

Rock Melon Ripeness Detection Using YOLOv8 and SE-Lightweight YOLOv8

Dewi Kania Widyawati

Department of Informatics Management, Politeknik Negeri Lampung, Indonesia
dewi_mi@polinela.ac.id (corresponding author)

Oki Arifin

Department of Software Engineering Technology, Politeknik Negeri Lampung, Indonesia
okiarifin@polinela.ac.id

Sylvia

Department of Software Engineering Technology, Politeknik Negeri Lampung, Indonesia
sylvia@polinela.ac.id

Zuriati

Department of Internet Engineering Technology, Politeknik Negeri Lampung, Indonesia
zuriati_mi@polinela.ac.id

Fahri Ali

Department of Horticultural Production Technology, Politeknik Negeri Lampung, Indonesia
fahrialihorti@polinela.ac.id

Sela Wissi Yani

Department of Informatics Management, Politeknik Negeri Lampung, Indonesia
23753036@student.polinela.ac.id

Dede Aprizal

Department of Software Engineering Technology, Politeknik Negeri Lampung, Indonesia
24783075@student.polinela.ac.id

Received: 12 November 2025 | Revised: 23 January 2026 and 4 February 2026 | Accepted: 7 February 2026

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | DOI: <https://doi.org/10.48084/etasr.16236>

ABSTRACT

Accurate detection of fruit ripeness is crucial for improving harvest efficiency and supporting smart agriculture systems. This study investigates the performance of You Only Look Once version 8 (YOLOv8) and Squeeze-and-Excitation Lightweight YOLOv8 (SE-Lightweight YOLOv8) for automatic rock melon ripeness detection based on visual features. A dataset of 2,000 high-resolution rock melon images was collected under real field conditions and annotated into 2,014 rock melon objects, categorized into three ripeness levels: fully ripe, half-ripened, and unripe. Model performance was evaluated using precision, recall, accuracy, F1-score, and mean Average Precision (mAP). Experimental results indicate that both models achieve comparably high detection performance. YOLOv8 demonstrates slightly higher precision (0.994), F1-score (0.994), and overall accuracy (0.992), reflecting a more balanced detection capability. In contrast, SE-Lightweight YOLOv8 attains a marginally higher recall (0.999), indicating improved detection of relevant melon ripeness instances. In terms of localization performance, both models achieve similar mAP50-95 scores (0.925) and nearly identical mAP50 values (0.995 for YOLOv8 and 0.994 for SE-Lightweight YOLOv8), suggesting comparable robustness across different Intersection-Over-Union (IoU) thresholds. These findings highlight a trade-off between detection accuracy and computational efficiency. YOLOv8 is better suited for applications that require high detection accuracy, whereas SE-Lightweight YOLOv8 is a viable alternative for real-time deployment on resource-constrained devices. The results

demonstrate the potential of YOLO-based object detection models to support precision agriculture and optimize rock melon harvesting processes.

Keywords-YOLOv8; SE-Lightweight YOLOv8; deep learning; rock melon; fruit ripeness detection

I. INTRODUCTION

In 2024, Indonesia's population reached 281,603,800, reflecting a 1.11% increase from the previous year [1]. Rapid population growth places increasing pressure on food systems, particularly in ensuring food quality, availability, and efficient post-harvest handling within the agricultural sector. Recent studies indicate that food loss and inefficiencies along the supply chain remain significant challenges, especially in regions facing food security pressures [2]. Consequently, improving post-harvest efficiency and quality assessment has become an essential component of modern smart agriculture systems.

The agricultural sector plays a critical role in maintaining food availability; however, crop losses caused by environmental factors, pests, and improper harvesting practices continue to affect both productivity and product quality. Advances in precision agriculture and computer vision technologies have been widely explored to address these challenges by enabling automated, objective, and scalable quality assessment of agricultural products [3, 4]. Such approaches reduce subjectivity and improve consistency compared to traditional manual inspection methods.

Melon (*Cucumis melo*) is a high-value horticultural crop widely consumed due to its distinctive flavor and aroma [5]. The market quality and economic value of melons are strongly influenced by their ripeness at harvest. Inaccurate ripeness assessment may lead to premature harvesting or delayed picking, resulting in quality degradation and increased post-harvest losses. Therefore, reliable and automated detection of melon ripeness is essential to support efficient harvesting decisions and to optimize agricultural production systems.

