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# Chili Ripeness Level Detection with YOLOv8 and Fuzzy Logic for Harvest Decision Making

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**ABSTRACT**

*Conventional chili harvesting relies on subjective human judgment, resulting in inconsistencies that necessitate a computer vision-based automation system. This study develops a decision support system integrating YOLOv8 for object detection and Mamdani fuzzy logic to assess chili ripeness levels. The YOLOv8 model was trained on 5,598 annotated chili images divided into three ripeness categories: ripe, unripe, and defective (rotten, diseased, or physically damaged), using an 80:20 training-testing split. YOLOv8 classification results serve as inputs to a fuzzy inference system that outputs three linguistic harvest decisions: delay, partial, or full harvest. Experimental evaluation indicates that YOLOv8 achieved 91.2% accuracy, 89.6% precision, and 87.3% recall on the test set. The fuzzy logic system obtained 88% accuracy in harvest decision-making on unseen data, demonstrating output consistency across repeated inferences. Overlapping triangular membership functions enable the fuzzy system to manage intra-class variations and image noise, thereby improving adaptability. These results confirm the feasibility of integrating YOLOv8 and fuzzy logic to support reliable and adaptive automated harvest decisions in chili farming, with potential application in precision agriculture.*

## 1. INTRODUCTION

Chili peppers (*Capsicum annuum* L.) are a high-value horticultural commodity with increasing demand in both households and industry in Indonesia (Rohaeti *et al*., 2019; (Saktriawindarta and Kusrini 2024)). Commonly consumed varieties include *C. annuum* L. and *C. frutescens* L., such as large red chilies, curly chilies, and paprika. The ripeness of chili peppers significantly impacts their quality and market value. Manual assessment is subjective and has the potential to reduce crop quality (Benos *et al*., 2021).

Advances in digital image processing and artificial intelligence (AI) technology open up opportunities for automating ripeness assessment (Archana & Jeevaraj 2024). One popular AI algorithm is YOLO (You Only Look Once), which has now reached version YOLOv8, with real-time object detection capabilities based on visual features (Zophie & Triharminto, 2020; Gao *et al*. 2025; He *et al*. 2025; Liang *et al*. 2025; Nagpal *et al*. 2023; Xu *et al*. 2024; Zheng *et al*. 2024). However, most previous studies have been limited to classification without integrating the results into agronomic decision-making systems. For example, Gamani *et al*. (2024) used only YOLOv8 for ripeness, and Zhu & Spachos (2021) focused on food quality grading.

The main problem of this research is to design a system that not only automatically detects chili ripeness but also converts the detection results into harvest recommendations that adapt to visual conditions. A fuzzy logic-based approach is considered relevant because it can handle uncertainty and produce linguistic outputs that are consistent with field practice (Gómez *et al*., 2025). Fuzzy logic enables the conversion of visual data into harvest decisions such as Delay, Partial, or Full (Vincent *et al*., 2019).

This study fills the research gap in the lack of a computer vision system that not only detects objects but also intelligently suggests actions based on heuristic rules. Weaknesses of previous approaches include not considering class distribution dynamics and image noise, and not integrating an adaptive and flexible linguistic inference system (Sapkota *et al*., 2024; Schneider *et al*., 2024). This research develops an automated system based on YOLOv8 and Mamdani fuzzy logic to generate precise linguistic harvest time recommendations. The YOLOv8 model was trained on a local chili image dataset to match the visual characteristics of the variety used, while the fuzzy system received class proportions as inference input (Chen *et al*., 2024; Sun *et al*., 2025). System evaluation included mAP, accuracy, and F1-score metrics to ensure its performance in supporting data-driven agricultural decision-making. Practically, this system is expected to help farmers improve harvest efficiency, and academically, it expands the application of AI in digital image-based intelligent decision-making in precision agriculture in Indonesia (Moya *et al*., 2024; Shrivastava *et al*., 2017).

## 2. MATERIALS AND METHODS

### 2.1. Research Design

This research was applied experimental study aimed at designing and testing an automated system for visually detecting chili ripeness using the You Only Look Once version 8 (YOLOv8) algorithm and generating harvest recommendations based on Mamdani fuzzy logic (Cordeiro *et al*., 2025; Moya *et al*., 2024; Terven *et al*., 2023). The experiment was conducted in a controlled laboratory environment without field testing, utilizing an open dataset from Roboflow. The dataset contained annotated images of local chili peppers captured in-house by the University of Southeastern Philippines, using controlled artificial lighting to maintain consistent visual quality (Aishwarya & Reddy 2024).

