CENTIVE
Conference on Electrical Engineering, Informatics,
Industrial Technology, and Creative Media

ISBN: 978-602-53004-0-0

Palm Fruit Ripeness and Quality Detection System Using YOLOv11

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Abstract — The ripeness level of palm fruit is a crucial factor that determines the quality and efficiency of palm oil production. Manual ripeness assessment is often subjective, inconsistent, and time-consuming, creating the need for an automated solution. Therefore, an automated approach using computer vision is needed to ensure efficiency and consistency. To address this need, this study implements the YOLOv11 deep learning model to classify palm fruit into four categories (unripe, underripe, ripe, and overripe). The dataset, obtained from Roboflow, consists of 800 annotated images evenly distributed across the four classes. Data preparation included resizing images to 640×640 pixels and applying augmentation techniques to improve model generalization. The model was trained for 100 epochs on google colab with GPU L4 acceleration. Evaluation results demonstrate high performance with mAP@0.5 of 97.4% and mAP@0.5:0.95 of 94.1%, alongside precision of 94.7% and recall of 90.6%. The best performance was achieved on the unripe and underripe classes, while the ripe category showed relatively lower accuracy due to visual similarities with adjacent classes. These findings confirm that YOLOv11 is an effective and efficient approach for automatic palm fruit ripeness detection, offering potential benefits for harvesting optimization and supporting smart farming practices.

Keywords – Palm fruit ripeness detection, YOLOv11, deep learning, computer vision, smart farming

I. INTRODUCTION

The palm oil industry is a very important economic pillar for countries in Southeast Asia, where Indonesia and Malaysia collectively contribute the majority of global palm oil production and exports. This sector is not only a major driver of economic growth but also a source of livelihood for millions of people, including independent smallholders [1]. The quality of harvested palm fruits affects the yield and efficiency of palm oil production. To determine fruit ripeness traditionally, manual inspection is usually used, which is very difficult, and prone to error. To support higher quality and sustainable palm oil production, an advanced system is needed that can automatically and accurately detect fruit ripeness [2].

Recent advances in computer vision and machine learning have brought about major changes in tasks such as object recognition and image classification. The You Only Look Once, or YOLO, algorithm is very popular for its efficiency and accuracy in detecting real-time data [3]. The latest version, YOLOv11, brings improvements to structures such as the C3k2 block and SPPF module, which improve the ability to capture features of various sizes and enhance performance in complex conditions [4].

Previous studies have shown that the YOLO model can be used in agriculture, such as classifying fruit ripeness levels, and recognizing diseases in rice plants [5]. For example, YOLO has been used to recognize the ripeness level of mangoes, achieving an overall F1 score of 0.92, with a class accuracy of 100% for ripe mangoes, but lower, at 68%, for unripe mangoes. This shows that even though the model is effective, there are still things that can be improved in the system to detect fruit ripeness more accurately [6]. YOLOv11 achieved an mAP score of 0.933 in apple orchard calculations, demonstrating YOLO's best performance in newer versions [7]. For detecting rice diseases, YOLOv11 increased mAP by 2.7%, showing that this model is more effective at recognizing small objects [8].

Several studies have been conducted that can be used as references. However, studies that focus specifically on recognizing the ripeness of palm fruits are still rare. This study aims to address this gap by creating an automatic detection system for palm fruit ripeness in four categories (unripe, underripe, ripe, and overripe) using YOLOv11 in the CRISP-DM framework. The performance of the model is assessed using several metrics such as Precision, Recall, F1 Score, and mAP. The results of this study provide a basis that can be used to integrate automatic ripeness detection into precision farming systems in the future. It is expected that the contributions from this study will improve efficiency in the harvesting process, reduce the influence of human subjectivity, and encourage the use of smart and sustainable agricultural practices in palm fruit plantations.

II. RESEARCH METHOD

This study uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) method, which provides a structured framework for developing data-based models [9]. The research process consists of five stages, namely Business Understanding, Data Understanding, Data Preparation, Modeling, and Evaluation. The workflow is illustrated in Figure 1.

