RIPENESS AND VARIETY CLASSIFICATION OF SOLO AND RED LADY PAPAYA (*Carica papaya L.*) VARIETIES USING YOLOv8. AN EXPERIMENTAL APPROACH

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Abstract— Papaya (Carica papaya L.) is one of the most consumed tropical fruits in the Philippines, with Solo and Red Lady being the dominant varieties. Due to the similarities in their external characteristics, particularly in skin color and shape, accurately identifying their variety and ripeness remains a challenge. This study presents an experimental approach using YOLOv8 for real-time, nondestructive classification, trained on 1,457 annotated images from local markets and farms in Cavite, Philippines, processed via Robotlow and Google Colab [5]. Through an iterative process, the second iteration achieved 93.1% variety classification accuracy (macro F1 score 0.957), 65.0% Red Lady ripeness accuracy (F1 0.57), 75.0% Solo ripeness accuracy (Fl 0.68), and 98.9% quality accuracy (F1 0.995). Dataset expansion and advanced contrast normalization improved pertormance from the first iteration's 86.2% variety accuracy (Fl 0.841). Challenges in Solo ripeness classification persist due to subtle visual differences at early stages. The system's real-time output supports automated sorting, shelf-life assessment, and quality grading, advancing agricultural automation.

Keywords—YOLOv8, Papaya, Object Classification, Ripeness Classification, Agricultural Automation, Machine Learning

I. INTRODUCTION

Papaya (Carica papaya L.), also known as papaws or pawpaws, is a tropical fruit from the Caricaceae family, widely consumed in the Philippines. It is available year-round and is known for its health benefits, such as helping to reduce the risk of diabetes, cancer, and heart disease. The fruit also aids in managing blood sugar levels, lowering blood pressure, and promoting wound healing. Among the common varieties in the Philippines are Solo and Red Lady, which are cultivated for their sweet flavor and market value.

Traditionally, the ripeness of papaya is judged by farmers through years of experience, relying on physical characteristics such as skin color, shape, and size. However, this method is subjective and difficult to teach or replicate. Factors such as lighting, skin color variation, and subtle changes in texture can affect the accuracy of manual classification. These limitations may lead to misidentification, causing problems in pricing, marketing, and overall consumer satisfaction.

The integration of computer vision and artificial intelligence (AI) in agriculture provides opportunities to solve these challenges. Digital technologies like image analysis help optimize harvesting, sorting, and quality control, improving productivity and reducing subjectivity. In this study, a YOLOv8 (You Only Look Once version 8) model was developed to classify papayas based on variety (Solo or Red Lady) and ripeness stages. The model focuses on identifying visual cues such as color, shape, and surface, which are critical in evaluating fruit maturity.

This research aims to demonstrate how a deep learning approach using YOLOv8 can be applied in agricultural classification tasks, offering a reliable, non-destructive, and scalable solution for fruit sorting. Through experimentation and model evaluation, the system's effectiveness in identifying papaya variety and ripeness is measured using standard metrics such as precision, recall, and F1 score.

II. LITERATURE REVIEW

A. Technical Background

The YOLO (You Only Look Once) family of models has gained prominence in computer vision for object detection tasks. YOLOv8, the latest iteration developed by Ultralytics, offers improved accuracy, speed, and support for tasks such as object detection, classification, and segmentation. It utilizes an anchor-free approach and integrates the CSPNet backbone and PAN-FPN neck, allowing it to detect objects of varying sizes with high performance.

B. YOLO in Agriculture

YOLO-based models have found extensive application in agriculture, particularly for tasks such as fruit detection, ripeness classification, and yield estimation. Recent studies show that YOLO adaptations can handle challenges such as variable lighting conditions and overlapping objects, which are common in farm environments. These systems enhance real-time decision-making in harvesting and quality control.

C. Papaya in the Philippines

Papaya is a widely cultivated and consumed fruit in the Philippines. The country's favorable tropical climate supports the growth of varieties such as Solo and Red Lady. Papayas are used both for direct consumption and as ingredients in processed foods. Their economic importance makes accurate classification of ripeness and variety essential for maximizing market value and reducing postharvest losses.

D. Ripeness Classification of Papaya

Ripeness classification is commonly done through visual inspection of skin color and texture. Red Lady papayas typically follow a 7-stage maturity scale (MS_0 to MS_6), while Solo papayas follow a 3-stage scale. Manual classification is prone to errors due to subjective judgment and inconsistent lighting. This has led to the development of machine learning approaches that use visual cues for more reliable classification.