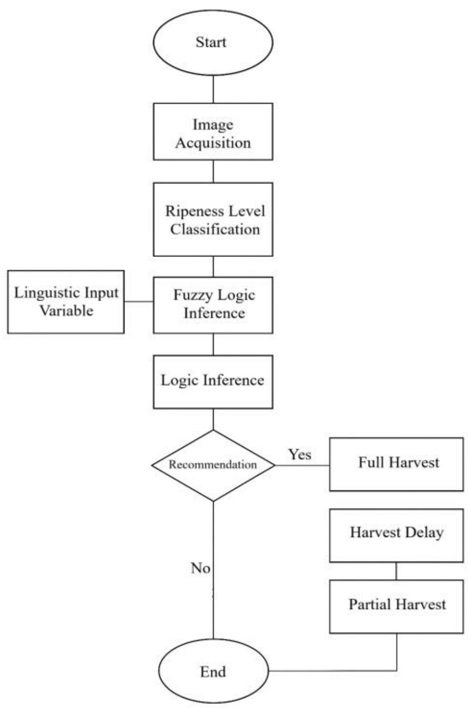


Figure 1. System flowchart

Figure 1 visualizes the system flow for ripeness detection and harvest decision-making. The process began with chili image acquisition, followed by classification using YOLOv8 into five visual categories. The classification results were then converted into linguistic variables (low, medium, high) based on the proportion of each class. These values were input to the fuzzy system, which was processed using expert-based if-then rules. Inference produced a linguistic harvest decision: Full Harvest, Partial Harvest, or Delay Harvest. If the input data was insufficient, the system did not provide a recommendation. All results were monitored via a dashboard in real-time for system evaluation. This approach demonstrated the integration of object detection and fuzzy logic as an adaptive and contextual harvest decision-making system for precision agriculture.

During the experiment, several variables were controlled, including light intensity, model training parameters (number of epochs, batch size, and learning rate), fuzzy rule configuration, and simulated ripeness scenarios and environmental parameters (temperature and humidity). The developed system consists of two main components:

1) The YOLOv8 detection model, which classifies chili images into five visual classes: ripe, unripe, diseased, rotten, and physically damaged.
2) The Mamdani fuzzy inference system, which converts the classification results into harvest recommendations, namely: "Delay Harvest," "Partial Harvest," or "Full Harvest," based on heuristically designed linguistic rules (Gómez *et al*., 2025).

The implementation was carried out using Python with the integration of libraries such as PyTorch, OpenCV, NumPy, scikit-fuzzy, and the Roboflow SDK to support preprocessing, model training, and dataset management (Shorten & Khoshgoftaar, 2019; Shrivastava *et al*., 2017).

### 2.2. Training the YOLOv8 Ripeness Detection Model

The YOLOv8 model was used as an object detector and classifier for chili images into five classes: unripe, ripe, rotten, diseased, and physically damaged (Wang *et al*. 2022; Wang *et al*. 2024). This model was chosen because of its spatially and temporally efficient single-stage detector, making it suitable for implementing real-time precision agriculture systems (Cordeiro *et al*., 2025; Terven *et al*., 2023). The dataset consisted of 5,598 images of local chili peppers obtained from the University of Southeastern Philippines' public repository through the Roboflow platform. All images have a native resolution of 640×640 pixels and were manually annotated using LabelImg to generate class labels and object coordinates. The data was randomly split, with a ratio of 80% training data (4,478 images) and 20% testing data (1,120 images).

Model training was performed using PyTorch with the YOLOv8s configuration, for 50 epochs, a batch size of 16, and an initial learning rate of 0.01 using Stochastic Gradient Descent (SGD) optimization. Training was run on a GPU to improve computational efficiency. To improve model generalization to varying real-world conditions, data augmentation was used in the form of horizontal flips, rotations, brightness adjustments, and scaling, as recommended by Shorten & Khoshgoftaar (2019).

Loss functions included objectness loss, classification loss, and localization loss to optimize spatial detection and classification. The number of epochs is determined based on observations of the training curve's convergence point. Model performance is evaluated using precision, recall, and mAP@0.5 metrics. These detection results are used as input to a fuzzy system to generate adaptive harvest recommendations.

Table 1. Composition of chili image data

| Dataset Category | Number of Images | Percentage |
|---|---|---|
| Training Data | 4,478 | 80% |
| Testing Data | 1,120 | 20% |
| **Total Dataset** | **5,598** | **100%** |

### 2.3. Fuzzy Logic Development

In this study, a harvest decision-making system was developed using the Mamdani-type fuzzy inference system (FIS)(Liu *et al*. 2018), widely used in image- and sensor-based agricultural recommendation systems to handle decision uncertainty (Gómez *et al*., 2025; Vincent *et al*., 2019). The FIS was used to interpret the visual classification results from the YOLOv8 model into linguistic recommendations for harvest decisions that are automated and precise.