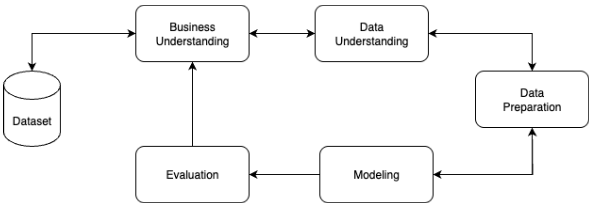


Fig.1. Research Process using CRISP-DM

A. Business Understanding

The research problem is the need to automatically detect and classify the ripeness level of palm fruits in order to support more efficient harvesting and improve the quality of palm fruit. The ultimate goal of this research is to create a classification model capable of recognizing four ripeness categories unripe, underripe, ripe, and overripe.

B. Data Understanding

The dataset used in this study is the Palm Fruit Ripeness v3 dataset obtained from Roboflow Universe, consisting of 800 annotated images divided evenly into four ripeness categories (unripe, underripe, ripe, and overripe). This dataset is split into training (70%), validation (15%), and testing (15%) subsets. Initial inspection was performed to analyze class distribution, annotation consistency, and potential imbalance between classes [10].

C. Data Preparation

Several pre-processing steps were applied to make the data more consistent and improve generalization [11], including:

a) Resizing images to 640 × 640 pixels.
b) Manual augmentation, such as horizontally mirroring images, changing color intensity saturation, brightness and contrast variation, mosaic, scale, and image shift.

D. Modeling

The model used to detect objects is YOLOv11 from the Ultralytics framework. The model was trained using Google Colab. The training configuration consists of:

a) Epoch: 100.
b) Batch Size: 16.
c) Image Size: 640.
d) Early stopping patience: 20.

E. Evaluation

Model performance is assessed based on validation and testing results using various metrics

a) Precision: the proportion of ripe fruit that is correctly detected from all detection results.
b) Recall: indicates the proportion of ripe fruit that is correctly detected from all actual examples.
c) F1 score: the mean of precision and recall.
d) mAP (mean Average Precision): the primary metric for object detection, evaluating both classification and localization accuracy.
e) mAP@0.5: Average precision at IoU ≥ 50%
f) mAP@0.5:0.95: Average across IoU thresholds 0.5-0.95 (COCO standard)

In object detection tasks, the most important evaluation metric is the Average Precision (AP) measured at a specific Intersection-over-Union (IoU) threshold. In this study, the model was evaluated using AP@0.5, which assesses detection accuracy when the predicted bounding box overlaps the ground truth by at least 50%. The mean Average Precision (mAP) is then computed across all classes to provide an overall measurement of detection performance. This metric is widely used in benchmark datasets and is essential for comparing object detection models. The evaluation results are compared with previous studies on similar detection tasks in agriculture to demonstrate the effectiveness of the model [12].

III. RESULT

The YOLOv11 training ran smoothly and converged successfully. The loss value continued to decrease throughout each epoch, and the validation metric remained stable after approximately the 40th epoch. This indicates that the hyperparameters used were sufficient to maintain good model performance without experiencing severe overfitting. The final evaluation of the test set achieved mAP@0.5 of 0.974 and mAP@0.5:0.95 of 0.941, with Precision (0.947), Recall (0.906), and F1-Score (0.88).

The distribution of results per class is presented in Table 1. The evaluation demonstrates excellent object detection performance. The mAP@0.5 of 0.974 indicates 97.4% of detections achieve ≥50% IoU overlap with ground truth, while mAP@0.5:0.95 of 0.941 confirms consistent performance across various strictness levels, following COCO evaluation standards. Per-class analysis shows Unripe (0.995), Underripe (0.988), Overripe (0.970), and Ripe (0.942) all achieving >94% detection accuracy. The supporting

Precision (0.947) and Recall (0.906) metrics validate both accurate predictions and comprehensive coverage.

Table 1. Distribution of Results per Class

No	***Metrics***	***mAP@0.5***	***mAP@0.5:0.95***
1	Unripe	0.995	0.994
2	Underripe	0.988	0.985
3	Ripe	0.942	0.935
4	Overripe	0.970	0.965

In addition to the numerical results, the detection results were also examined visually. Figure 2 shows examples of the model's predictions on previously unseen test images, demonstrating the model's success in detecting fruit under various lighting conditions, positions, and levels of obstruction. The bounding boxes were placed accurately, and the confidence scores showed that the model was able to reliably distinguish between the four ripeness categories. Overall, these results show that YOLOv11 is capable of providing good detection and classification of palm fruit ripeness levels, and provides a strong basis for further development.

