promote smart agriculture in a precise, efficient and sustainable way.

In future trials, a formal comparison between YOLOv11-FRiMan predictions and human expert assessments will be conducted to measure alignment across different ripeness stages. Preliminary observations already suggest that the system is more consistent than manual judgments, especially in borderline cases such as Partially Ripe and Overripe stages, where subjectivity plays a larger role.

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