#### a) Fuzzy Variables and Membership Functions

The three main input variables in this fuzzy system included (1) CM (Ripe Chili): Percentage of ripe chilies in a single image, (2) CMe (Unripe Chili): Percentage of unripe chilies, and (3) CB (Problematic Chili): Percentage of damaged, rotten, or infected chilies. The three input variables were categorized into three linguistic sets: Low (R), Medium (S), and High (T), using a triangular membership function with a value range of 0–30 for low, 20–60 for medium, and 60–100 for high. Meanwhile, the output variable, Harvest Decision (KP), was represented on a scale of 0–10 and categorized as follows: (•) Delayed Harvest (TP): [0–3], (•) Partial Harvest (PS): [3–7], and (•) Full Harvest (PP): [7–10].

The membership functions for all variables used overlapping values in the ranges 20–30 (R∩S) and 60–70 (S∩T). This approach has proven effective in handling agricultural image variability and visual noise (Cordeiro *et al*., 2025; Sun *et al*., 2025). A visualization of the membership function is presented in Figure 2.

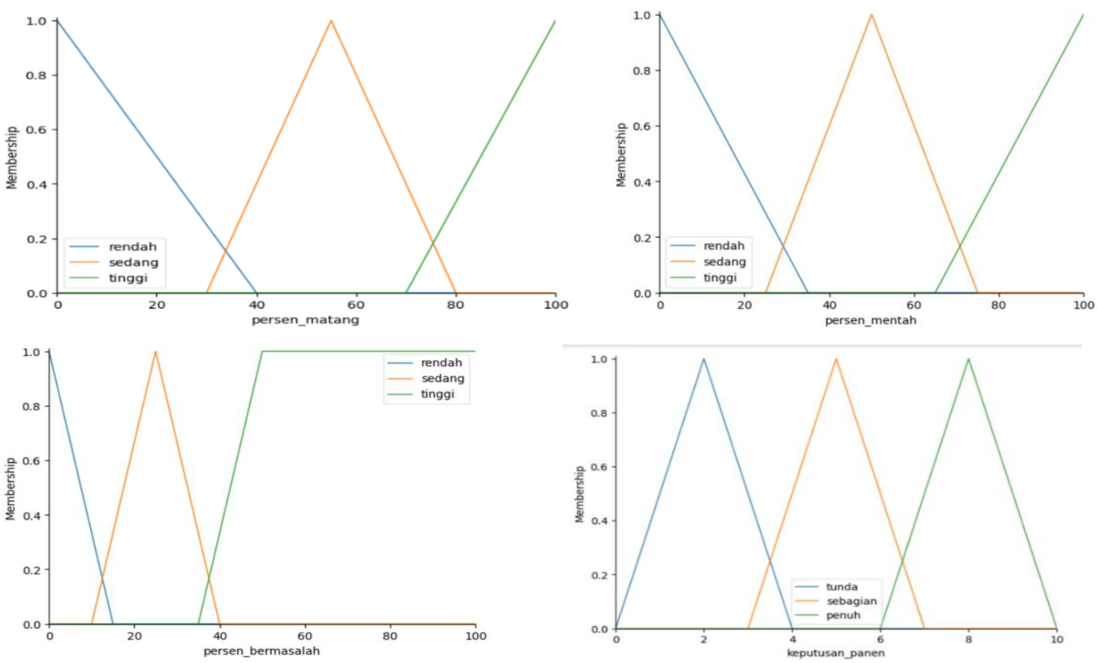


Figure 2. Membership function

Figure 2 illustrates the triangular membership function applied to all variables in the fuzzy system. This membership structure is designed to reflect the gradual transition of values through overlapping areas between linguistic sets, thereby capturing uncertainty in visual classification data. This approach also supports efficient Mamdani logic-based inference processes in the context of automated harvest decision-making for horticultural commodities.

**b) Fuzzy Rule Base**

This fuzzy rule-base design adopts a heuristic approach also applied to fruit ripeness decision-making and agricultural grading based on YOLO and fuzzy systems (Camacho & Morocho-Cayamcela, 2023; Moya *et al*., 2024). A total of 27 if–then rules were constructed based on combinations of the three inputs (Table 2), with the following inference principles.