Rock melon can contribute significantly to food security in Indonesia. With the development of technology, the ripeness of fruit can now be detected [6]. The melon harvesting process requires high accuracy in identifying fruit ripeness to ensure optimal, efficient yields. In this context, deep learning-based computer vision can assist farmers in automatically classifying and detecting objects in the field. Recent studies indicate that the development of lightweight You Only Look Once (YOLO) models has become a key focus to support computational efficiency, particularly on devices with limited resources, such as edge devices or embedded systems. The YOLO-LWNet model is proposed as a lightweight variant of YOLO that maintains high accuracy while reducing network complexity and inference time, making it suitable for real-time object detection in agricultural environments [7].

The use of deep learning is advancing smart agriculture [8], providing innovative solutions to improve food security and enhance fruit quality. Deep learning technology is developing rapidly [6] and can achieve performance that sometimes exceeds human capabilities [8], making it effective for tasks such as fruit ripeness detection. Several previous studies have applied YOLOv5 to detect agricultural objects with good

results. Authors in [9] developed a YOLOv5 model optimized for tomato leaf disease classification using a field dataset, demonstrating its effectiveness under natural lighting conditions. Furthermore, authors in [10] improved YOLOv5 through a clustering fusion approach to detect *Camellia oleifera* fruit with high occlusion levels, showing that improving the backbone structure can increase detection accuracy. Based on these results, this study uses the newer, lighter YOLOv8 model to detect melon ripeness in real time.

YOLOv8 was developed by Ultralytics as the latest generation of the YOLO family, integrating a more efficient backbone architecture, improved multi-scale detection, and faster real-time inference capabilities [11]. YOLO reformulates object detection as a single regression problem, mapping image pixels directly to bounding box coordinates and class probabilities. Conventional fruit harvesting incurs high costs, so this transformation is expected to increase rock melon farmers' productivity [12]. Since 2020, the YOLO model has been continuously improved, starting from YOLOv5, YOLOv6, YOLOv7, YOLOv8, YOLOv9, and YOLOv10 [13]. The YOLO model's estimates can be used to detect the ripeness of rock melons from images taken during the farming process, so farmers can determine when to harvest. This is expected to support the smart farming policy promoted by the Indonesian government, particularly by the National Research and Innovation Agency, as set out in Presidential Regulation of the Republic of Indonesia Number 81 of 2024.

YOLOv8 was selected for fruit ripeness detection due to its high accuracy and ability to incorporate advanced techniques such as mosaic augmentation, which allows the model to learn from varied object positions and conditions [7, 14]. However, despite its accuracy, YOLOv8 requires substantial computational resources, which can be a limitation for deployment on resource-constrained devices. Therefore, SE-Lightweight YOLO can be used to overcome this problem. It is a lightweight framework with a fundamental, technical approach that operates efficiently. Thus, the latest approach using deep learning and Squeeze-and-Excitation Lightweight YOLOv8 (SE-Lightweight YOLOv8) is expected to be applied to limited devices more efficiently and accurately [15].

II. IMAGE DETECTION MODELING

The stages of this study include dataset collection, exploration, modeling, and model evaluation. The model creation process is divided into three main phases: data preprocessing, model training, and testing on YOLOv8 and SE-Lightweight YOLOv8. The study's stages are shown in Figure 1.

A. Dataset

The dataset consists of 2,000 rock melon images collected from the Arvino Farm plantation located in Braja Harjosari, Braja Selebah, Sukadana, East Lampung, Indonesia. The images were captured under real field conditions using

observable visual characteristics relevant to ripeness assessment [16]. Image acquisition was conducted on sunny days between 11:00 a.m. and 4:00 p.m. Western Indonesian Time (WIB) using a Nikon D3100 DSLR camera (Nikon Corporation, Tokyo, Japan) equipped with an AF-S DX NIKKOR 18–55 mm f/3.5–5.6G VR lens. All images were recorded in high-resolution JPG format to preserve visual detail and sharpness.