E. Related Studies

Several studies have demonstrated the feasibility of automated fruit classification. Fracarolli et al (2017). used ImageJ to classify papayas by shape and color [4]. Wang et al (2024). applied YOLOv8+ for strawberry detection and achieved high accuracy [9]. Faza et al (2024). used R-FCN ResNet101 for papaya classification but noted limitations in handling similar-looking varieties [3]. These studies highlight the potential of computer vision and deep learning in fruit classification.

III. METHODOLOGY

The proposed system is designed to classify the variety (Solo or Red Lady), ripeness stages, and quality of papaya fruits (Carica papaya L.) using the YOLOv8 algorithm in a real-time, non-destructive manner. The methodology encompasses data acquisition, preprocessing, model development, training, classification, and evaluation, with classification results displayed as text overlaid on a live video feed. The system leverages computer vision techniques to analyze visual cues such as color, and shape, ensuring accurate classification for agricultural applications. A table summarizing the dataset split is included to provide a clear overview of the system specifications.

Data Acquisition and Preprocessing

A dataset of 1,457 images of Solo and Red Lady papayas was collected from local farms, markets, and commercial outlets in Cavite, Philippines. To capture real-world variations, images were acquired under diverse lighting conditions and from multiple angles using a webcam with 1080p resolution at 30 frames per second (fps). Videos in MP4 format were converted into individual frames to create the image dataset. The Roboflow platform was utilized for annotation and data augmentation, addressing issues such as inconsistent lighting, shadows, and image variations through techniques like rotation, scaling, and color adjustments [5].

Software Design

This project's software is designed to test its ability to classify two Papaya varieties: Solo, and Red Lady, and determine its ripeness stage. By analyzing the skin color from vertical images of the fruits, it uses a trained model based on the YOLOv8 algorithm. The researchers will utilize the incremental process model in developing the program. The incremental process model will include the analysis, design code and test phase.

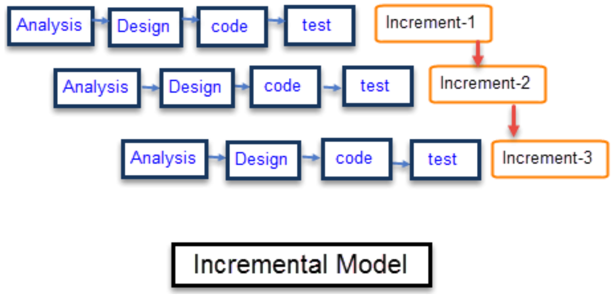

Figure 1. Incremental Process Model [1]

Conceptual Framework

This conceptual framework outlines the development of a machine learning model for classifying papaya variety and ripeness. It begins with the input stage, which includes collecting video and image datasets, possessing skills in Python programming and dataset annotation, and using tools such as Visual Studio Code, Roboflow, and Google Colab. The process stage involves dataset preprocessing, model training, annotation, and code development for model utilization. The output is an automated system capable of accurately identifying the variety and ripeness of Red Lady and Solo papayas based on visual features.

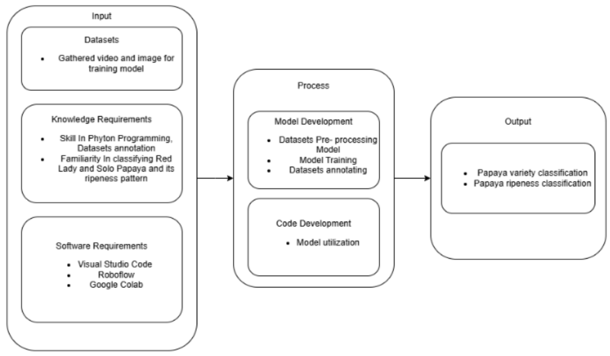

Figure 2. Conceptual Framework

Ripeness stages were defined based on established standards. For Red Lady papayas, six maturity stages (MS0 to MS6) were categorized using skin and pulp color, firmness, and Total Soluble Solids (TSS), as per Subedi et al [5]. (2021). Solo papayas were classified into three ripeness stages (25% yellow, 50% yellow, and full yellow) based on Serry (2011) [4]. A CM-200S handheld colorimeter measured skin color in the CIELAB color space, capturing L* *(brightness), a** (redness/greenness), and b* (yellowness/blueness) values to ensure precise ripeness quantification. The dataset was split into training (70%), validation (20%), and testing (10%) sets, as shown in Table I, to support robust model development.