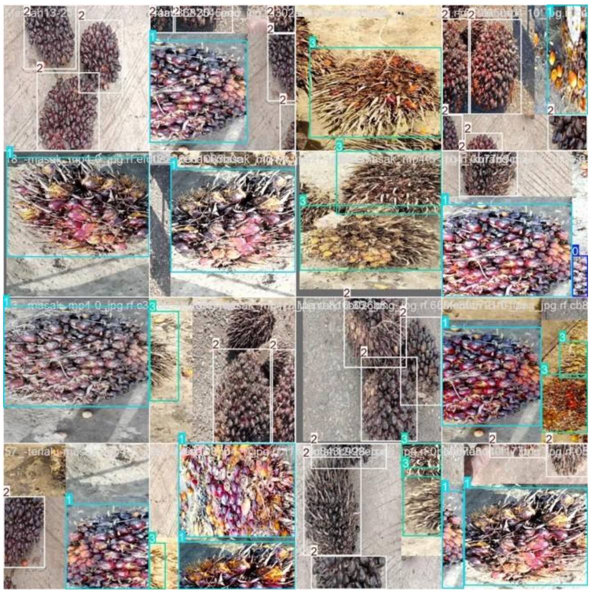


Fig.2. Train Process

The training process resulted in continuous improvement in the model's ability to detect palm fruit bunches. During the training period, the model was able to accurately recognize palm fruit bunches in four different categories, with appropriate bounding boxes and class labels. Gradual improvements in the bounding boxes and confidence values throughout the training process indicate that the model has learned to recognize the features that distinguish the maturity levels of palm fruit bunches.

The validation results are shown in Figure 3, where the model was tested using previously unseen data. The detection output shows that the model is able to work well in various lighting conditions and fruit positions. Each bounding box is accompanied by a confidence score, with most predictions scoring above 0.90, indicating that the model performs very reliably in classifying fruit ripeness into categories such as unripe, underripe, ripe, and overripe.

Fig.3. Validation Process

IV. DISCUSSION

The achieved mAP@0.5:0.95 of 0.941 demonstrates state-of-the-art performance, comparable to recent agricultural detection studies: mango detection (0.92) [6], apple disease detection (0.933) [7], and rice disease detection [8]. The high mAP values indicate the model not only correctly classifies ripeness levels but also accurately localizes fruit bunches, essential for automated harvesting systems. This comprehensive evaluation following COCO standards ensures reliability across different detection strictness requirements.

This research aims to create a system that uses machine learning technology to assist in the process of automatically determining the ripeness and quality of palm fruit. This system uses the YOLOv11 method to recognize the ripeness of palm fruit, as well as provide fast and accurate results for users. This technology is beneficial for palm fruit farmers as it supports the automatic classification of fruit ripeness, thereby improving harvesting efficiency and reducing reliance on manual assessment. With this system, the process of sorting and determining the ripeness of palm fruit becomes easier, without having to rely on manual methods that require a lot of time and energy. In addition, this system also has the potential to increase the efficiency of the harvesting process, improve the quality of palm fruit production, and help maintain a more sustainable supply chain. It is hoped that this automatic palm fruit ripeness detection technology can be widely used in the plantation sector, thereby contributing to increased yields and the welfare of farmers.