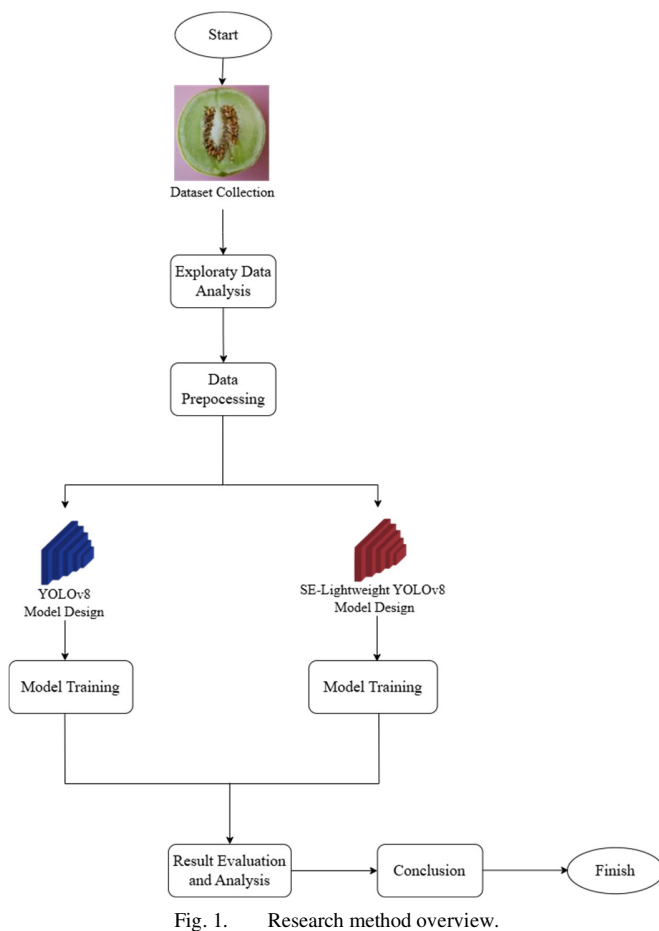


Fig. 1. Research method overview.

B. Data Preprocessing

The rock melon dataset consists of high-resolution images resized to 640×640 pixels, with each fruit individually annotated. Deep learning-based methods enable automated analysis of fruit ripeness in real-field conditions, making them suitable for the rock melon dataset used in this study [17]. The dataset was divided into training, validation, and testing sets comprising 1,873, 95, and 46 images, respectively. All dataset splitting was performed at the image level to ensure reliable evaluation and to prevent data leakage between subsets. Each rock melon image was categorized into three ripeness classes, namely unripe, half-ripened, and fully ripe [16]. This categorization follows the principles of the Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie (BBCH) scale, enabling consistent and repeatable ripeness classification. Data preprocessing plays an important role in

improving data diversity and enhancing model training effectiveness [18].

The BBCH scale is a standardized system for coding plant phenological growth stages based on observable morphological characteristics. It has been widely applied in horticultural studies to describe fruit development and ripening using visual indicators such as color, texture, and surface structure [19]. For melon ripening, BBCH stages 79–91 are particularly relevant and were adapted in this study to define three practical visual categories for object detection. The unripe category covers BBCH stages 79–81 and is characterized by a dominant green skin color and smooth surface texture. The half-ripened category corresponds to transitional stages (BBCH 85–87), during which partial color change and initial netting patterns begin to appear. The fully ripe category represents advanced ripening stages (BBCH 89–91), indicated by a yellowish skin color, well-developed netting, and mature surface texture.

The labeling process was conducted through manual visual inspection during data collection and validated by referencing BBCH stage descriptions to ensure consistency across samples. This BBCH-guided categorization provides a transparent and reproducible basis for ground-truth annotation used to train and evaluate the proposed detection models. Examples of the labeling results for rock melon fruit images are illustrated in Figure 2.



Fig. 2. The process of labeling rock melons.

C. YOLOv8 and SE-Lightweight YOLOv8 Modeling

YOLO is generally known as a model capable of detecting objects in real time [14]. YOLO is designed to perform object detection in a single forward pass, directly predicting bounding boxes and object classes. In its latest version, YOLOv8, several significant architectural changes have been introduced compared to previous versions. One major change in YOLOv8 is the removal of predefined anchor boxes, allowing the model to directly predict bounding box coordinates in an anchor-free manner [13]. This design reduces redundancy and improves detection accuracy.

YOLOv8 retains the grid-based image processing mechanism, where the input image is divided into multiple grids, and each grid predicts object classes and bounding boxes while optimizing both accuracy and inference speed. The backbone architecture of YOLOv8 employs the C2f (Cross Stage Partial Fusion) module, which improves gradient flow across layers and enhances the model's ability to generalize visual features. This architectural design enables YOLOv8 to effectively capture multi-scale spatial information, which is

essential for distinguishing subtle differences in rock melon ripeness based on texture and color characteristics. Figure 3 shows the YOLOv8 architecture [11].