Dataset Split	Percentage	Number of Images
Training	70%	1,020
Validation	20%	291
Testing	10%	146

Table I. Dataset Split for Model Training and Evaluation

Model Development and Training

The YOLOv8 model, developed by Ultralytics, was selected for its anchor-free architecture and enhanced feature extraction capabilities via the CSPDarknet53 backbone and FPN+PAN neck [8]. The model was implemented using Python 3.10 in a Google Colab environment with GPU acceleration, supported by libraries such as PyTorch, OpenCV-Python, NumPy, and Ultralytics. The training process involved feeding the preprocessed dataset into the YOLOv8 model, which was fine-tuned to classify papaya varieties and ripeness stages based on visual features. Hyperparameters were optimized to ensure effective learning while minimizing overfitting, and data augmentation enhanced the model's ability to generalize across varied conditions.

System Architecture

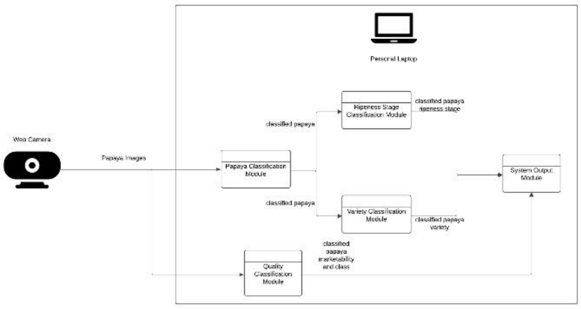

Figure 3. System Architecture

The system operates as a real-time classification pipeline. A webcam captures a live video feed at 1080p resolution and 30 fps. Frames are extracted and preprocessed to standardize image dimensions and enhance quality. Each frame is passed to the YOLOv8 classification module, where the pre-trained model analyzes visual features to determine the papaya's variety (Solo or Red Lady), ripeness stage, and quality [8]. The classification results are displayed as text overlaid in the corner of the live video feed, indicating the predicted variety, ripeness stage, and quality. This overlaid text output enables farmers, sellers, and quality inspectors to make informed decisions regarding papaya marketability and quality in real time. The system runs in a continuous loop, processing incoming frames for ongoing classification and display.

Implementation Details

The system was developed and tested on a laptop running a 64-bit Windows 11 operating system, equipped with an AMD Ryzen 5 4600H processor, NVIDIA GTX 1650 graphics card, and 8 GB of 3200 MHz RAM. The YOLOv8 model was deployed within a Jupyter Notebook environment in Google Colab, ensuring compatibility with the required libraries. The webcam used for real-time testing matched the specifications used for data collection (1080p, 30 fps) to maintain consistency. Ethical considerations were addressed by adhering to non-destructive testing protocols and ensuring dataset annotations were validated to avoid bias. The classification output aligns with Codex Alimentarius standards for papaya quality (Extra Class, Class I, and Class II), enhancing practical applicability in agricultural settings [1].

Model Evaluation

The performance of the YOLOv8 model was assessed using accuracy, precision, recall, and F1 score, which are well-suited for evaluating classification tasks, particularly with imbalanced datasets. These metrics were calculated on the test dataset, with the model's output compared against ground-truth annotations from the Roboflow platform [5]. The evaluation process involved analyzing the model's ability to classify Solo and Red Lady varieties, ripeness stages, and quality categories, ensuring alignment with Codex Alimentarius standards [2]. The following equations define the metrics used:

- **Accuracy**: Measures the proportion of correct predictions among all predictions, calculated as:
  $$\left[\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}\right]$$
  where (TP) is true positives, (TN) is true negatives, (FP) is false positives, and (FN) is false negatives.
- **Precision**: Quantifies the proportion of correctly identified positive instances among all predicted positives, defined as:
  $$\left[\text{Precision} = \frac{TP}{TP + FP}\right]$$
- **Recall**: Measures the proportion of correctly identified positive instances among all actual positives, expressed as:
  $$\left[\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}\right]$$
- **F1 Score**: The harmonic mean of precision and recall, providing a balanced metric for model performance, calculated as:
  $$\left[\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}\right]$$

These metrics were computed for each class (variety, ripeness stage, and quality) to evaluate the model's sensitivity and robustness.