**c) Fuzzy System Flowchart**

To clarify the process, Figure 3 presents a flowchart of the fuzzy logic system, from the YOLOv8 classification input to the final decision. This flowchart illustrates the fuzzy logic-based harvest decision-making system, starting with input data from visual detection of chili peppers (ripe, unripe, problematic), followed by a fuzzification process using triangular membership functions. The resulting linguistic values are processed through fuzzy inference based on 27 if-then rules, then converted back into crisp values through defuzzification using the centroid method. The final results are mapped into harvest decision categories: Delay Harvest, Partial Harvest, or Full Harvest, to support automatic and precise harvest recommendations.

Table 2. Rule base

| No | Ripe Chili (RC) | Unripe Chili (UC) | Defective Chili (DC) | Harvest Decision |
|---|---|---|---|---|
| 1 | Low | Low | Low | Postpone Harvest |
| 2 | Low | Low | Medium | Postpone Harvest |
| 3 | Low | Low | High | Postpone Harvest |
| 4 | Low | Medium | Low | Postpone Harvest |
| 5 | Low | Medium | Medium | Postpone Harvest |
| 6 | Low | Medium | High | Postpone Harvest |
| 7 | Low | High | Low | Postpone Harvest |
| 8 | Low | High | Medium | Postpone Harvest |
| 9 | Low | High | High | Postpone Harvest |
| 10 | Medium | Low | Low | Partial Harvest |
| 11 | Medium | Low | Medium | Postpone Harvest |
| 12 | Medium | Low | High | Postpone Harvest |
| 13 | Medium | Medium | Low | Partial Harvest |
| 14 | Medium | Medium | Medium | Partial Harvest |
| 15 | Medium | Medium | High | Postpone Harvest |
| 16 | Medium | High | Low | Postpone Harvest |
| 17 | Medium | High | Medium | Postpone Harvest |
| 18 | Medium | High | High | Postpone Harvest |
| 19 | High | Low | Low | Full Harvest |
| 20 | High | Low | Medium | Partial Harvest |
| 21 | High | Low | High | Postpone Harvest |
| 22 | High | Medium | Low | Partial Harvest |
| 23 | High | Medium | Medium | Partial Harvest |
| 24 | High | Medium | High | Postpone Harvest |
| 25 | High | High | Low | Postpone Harvest |
| 26 | High | High | Medium | Postpone Harvest |
| 27 | High | High | High | Postpone Harvest |

**d) Defuzzification Method**

The result of the fuzzy inference block is a fuzzy output that still has a degree of membership. The defuzzification process uses the centroid method because it produces representative values that are most stable against the fuzzy distribution. This method is also widely used in YOLO-based decision-making systems for agriculture due to its robustness to sensory data (Joshi, 2024; Saatchi, 2024). The final score is on a scale of 0–10 and is interpreted into a linguistic harvest decision.

### 2.4. Ripeness Classification and Classification Results

After training was completed, the YOLOv8 model was used to classify chili peppers in new images based on dominant visual characteristics such as color and texture (Camacho & Morocho-Cayamcela, 2023). The classification process resulted in five categories: Unripe (green), Ripe (red), Rotten (dark), Diseased (abnormal spots), and Physical Damage (cracks or deformation), according to the visual annotations in the training data (Chen *et al*., 2024; Cordeiro *et al*., 2025; Schneider *et al*., 2024). Each detection result included a bounding box, class label, and confidence value to indicate model confidence (Ma & Zhang, 2025). Based on testing, the highest accuracy was obtained in the Ripe and Physical Damage classes (97%), followed by Rotten (96%), while the Diseased (80%) and Unripe (74%) classes showed lower performance due to similar visual features and background noise (Gamani *et al*., 2024; Gao *et al*. 2025; Liang *et al*. 2025). All detections were converted to a percentage of objects per class and used as linguistic input to the fuzzy logic system. The three main variables analyzed were the level of ripeness (green, orange, red), the number of ripe fruits in one image (few, medium, many), and environmental conditions (humidity and temperature). Through a linguistic rule-based fuzzy inference process, the system generated action recommendations in the form of: no action, fertilization preparation, or harvest preparation. Simulations showed that the dominance of ripe fruits with optimal environmental conditions resulted in a harvest recommendation, while the dominance of unripe fruits encouraged a delay. These results confirm that the integration of YOLOv8 and fuzzy logic is effective in forming an adaptive, precise, and relevant harvest decision-making system for smart agriculture applications (Badgujar *et al*., 2024; Schneider *et al*., 2024; Liu *et al*. 2018).