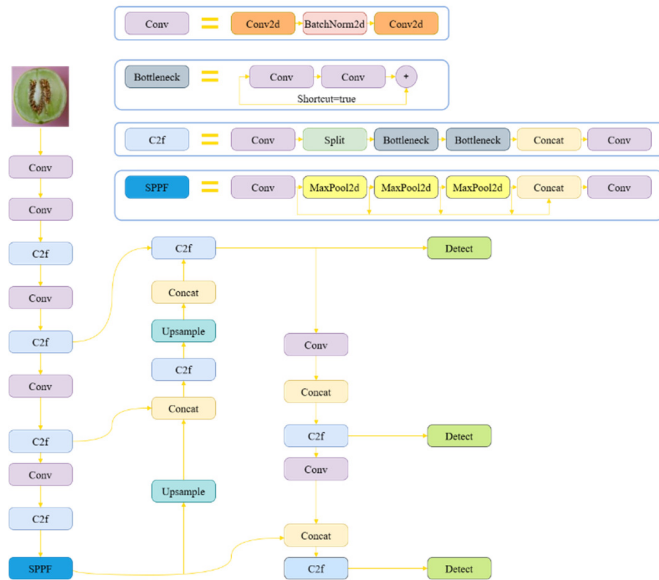


Fig. 3. YOLOv8 architecture.

SE-Lightweight YOLOv8 is a modification of the YOLO architecture designed to reduce model complexity while maintaining acceptable detection accuracy, achieved by incorporating the SE mechanism [20]. The SE mechanism enables channel-wise feature recalibration by emphasizing informative features and suppressing less relevant ones, thereby improving computational efficiency.

Figure 4 shows the architecture of SE-Lightweight YOLOv8, which is built upon the lightweight YOLOv8 nano variant (YOLOv8n). This nano version of YOLOv8 employs the C2f module to improve detection speed while preserving essential feature representation [13]. As a result, the SE-Lightweight YOLOv8 model is well-suited to real-time applications on devices with limited computational resources.

D. Implementation Details and Training Configuration

All experiments were conducted using the Ultralytics YOLOv8 framework. Prior to training, all input images were resized to 640×640 pixels to ensure uniform input dimensions. Both YOLOv8 and SE-Lightweight YOLOv8 models were trained for 100 epochs using a batch size of 16. The Adam optimizer was employed with an initial learning rate of 0.001. Standard data augmentation techniques provided by the YOLOv8 framework, including random scaling, horizontal flipping, and mosaic augmentation, were applied during training to increase data diversity and improve model generalization to unseen samples.

Model training and evaluation were performed on a workstation equipped with Python 3.12.12 and PyTorch 2.9.0+cu126 with CUDA:0 (NVIDIA A100-SXM4-40GB, 40507MiB) on a Windows operating system.

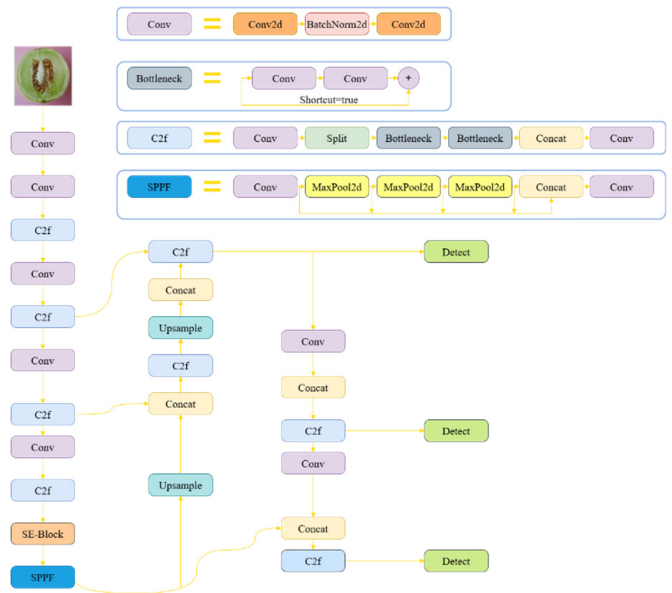


Fig. 4. SE-Lightweight YOLOv8 architecture.

E. Evaluation Method

The performance of the object detection model was evaluated using precision, recall, and mean Average Precision (mAP), key metrics for assessing the effectiveness of YOLO-based models. These metrics describe the balance between the model's ability to detect true positives and minimize false positives. In addition, mAP is considered the most comprehensive measure because it accounts for detection performance across different confidence thresholds. Thus, evaluating these three metrics provides a more objective assessment of the model's quality in automatically detecting melon ripeness [21]. Precision indicates the proportion of correct positive predictions:

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

Recall measures how well the model performs in finding existing positive cases:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

The mAP is computed as the average of the average precision (AP) values over all classes (C):

$$\text{mAP} = \frac{\sum_{i=1}^C AP_i}{C} \times 100\% \quad (3)$$

III. RESULTS AND DISCUSSION

A. YOLOv8 Results

YOLOv8 was trained for 100 epochs to achieve a balance between convergence and overfitting mitigation. The training process used high-resolution rock melon images resized to 640×640 pixels, captured under real harvesting conditions to ensure practical relevance. The dataset initially consisted of 2,000 rock melon images. During annotation, each detectable fruit instance was labeled with bounding boxes. As several images contained multiple rock melons, the object-based

annotation yielded 2,014 labeled rock melon objects. Therefore, the dataset distribution reported in Table I is based on the number of annotated objects (bounding boxes) rather than the number of images, which is consistent with the YOLO detection framework.