IV. RESULTS AND DISCUSSION

This section presents the performance of the YOLOv8 model in classifying papaya varieties (Solo and Red Lady), ripeness stages, and quality, evaluated on the test dataset (Table I) against Roboflow annotations [5]. Results are displayed as text overlaid on a live video feed (e.g., "Solo, 50% Yellow, Class I"). Performance metrics (accuracy, precision, recall, F1 score) are summarized in Tables III, IV, V, and VI for variety, Red Lady ripeness, Solo ripeness, and quality classification, respectively. Two iterations were conducted, with the second iteration improving performance through dataset expansion and preprocessing refinements.

Key findings, practical implications, and limitations are discussed.

Performance Evaluation

The YOLOv8 model was evaluated across two iterations. The first iteration achieved 86.2% variety classification accuracy (macro F1 score 0.841), 63.0% Red Lady ripeness accuracy (F1 0.55), 73.0% Solo ripeness accuracy (F1 0.656), and 98.7% quality accuracy (F1 0.99). Challenges in ripeness classification, particularly for Red Lady MS1 and MS5, prompted a second iteration with additional images (e.g., for MS1, MS5, Solo Stage 1) and advanced preprocessing (e.g., Data Augmentation). The second iteration improved performance, as shown in Tables II–V.

Variety	Train Data	Valid Data	Test Data	Precision	Recall	F1 Score
Red Lady	253	92	40	0.90	0.98	0.94
Solo	106	31	15	0.95	0.90	0.92
Total/ Macro	352	123	55	0.925	0.94	0.957

Table II. Distribution and Performance Metrics for Variety Classification

Overall Accuracy: 93.1%

Ripeness Stage	Train Data	Valid Data	Test Data	Precision	Recall	F1 Score
MS0	48	29	14	0.50	0.65	0.56
MS1	7	4	2	0.20	0.80	0.30
MS2	60	24	14	0.85	0.40	0.54
MS3	23	15	7	0.90	0.60	0.72
MS4	11	3	2	0.80	0.90	0.85
MS5	30	23	10	0.10	0.80	0.15
MS6	33	22	10	0.95	0.98	0.96
Total/ Macro	212	120	59	0.61	0.73	0.57

Table III. Distribution and Performance Metrics for Red Lady Ripeness Classification

Overall Accuracy: 65.0%

Ripeness Stage	Train Data	Valid Data	Test Data	Precision	Recall	F1 Score
Stage 1	17	13	6	0.90	0.35	0.48
Stage 2	35	6	12	0.75	0.95	0.84
Stage 3	25	15	7	0.95	0.70	0.80
Total/ Macro	77	34	25	0.87	0.67	0.68

Table IV. Distribution and Performance Metrics for Solo Ripeness Classification

Overall Accuracy: 75.0%

Quality Class	Train Data	Valid Data	Test Data	Precision	Recall	F1 Score
Extra Class	57	17	8	1.00	0.98	0.99
Class I	108	31	15	1.00	1.00	1.00
Class II	109	31	16	1.00	1.00	1.00
Total/ Macro	274	79	39	1.00	0.99	0.995

Table V. Distribution and Performance Metrics for Quality Classification

Overall Accuracy: 98.9%

Discussion

The first iteration's variety classification (86.2%, F1 0.841) showed robust performance, but Solo's lower recall (0.646) indicated misclassifications as Red Lady due to early-stage color similarities. The second iteration, with additional images and preprocessing, improved variety accuracy to 93.1% (F1 0.957), with Red Lady (F1 0.94) and Solo (F1 0.92) benefiting from balanced data (352 training images). Red Lady ripeness classification improved from 63.0% (F1 0.55) to 65.0% (F1 0.57), with MS6 (F1 0.96) and MS4 (F1 0.85) performing well, but MS1 (F1 0.30) and MS5 (F1 0.15) remained challenging due to limited samples (7 training images for MS1) and subtle transitions [5]. Solo ripeness classification improved from 73.0% (F1 0.656) to 75.0% (F1 0.68), with Stage 2 (F1 0.84) excelling, but Stage 1 (F1 0.48) struggled due to a small dataset (17 training images). Quality classification improved from 98.7% (F1 0.99) to 98.9% (F1 0.995), with near-perfect metrics across classes, aided by balanced data (274 training images) and consistent lighting [8].

Practical Implications

The real-time system supports automated sorting and grading. The 98.9% quality accuracy aligns with Codex Alimentarius standards, ideal for export markets [8]. The 93.1% variety accuracy enhances sorting efficiency, while ripeness accuracies (65.0% Red Lady, 75.0% Solo) inform shelf-life assessment, though early stages need refinement.