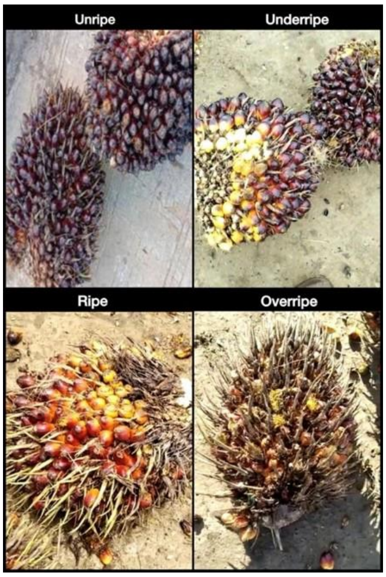
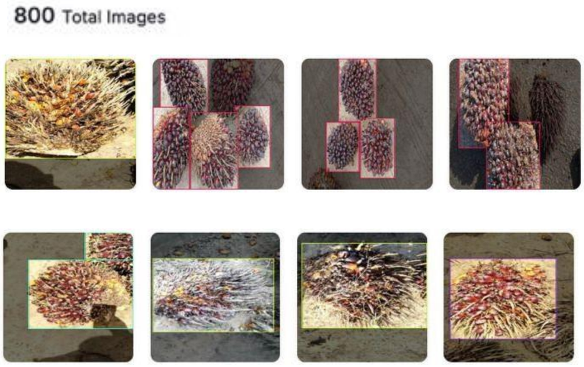


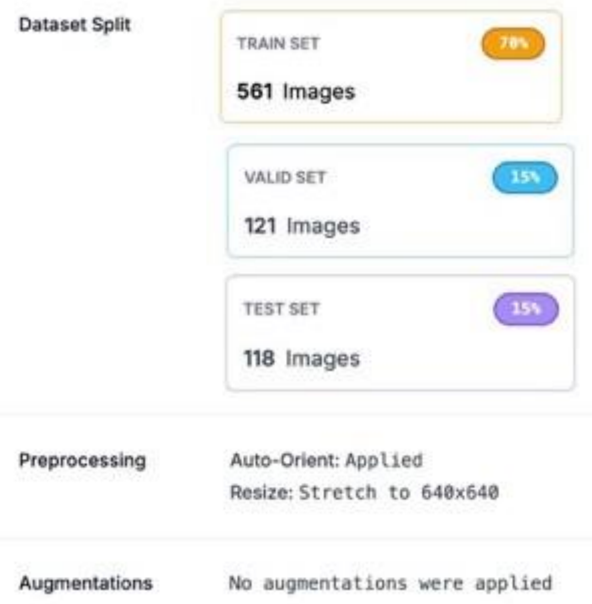
Fig.4. Image Sample

The dataset used is a consists of 800 images of palm fruits divided evenly into four ripeness categories (unripe, underripe, ripe, and overripe) with 200 images distributed in each class. Each class has distinctive visual characteristics. Unripe fruit is predominantly dark purple or black in color and still firmly attached to the bunch. Underripe fruit is predominantly reddish purple with uneven orange or yellow spots. Ripe fruit has a bright orange-red color, a shiny surface, and some fruit has begun to detach from the bunch. Overripe fruit has a dark red to black color, and much of the fruit has detached, leaving the bunch looking empty. Examples of images from the four classes are shown in Fig. 4.

The dataset was processed using preprocessing from Roboflow and additional augmentation was performed during the training phase with YOLOv11. All images were resized to 640 × 640 pixels with auto-orient feature to maintain consistency. The dataset was divided into 70% for training (561 images), 15% for validation (121 images), and 15% for testing (118 images). During training, augmentation was performed in the form of horizontal flip, color adjustment, mosaic, scale, and translation. This combination of augmentations increases the visual variation of the dataset, making the model more resistant to differences in lighting, angle, and object position. This process is shown in Fig. 5, which shows the annotation results and dataset division.



800 Total Images



Dataset Split

TRAIN SET 70%
561 Images

VALID SET 15%
121 Images

TEST SET 15%
118 Images

Preprocessing
Auto-Orient: Applied
Resize: Stretch to 640x640

Augmentations
No augmentations were applied

Fig.5. Data Split

This stage focuses on data training to generate models using the YOLOv11 algorithm. YOLOv11 is the latest version of Ultralytics object detection technology, released in 2024. This model offers improvements in architecture, feature extraction, and training methods compared to previous versions. YOLOv11 is equipped with object detection, segmentation, image classification, and pose detection functions. Its main improvements are the introduction of the C2PSA (Cross-Stage Partial with Self-Attention) module, which combines cross-stage partial and self-attention for more accurate detection of small objects, and the C3k2 block, which uses two small convolutions to improve efficiency without reducing accuracy [13].