TABLE I. DATASET DISTRIBUTION

Dataset split	Unripe	Half-ripened	Fully ripe	Total objects	Image count
Train	414	493	966	1,873	1,859
Validation	18	26	51	95	95
Test	8	16	22	46	46

These annotated objects were divided into training, validation, and testing sets to enable reliable performance evaluation. The detailed distribution across ripeness categories (unripe, half-ripened, and fully ripe) and dataset splits is presented in Table I.

On the mAP50–95 and mAP50 metrics, YOLOv8 achieved scores of 0.926 and 0.995, respectively. These results indicate that YOLOv8 delivers strong, stable detection performance across multiple Intersection-Over-Union (IoU) thresholds, with particularly high accuracy at 0.5. A detailed comparative performance analysis between YOLOv8 and SE-Lightweight YOLOv8 is presented in Table II.

Figure 5 presents the YOLOv8 confusion matrix, showing that most samples are correctly classified across ripeness categories, with limited misclassification between adjacent classes. Most classification errors occur between adjacent ripeness stages.

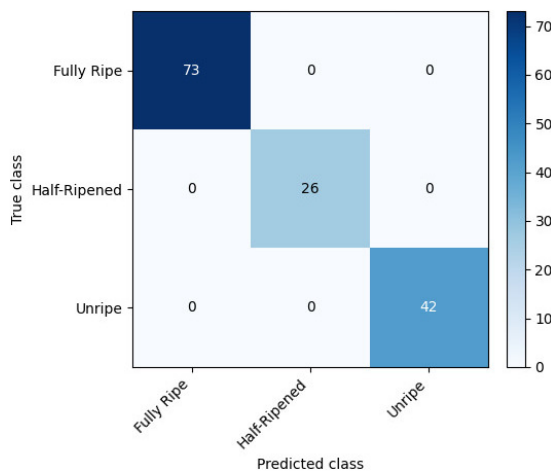


Fig. 5. Confusion matrix for YOLOv8.

B. SE-Lightweight YOLOv8 Results

The performance of the SE-Lightweight YOLOv8 model is consistent with previous studies that used YOLO-based approaches for agricultural object detection. Prior work using YOLOv4 for mango ripeness detection reported high accuracy, demonstrating the applicability of YOLO architectures to fruit ripeness classification tasks. These findings indicate that both standard and lightweight YOLO variants can be effectively applied to agricultural imagery involving complex color and

texture variations, including melon ripeness detection [22]. Figure 6 presents the confusion matrix for SE-Lightweight YOLOv8, showing that misclassifications primarily occur between adjacent ripeness categories. Despite these errors, the model maintains consistent classification performance across all classes.

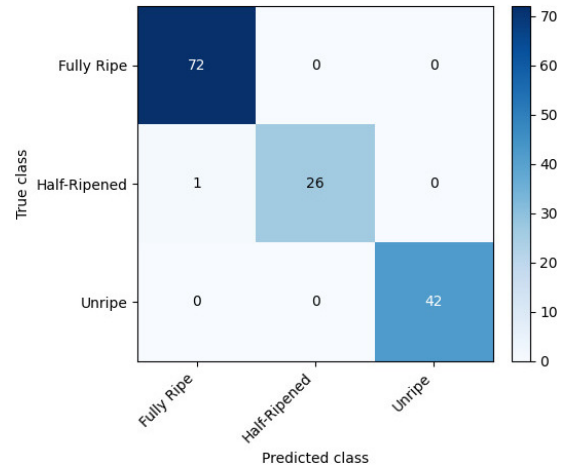


Fig. 6. Confusion matrix for SE-Lightweight YOLOv8.

C. Comparison of YOLOv8 and SE-Lightweight YOLOv8

Table II summarizes the performance comparison between YOLOv8 and SE-Lightweight YOLOv8 based on multiple evaluation metrics. YOLOv8 achieves higher accuracy across all metrics, whereas SE-Lightweight YOLOv8 demonstrates reduced computational complexity and faster inference. This comparison highlights the trade-off between detection accuracy and computational efficiency for the two models.