Limitations

Lighting variations affected ripeness classification (Red Lady MS1, MS5; Solo Stage 1). Dataset imbalances (e.g., 7 training images for Red Lady MS1) and Solo's small dataset (77 training images) limited performance. Visual similarities between varieties at early stages caused misclassifications. Computational requirements may challenge low-cost deployment.

Recommendation

To improve the system's performance, reliability, and applicability in real-world agricultural environments, several enhancements are recommended. First, the integration of multispectral or hyperspectral imaging can provide access to internal quality indicators such as sugar content and flesh color, which are not captured by standard RGB cameras. These imaging techniques can significantly improve classification accuracy, especially for fruits with visually similar external features. Second, developing a mobile application would make the system more accessible to farmers and sellers, enabling real-time classification using a smartphone camera. Additional features such as result saving and batch tracking can further enhance its practical utility in the field. Third, expanding the dataset by collecting ripeness samples from diverse farm locations and under varying lighting conditions is essential, particularly for early ripeness stages that are often underrepresented and more difficult to classify. Fourth, employing advanced annotation and preprocessing tools like LabelImg, CVAT, or Supervisely may improve labeling accuracy and dataset diversity. Enhanced preprocessing techniques including data augmentation, can also aid in more robust feature extraction. Lastly, incorporating non-visual data sources such as weight, texture, or smell sensors can support the visual classification pipeline. Multi-modal data fusion may lead to more accurate and reliable predictions, especially in cases where visual indicators alone are insufficient.

V. CONCLUSION

This study developed and evaluated a YOLOv8-based system for real-time, non-destructive classification of papaya varieties (Solo and Red Lady), ripeness stages, and quality. The system achieved an overall accuracy of 86.2% for variety classification, with a macro F1 score of 0.841, demonstrating robust performance in distinguishing Red Lady papayas (F1 score of 0.897) but lower accuracy for Solo papayas (F1 score of 0.785) due to visual similarities at early ripeness stages. Red Lady ripeness classification yielded a 63.0% accuracy, with a macro F1 score of 0.55, performing well for MS6 (F1 score of 0.96) but struggling with MS1 and MS5 (F1 scores of 0.26 and 0.10) due to uneven data distribution and subtle color transitions. Solo ripeness classification achieved a 73.0% accuracy, with a macro F1 score of 0.656, excelling at Stage 2 (F1 score of 0.81) but facing challenges with Stage 1 (F1 score of 0.438). Quality classification was highly effective, with a 98.7% accuracy and a macro F1 score of 0.99, aligning closely with Codex Alimentarius standards (Extra Class, Class I, Class II) [8].

The system's real-time output via a live video feed enhances its practical applicability for farmers, sellers, and quality inspectors, supporting automated sorting, shelf-life assessment, and quality grading in agricultural settings. However, limitations such as sensitivity to lighting variations, uneven dataset distribution (e.g., only 7 training images for Red Lady MS1), and the small Solo ripeness dataset (77 training images) constrained performance, particularly for ripeness classification. These challenges highlight the need for further refinement to ensure robustness in diverse real-world conditions.

Based on the study's findings, the following recommendations are proposed for future improvements:

1. Employ multispectral or hyperspectral imaging to capture internal ripeness features, such as sugar content or flesh color, which are undetectable by standard cameras. These technologies can enhance model accuracy by revealing subtle internal differences, particularly for fruits with similar external appearances.
2. Develop a mobile application enabling users to scan papayas using smartphone cameras, increasing accessibility for farmers and sellers. Features like result storage and batch tracking would enhance field usability.
3. Collect more diverse ripeness samples from various farms and lighting conditions, focusing on early ripeness stages that are difficult to detect. A broader dataset would improve the model's ability to recognize subtle differences, enhancing reliability in real-world scenarios.
4. Explore alternative annotation and preprocessing tools, such as LabelImg, CVAT, or Supervisely, to improve dataset quality. These platforms may offer superior labeling precision or advanced augmentation options, leading to cleaner, more diverse training data and higher model accuracy.
5. Integrate additional data sources, such as weight, texture, or olfactory sensors, to complement visual information. Combining multiple sensor inputs can improve decision-making reliability, as visual cues alone may be insufficient for accurate ripeness and quality assessments in practical settings.

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