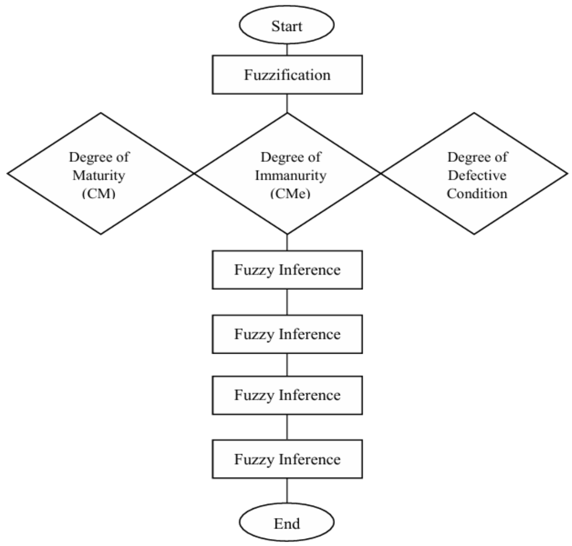


Figure 3. Fuzzy system flowchart

### 2.5. Caching and Training the YOLOv8 Model

This study implemented a caching mechanism to improve inference efficiency (Joshi, 2024). This strategy has proven effective in accelerating system response, reducing resource consumption, and avoiding bottlenecks in the inference pipeline. In the training phase, the YOLOv8 model was trained for 50 epochs with parameter configurations optimized through exploration of batch size, learning rate, and the training-test data ratio. Evaluation was performed using recall, mAP@50, and mAP@50–95 metrics to identify the best model. The training results showed a steady decrease in the loss curves (box, classification, and distribution focal loss) without any indication of overfitting. The mean Average Precision reached 0.88 for mAP@50 and 0.63 for mAP@50–95, indicating good detection performance at various levels of Intersection over Union (Chen *et al*., 2024; Sun *et al*., 2025). Optimal convergence was achieved at epoch 50, with the metric curves beginning to plateau. To improve accuracy for lower-performing classes like Sick and Raw, data augmentation and hyperparameter adjustments, including the use of a learning rate scheduler and early stopping, are recommended. The combination of optimal model training and an efficient caching strategy enables the system to be fast, accurate, and adaptive for AI-based precision agriculture.

## 3. RESULTS AND DISCUSSION

### 3.1. Evaluation Results of the YOLOv8 Model for Chili Ripeness and Condition Detection

The YOLOv8 model in this study was used to detect chili peppers and classify them into five visual classes: Ripe, Unripe, Rotten, Diseased, and Physically Damaged. Training and testing results demonstrated good detection performance, with accurate bounding box visualizations and high precision and recall values, particularly for the Ripe and Unripe classes. However, confusion matrix analysis revealed a relatively high false negative rate for the Unripe and Diseased classes, due to the similarity of visual features between these classes. Furthermore, the Physically Damaged class still showed low recall, indicating that some objects were not optimally detected. The Recall-Confidence curves indicate that classification performance can still be improved by adjusting the confidence threshold. To address misclassification issues, data augmentation specifically for problematic classes is necessary, as well as the application of hard negative mining techniques to enhance learning on difficult samples (Shorten & Khoshgoftaar, 2019; Shrivastava *et al*., 2017). With this strategy, the model's accuracy and sensitivity to objects with complex visual characteristics can be significantly improved.

Figure 4 displays the visualization of the validation image annotation results for the YOLOv8 training batch, namely (a) val_batch0_labels and (b) val_batch2_labels, which represent the location and class of objects based on ground truth labels. Three main categories are displayed: Ripe, Unripe, and Problematic Chilies (including rotten, physically damaged, and pest-infested), with each object assigned a bounding box according to its class. This visualization serves as initial validation that the annotation process has been carried out accurately and representative of actual conditions in the field. The diversity of objects in a single image, from ripe to damaged chilies, demonstrates comprehensive data coverage, which is essential for the model to recognize class variations. Furthermore, this annotation serves as the primary reference in tshe model performance evaluation process, particularly for calculating metrics such as precision, recall, and mean average precision (mAP), which indicates the success of accurate object detection.