TABLE II. COMPARISON OF YOLOv8 AND SE-LIGHTWEIGHT YOLOv8

Evaluation metric	YOLOv8	SE-Lightweight YOLOv8	Description
mAP50–95	0.925	0.925	Both models achieve comparable detection performance across a wide range of IoU thresholds, with negligible differences
mAP50	0.995	0.994	Both models show nearly identical detection performance at an IoU threshold of 0.5, indicating similar object localization capability
Precision	0.994	0.988	YOLOv8 achieves higher precision, indicating fewer false positives in melon ripeness classification
Recall	0.994	0.999	SE-Lightweight YOLOv8 slightly outperforms YOLOv8 in recall, indicating fewer missed detections of relevant melon instances
Accuracy	0.992	0.979	YOLOv8 achieves higher overall classification accuracy than the lightweight variant
F1-score	0.994	0.993	YOLOv8 achieves a marginally higher F1-score, indicating a slightly better balance between precision and recall

Figure 7 presents a visual comparison of YOLOv8 and SE-Lightweight YOLOv8 across multiple evaluation metrics. The results indicate that both models achieve comparably high detection performance. YOLOv8 demonstrates slightly higher values in precision, F1-score, and overall accuracy, reflecting a more balanced trade-off between precision and recall. In contrast, SE-Lightweight YOLOv8 attains a marginally higher recall, indicating improved detection of relevant melon ripeness instances.

Overall, while YOLOv8 offers more balanced detection performance, SE-Lightweight YOLOv8 remains competitive and suitable for deployment scenarios that prioritize computational efficiency with minimal performance degradation.

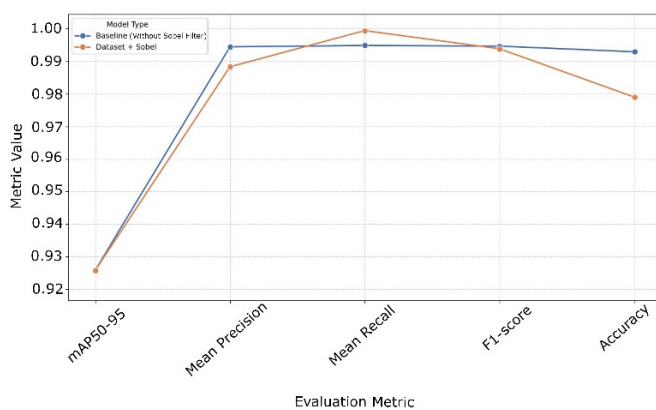


Fig. 7. YOLOv8 vs SE-Lightweight YOLOv8 comparison.

IV. DISCUSSION

The comparative evaluation demonstrates that YOLOv8 achieves slightly higher detection performance than SE-Lightweight YOLOv8 across most evaluation metrics. This performance advantage can be attributed to the more expressive backbone architecture of YOLOv8, which enables richer feature extraction and improved representation of color and texture variations that are critical for distinguishing different ripeness levels of rock melon. Similar performance trends have been reported in recent studies applying YOLOv8 for fruit ripeness detection, where the anchor-free design and enhanced feature fusion mechanisms contribute to improved localization and classification accuracy [11, 12].

In contrast, SE-Lightweight YOLOv8 adopts a compact architecture that prioritizes computational efficiency through lightweight design strategies and channel-attention mechanisms. Although this architectural simplification leads to a slight reduction in detection accuracy, the model maintains competitive performance while offering faster inference and lower computational requirements. Such accuracy–efficiency trade-offs are consistent with findings from recent studies on lightweight YOLO-based models for agricultural applications, particularly for melon and tomato ripeness detection in resource-constrained environments [15, 20].

The observed differences in precision and recall further reflect this trade-off. YOLOv8 exhibits more stable detection

performance with fewer misclassifications across ripeness categories, as reflected by its higher precision and F1-score. Meanwhile, SE-Lightweight YOLOv8 attains a marginally higher recall, indicating improved detection of relevant melon ripeness instances. These results suggest that while YOLOv8 offers more balanced detection performance, SE-Lightweight YOLOv8 remains suitable for real-time agricultural monitoring scenarios that must consider hardware constraints [15].

Overall, the findings indicate that model selection should be guided by application-specific requirements. YOLOv8 is better suited for applications that demand high detection accuracy, such as decision-support systems for harvest timing and quality assessment. In contrast, SE-Lightweight YOLOv8 represents a practical alternative for deployment on edge devices and systems with limited computational resources, where efficiency and inference speed are prioritized without significant performance degradation, as also emphasized in recent YOLO-based agricultural studies [11, 20].

V. CONCLUSION

This study evaluates the performance of You Only Look Once version 8 (YOLOv8) and Squeeze-and-Excitation Lightweight YOLOv8 (SE-Lightweight YOLOv8) for automatic detection of rock melon ripeness under real-field conditions. Experimental results indicate that both models achieve comparably high detection performance across multiple evaluation metrics. YOLOv8 shows slightly higher values for precision (0.994), F1-score (0.994), and overall accuracy (0.992), indicating a more balanced detection capability. In contrast, SE-Lightweight YOLOv8 attains a marginally higher recall (0.999), indicating improved detection of relevant melon ripeness instances.