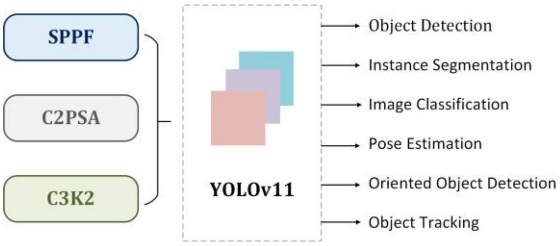


Fig.6. YOLOv11 architecture module

Model training was conducted for 100 epochs with a batch size of 16 and an early stopping mechanism (patience 20) to prevent overfitting. In the model training process, one epoch means that all training data is presented to the model once. At each epoch, the model calculates the gradient of the loss function and updates the parameters using an optimizer [14]. In its implementation, the model was run on Google Colab with Python 3 and an L4 GPU accelerator, which enabled faster computation in deep learning-based model training. Fig. 7 shows the results of testing the YOLOv11 model after training for 100 epochs using an L4 GPU. These results show that the model is quite good overall, but there are differences in performance between classes, especially in distinguishing the Ripe class from other classes.

Table 2. Training Result

Class	Images	Instances	Precision	Recall
all	121	212	0.907	0.861
Underripe	62	129	0.932	0.95
Ripe	36	36	0.8	0.665
Unripe	9	30	0.964	0.886
Overripe	14	17	0.933	0.41

Speed: 0.2ms preprocess, 7.2ms inference, 0.0ms loss, 3.3ms postprocess per image. mAP@0.5 measures detection accuracy at IoU threshold ⩾ 0.5, while mAP@0.5:0.95 evaluates performance across multiple IoU thresholds (0.5-0.95), following COCO evaluation standards.

The evaluation aims to assess the performance of the model that has been built using test data. In this study, Precision, Recall, and mAP metrics are used to measure the effectiveness of the model in detecting the maturity level of palm fruits. In addition, the model is not only determined by high numbers, but also demonstrated by a consistent decrease in loss during the training process and an increase in metric values at each epoch. The model was able to achieve an average Precision of 0.947, Recall of 0.906, and mAP of 0.974, which indicates stable detection performance.