(a) (b)

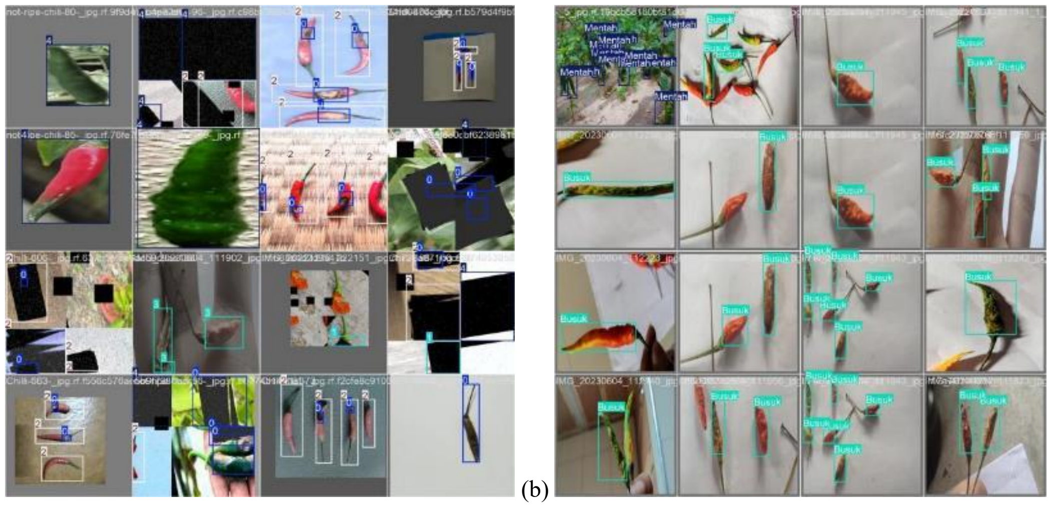

Figure 4. (a) val_batch0_labels (b) val_batch2_labels

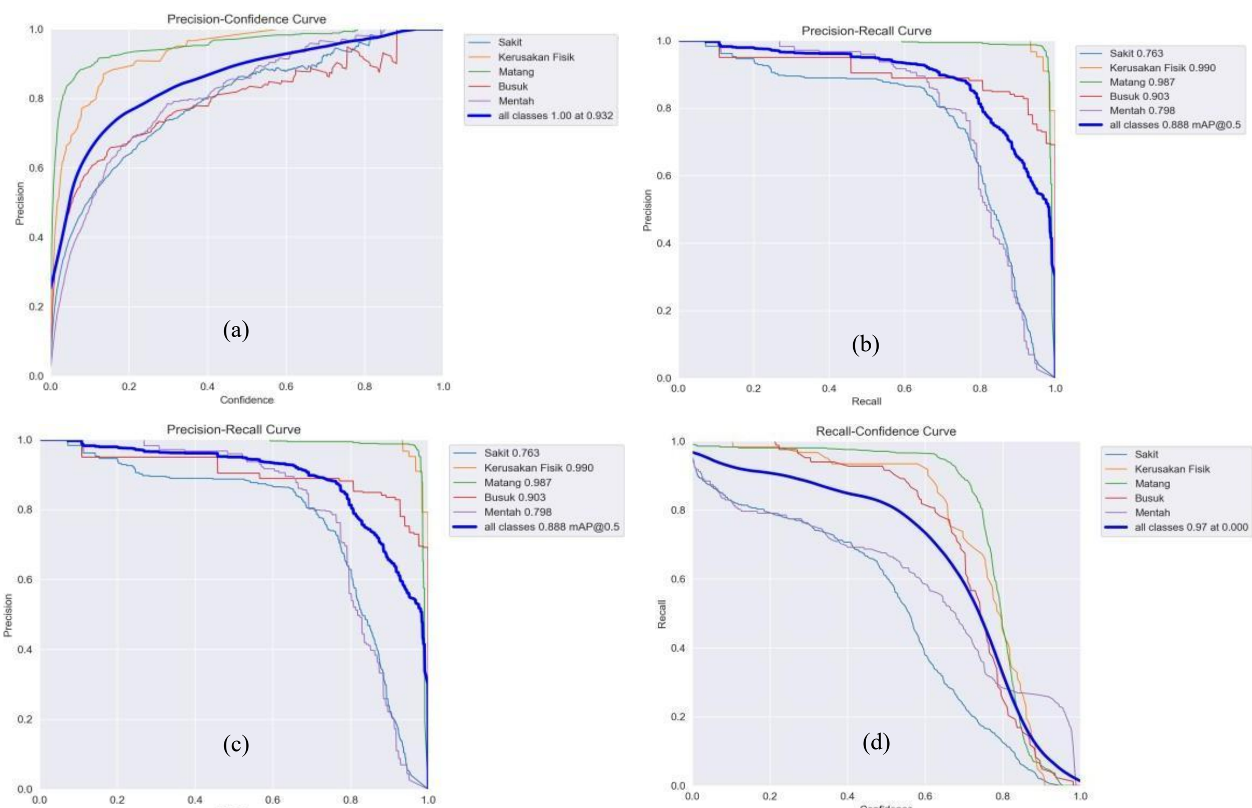


Figure 5. (a) F1 Curve (b) PCurve; (c) PRCurve; (d) Rcurve

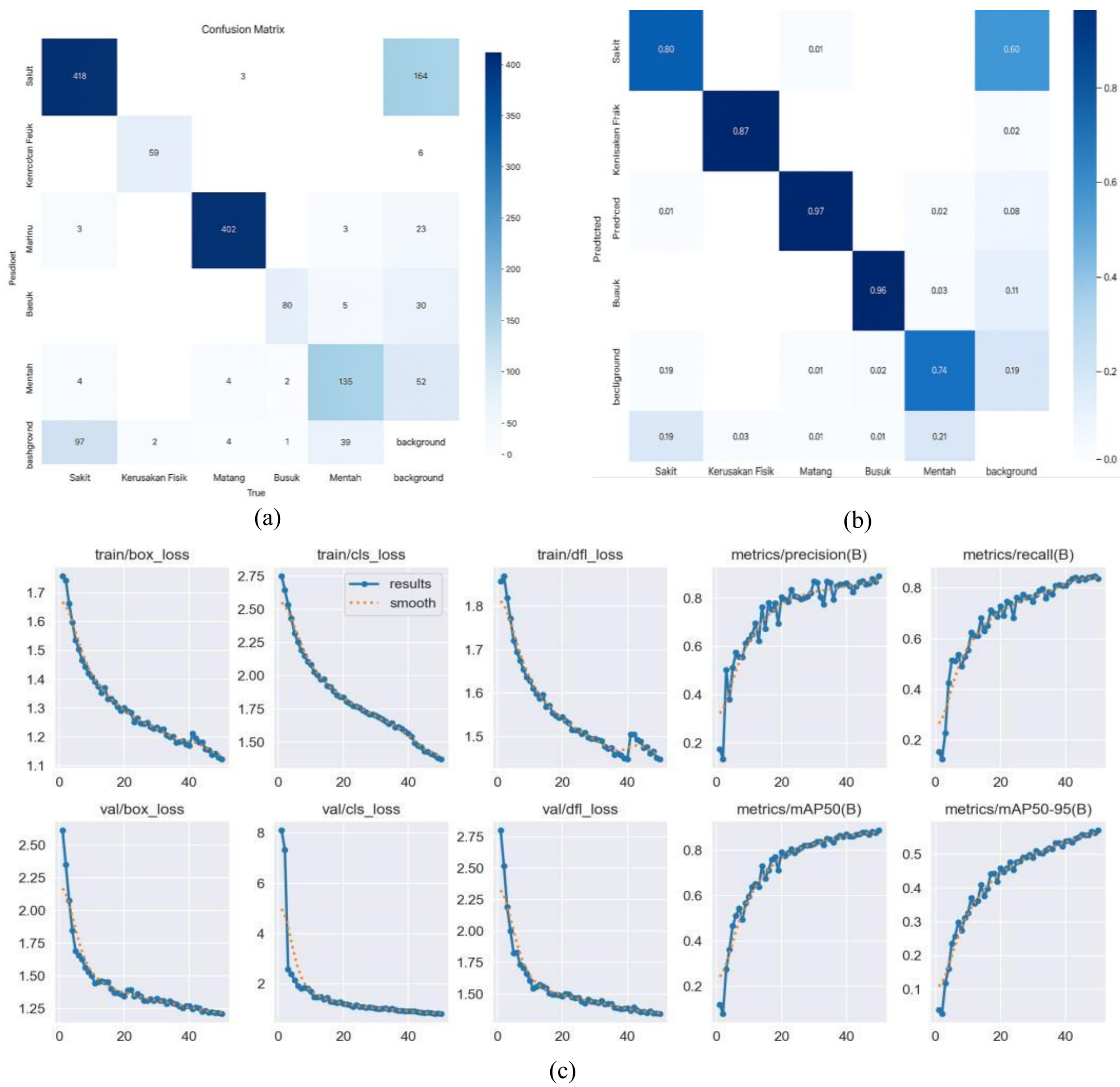


Figure 6. (a) Confusion_matrix (b) Confusion_matrix_normalized; (c) Result

Figure 6 presents a performance evaluation of the YOLOv8 model, consisting of a confusion matrix (Figure 6a), classification metrics (Figure 6b), and training loss curve (Figure 6c). Figure 6a shows the confusion matrix results, showing that the model has high accuracy in the Ripe and Rotten classes, characterized by a predominance of true positives and low prediction errors. However, significant misclassifications occurred in the Raw and Diseased classes. Raw chilies were frequently misclassified as Ripe due to the similarity in color during the transition phase, while diseased chilies were often identified as Rotten or Physically Damaged due to the similarity in surface texture. In addition to false negatives, several false positives were also found in the Physically Damaged class, primarily caused by visual artifacts such as shadows or reflections that resemble defects. Figure 6b reinforces these findings through high F1-scores in the Ripe and Rotten classes, and low in the Diseased class, indicating an imbalance between precision and sensitivity. Figure 6c shows that the training process has reached convergence, but generalization improvements are still needed, especially for minor classes. To address this, it is recommended to implement data augmentation strategies such as color jitter, rotation, zoom, and lighting to expand intra-class variation and improve the model's robustness to diverse field conditions (Shorten & Khoshgoftaar, 2019). Furthermore, a hard negative mining approach can be used to focus learning on difficult samples that often lead to misclassification, such as chilies in transition or with minor damage (Shrivastava *et al*., 2017). This combination of strategies is expected to increase the model's sensitivity to ambiguous classes and strengthen the accuracy of the fuzzy system's input for harvest decision-making.