In terms of localization performance, both models achieve similar mean Average Precision (mAP)50–95 scores (0.925) and nearly identical mAP50 values (0.995 for YOLOv8 and 0.994 for SE-Lightweight YOLOv8), suggesting comparable robustness across different Intersection-Over-Union (IoU) thresholds. These results confirm that YOLOv8 offers more balanced overall detection performance, whereas SE-Lightweight YOLOv8 remains competitive despite its lightweight design.

From a deployment perspective, the results highlight a clear trade-off between detection accuracy and computational efficiency. YOLOv8 is better suited to applications that prioritize detection accuracy and classification reliability, such as decision-support systems for harvest timing and quality assessment. Meanwhile, SE-Lightweight YOLOv8 provides a practical alternative for real-time deployment on resource-constrained devices, where reduced computational complexity and faster inference are essential.

Future work may focus on extending the dataset to include a wider range of environmental conditions, such as varying illumination, occlusion, and weather conditions, to improve model robustness. Further optimization through model compression techniques and deployment on embedded or Internet of Things (IoT)-based agricultural monitoring systems is also recommended to support large-scale, real-world implementation.

DATA AVAILABILITY

The dataset used in this study, consisting of annotated rock melon images for ripeness detection, is publicly available to support transparency, reproducibility, and future research. The dataset can be accessed at: <https://drive.google.com/drive/folders/1GwIRZuPEgtpiqL5AjYrMwlwInQxAju-I>.

ACKNOWLEDGMENT

The authors would like to express their gratitude to the Research and Community Service Center (P3M) of Politeknik Negeri Lampung, Indonesia, for administrative and institutional support. The authors also acknowledge Arvino Farm for providing the Research site and facilitating data collection. This research was financially supported by the Directorate of Research and Community Service (DPPM), Ministry of Higher Education, Science, and Technology of the Republic of Indonesia, under the Fundamental Research – Regular Scheme, Contract No. 174/C3/DT.05.00/PL-BATCH II/2025.