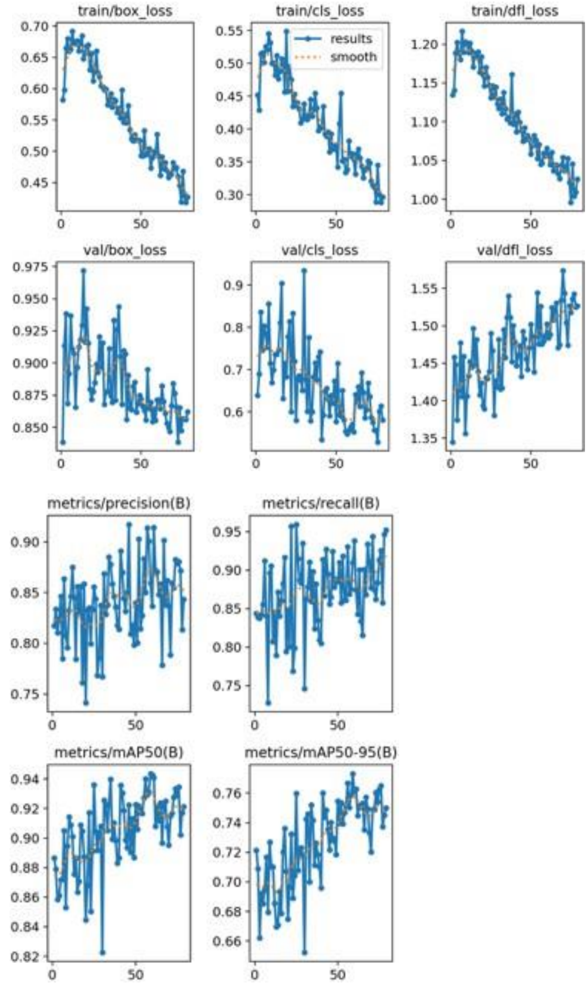


Fig.8. Model build performance

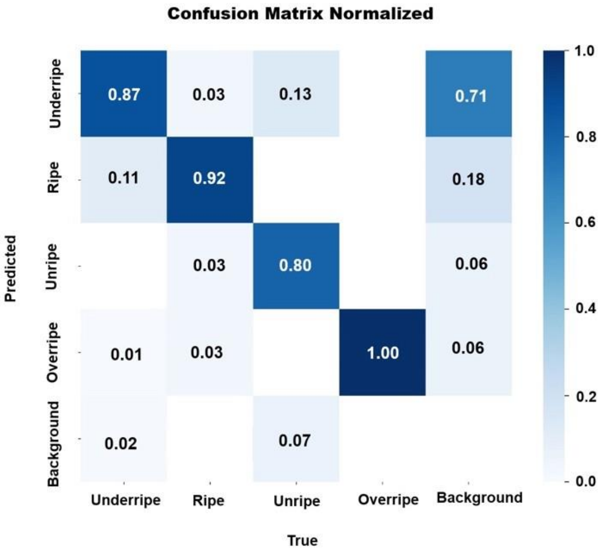


Fig.9. Confusion Matrix Model

Figure 9 shows the confusion matrix results, where most predictions are on the diagonal of the matrix, indicating consistency with the actual labels. The best performance was shown by the Unripe class, while the Ripe class was relatively more difficult to distinguish. This shows that the model still faces challenges in distinguishing the ripe class from other categories that have visual similarities.

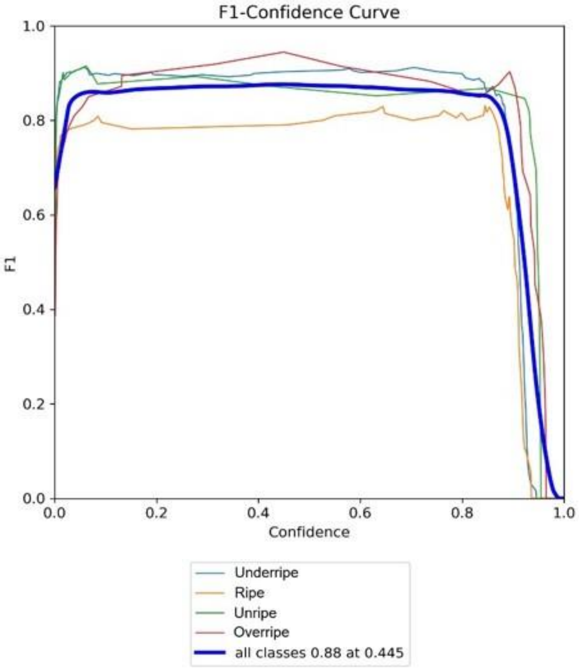


Fig.10. F1 Curve

Figure 10 shows the F1-score curve against the confidence level. The results indicate that the model has stable performance across various confidence values, with an average F1-score of 0.88 at a confidence level of 0.445. Although some classes, such as Ripe, are slightly more challenging, overall the model performs well in identifying the four categories of palm fruit ripeness.

V. CONCLUSSION

This study successfully applied the YOLOv11 model to detect the ripeness level of palm fruits in four categories (Unripe, Underripe, Ripe, and Overripe). This model was trained using the Palm Fruit Ripeness v3 dataset consisting of 800 images, divided into training, validation, and testing subsets. The evaluation results show that YOLOv11 is capable of providing high detection performance with an average Precision value of 0.947, Recall of 0.906, and mAP of 0.974. The best performance was achieved in the Unripe class with an mAP of 0.995, while the Ripe class was relatively more difficult to distinguish with an mAP of 0.942. Analysis of the loss curve, confusion matrix, and F1-score curve shows that the model is stable at various confidence levels with an average F1-score of 0.88 at a confidence level of 0.445.

Overall, this study proves that YOLOv11 can be an effective solution for automatically detecting the ripeness of palm fruit. This technology has the potential to improve efficiency in the palm fruit harvesting and sorting process, reduce dependence on manual assessment, and support smart farming practices in plantations. For further development, it is recommended to use a larger dataset with a variety of field conditions, as well as explore other architecture variants or integration with edge computing devices so that the system can run in real-time in the field.

ACKNOWLEDGMENT

The author would like to thank Telkom University for the academic support and resources provided during the completion of this research. Special thanks are also extended to the supervising lecturer for the guidance and valuable input provided throughout the research process.

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