### 3.2. Fuzzy Logic Integration

The performance evaluation of the fuzzy system was conducted to assess the accuracy of harvest decision recommendations based on the visual classification results of the YOLOv8 model. Testing was conducted on 50 test images verified by horticultural experts as validation data. The results showed that the fuzzy system produced decisions that matched expert recommendations in 44 out of 50 cases, resulting in a system accuracy rate of 88%. The discrepancies in six cases were caused by accumulated visual classification errors, particularly in the visually overlapping Diseased and Unripe chili classes. Furthermore, the accuracy of the fuzzy decisions was verified through limited field simulations, comparing the system's harvest recommendations to actual farmer decisions. The evaluation showed that the system was able to reduce premature harvest decisions and increase harvest selectivity, particularly for chilies with ambiguous maturity levels. These results indicate that the fuzzy system not only represents expert decision logic, but also has potential applications in supporting precise, data-driven harvest decision-making in the field (Gómez *et al*., 2025).

### 3.3. Ripeness Detection Model Training Results

#### 3.3.1. Model Classification Performance Evaluation

The YOLOv8 model performance evaluation was conducted using a confusion matrix and F1-Score curve analysis to measure classification accuracy and the balance between precision and recall for six target classes: Sick, Physically Damaged, Ripe, Rotten, Raw, and Background. Based on the absolute matrix, the model achieved high accuracy for the Ripe (432) and Sick (419) classes, although misclassifications to the background occurred, particularly in the Sick class (87 cases). The Rotten (88) and Raw (135) classes showed moderate detection rates, while Physically Damaged was only detected 68 times, likely due to limited data. The background was also frequently misclassified as chili peppers, particularly Sick (164), indicating a lack of visual feature separation between object and background.