REFERENCES

- [1] N. M. G. Puspamurti, I. A. Oktavianti, and D. P. E. Nilakusmawati, "Population Projection Based on the Cohort-Component Method: A Comparative Study of Global and Indonesian Approaches," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 6, no. 4, pp. 551–559, July 2025, <https://doi.org/10.54660/IJMRGE.2025.6.4.551-559>.
- [2] D. Durán-Sandoval, G. Durán-Romero, and F. Uleri, "How Much Food Loss and Waste Do Countries with Problems with Food Security Generate?," *Agriculture*, vol. 13, no. 5, Apr. 2023, Art. no. 966, <https://doi.org/10.3390/agriculture13050966>.
- [3] S. Ghazal, A. Munir, and W. S. Qureshi, "Computer vision in smart agriculture and precision farming: Techniques and applications," *Artificial Intelligence in Agriculture*, vol. 13, pp. 64–83, Sept. 2024, <https://doi.org/10.1016/j.aiaa.2024.06.004>.
- [4] B. Nath, G. Chen, C. M. O'Sullivan, and D. Zare, "Research and Technologies to Reduce Grain Postharvest Losses: A Review," *Foods*, vol. 13, no. 12, June 2024, Art. no. 1875, <https://doi.org/10.3390/foods13121875>.
- [5] E. Cozzolino *et al.*, "Assessing Yield and Quality of Melon (*Cucumis melo* L.) Improved by Biodegradable Mulching Film," *Plants*, vol. 12, no. 1, Jan. 2023, Art. no. 219, <https://doi.org/10.3390/plants12010219>.
- [6] W. Zhang, "A Fruit Ripeness Detection Method using Adapted Deep Learning-based Approach," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 9, pp. 1163–1169, Oct. 2023, <https://doi.org/10.14569/IJACSA.2023.01409121>.
- [7] Z. Zhong, L. Yun, F. Cheng, Z. Chen, and C. Zhang, "Light-YOLO: A Lightweight and Efficient YOLO-Based Deep Learning Model for Mango Detection," *Agriculture*, vol. 14, no. 1, Jan. 2024, Art. no. 140, <https://doi.org/10.3390/agriculture14010140>.
- [8] I. Attri, L. K. Awasthi, T. P. Sharma, and P. Rathee, "A review of deep learning techniques used in agriculture," *Ecological Informatics*, vol. 77, Nov. 2023, Art. no. 102217, <https://doi.org/10.1016/j.ecoinf.2023.102217>.
- [9] R. Rajamohanam and B. C. Latha, "An Optimized YOLO v5 Model for Tomato Leaf Disease Classification with Field Dataset," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12033–12038, Dec. 2023, <https://doi.org/10.48084/etasr.6377>.
- [10] S. Chen, X. Zou, X. Zhou, Y. Xiang, and M. Wu, "Study on fusion clustering and improved YOLOv5 algorithm based on multiple occlusion of *Camellia oleifera* fruit," *Computers and Electronics in Agriculture*, vol. 206, Mar. 2023, Art. no. 107706, <https://doi.org/10.1016/j.compag.2023.107706>.
- [11] B. Xiao, M. Nguyen, and W. Q. Yan, "Fruit ripeness identification using YOLOv8 model," *Multimedia Tools and Applications*, vol. 83, no. 9, pp. 28039–28056, Mar. 2024, <https://doi.org/10.1007/s11042-023-16570-9>.
- [12] A. Wang *et al.*, "NVW-YOLOv8s: An improved YOLOv8s network for real-time detection and segmentation of tomato fruits at different ripeness stages," *Computers and Electronics in Agriculture*, vol. 219, Apr. 2024, Art. no. 108833, <https://doi.org/10.1016/j.compag.2024.108833>.
- [13] M. Yaseen, "What is YOLOv9: An In-Depth Exploration of the Internal Features of the Next-Generation Object Detector." arXiv, Sept. 12, 2024, <https://doi.org/10.48550/arXiv.2409.07813>.
- [14] M. K. Jahan *et al.*, "Enhancing the YOLOv8 model for realtime object detection to ensure online platform safety," *Scientific Reports*, vol. 15, no. 1, July 2025, Art. no. 21167, <https://doi.org/10.1038/s41598-025-08413-4>.
- [15] G. Chen, Y. Hou, H. Chen, L. Cao, and J. Yuan, "A lightweight Color-changing melon ripeness detection algorithm based on model pruning and knowledge distillation: leveraging dilated residual and multi-screening path aggregation," *Frontiers in Plant Science*, vol. 15, July 2024, Art. no. 1406593, <https://doi.org/10.3389/fpls.2024.1406593>.
- [16] X. Jing, Y. Wang, D. Li, and W. Pan, "Melon ripeness detection by an improved object detection algorithm for resource constrained environments," *Plant Methods*, vol. 20, no. 1, Aug. 2024, Art. no. 127, <https://doi.org/10.1186/s13007-024-01259-3>.
- [17] W. Karamti, S. E. Khediri, and T. Moulahi, "Sustainable Wastewater Management in Agriculture: A Deep Learning-based Olive Classification for Resource Efficiency in Water-Scarce Regions," *Engineering, Technology & Applied Science Research*, vol. 15, no. 3, pp. 24061–24069, June 2025, <https://doi.org/10.48084/etasr.10667>.
- [18] H. You *et al.*, "A Blueberry Maturity Detection Method Integrating Attention-Driven Multi-Scale Feature Interaction and Dynamic Upsampling," *Horticulturae*, vol. 11, no. 6, May 2025, Art. no. 600, <https://doi.org/10.3390/horticulturae11060600>.
- [19] F. Feldmann and A. Rutikanga, "Phenological growth stages and BBCH-identification keys of Chilli (*Capsicum annum* L., *Capsicum chinense* JACQ., *Capsicum baccatum* L.)," *Journal of Plant Diseases and Protection*, vol. 128, no. 2, pp. 549–555, Apr. 2021, <https://doi.org/10.1007/s41348-020-00395-x>.
- [20] X. Deng, T. Huang, W. Wang, and W. Feng, "SE-YOLO: A sobel-enhanced framework for high-accuracy, lightweight real-time tomato detection with edge deployment capability," *Computers and Electronics in Agriculture*, vol. 239, Dec. 2025, Art. no. 110973, <https://doi.org/10.1016/j.compag.2025.110973>.
- [21] R. Ayachi, Y. Said, M. Afif, A. Alshammari, M. Hleili, and A. Ben Abdelali, "Assessing YOLO models for real-time object detection in urban environments for advanced driver-assistance systems (ADAS)," *Alexandria Engineering Journal*, vol. 123, pp. 530–549, June 2025, <https://doi.org/10.1016/j.aej.2025.03.077>.
- [22] Z. Cao and R. Yuan, "Real-Time Detection of Mango Based on Improved YOLOv4," *Electronics*, vol. 11, no. 23, Nov. 2022, Art. no. 3853, <https://doi.org/10.3390/electronics11233853>.