In the row-by-row normalized matrix, the highest recall value was achieved by the Ripe class (0.87), followed by Rotten (0.81), Sick (0.80), Raw (0.74), and Physically Damaged (0.67), while the background class had the lowest recall value (0.02). The main errors occurred in the Raw and Sick classes, which experienced 21% and 17% false negatives, respectively. This indicates the need to improve the quality of the background data and implement visual augmentation strategies to strengthen the model's performance on minor classes.

The F1-Score curve at the confidence threshold shows that the optimum point was reached at a threshold of 0.453, with the highest average F1-score of 0.86. The Ripe and Physically Damaged classes recorded F1-scores approaching 0.95, followed by Sick and Rotten (0.83–0.85), while the Raw class had the lowest value (0.75–0.77), indicating high sensitivity to threshold changes. This indicates the model's less stable detection of unripe chilies due to visual similarity. In general, the evaluation results indicate that the model performed well, but still requires improvement in classes with low accuracy to improve the system's consistency and reliability under complex field conditions (Badgujar *et al*., 2024).

#### 3.3.2. Results

Figure 7 shows the system interface that integrates object detection using YOLOv8 with a fuzzy logic-based harvest decision-making process. To assess the system's reliability, an internal evaluation was conducted using 20 additional test images from the Roboflow public dataset excluded in the training process. The test results showed that the system was able to generate harvest recommendations that matched the ground truth labels in 17 out of 20 cases, with an estimated fuzzy decision accuracy of 85%. The most consistent recommendations were generated in the Full Harvest and Delayed Harvest classes, while minor differences appeared in the Partial Harvest category, influenced by the composition of the ripeness mix within a single frame. Furthermore, a repeatability test was conducted by processing the same image in five different runs. The results show that the system provides stable recommendation output without variation, indicating the consistency of fuzzy inference against similar image inputs. Although not yet directly tested in field conditions, the results indicate the system has good functional potential in visual-based automated harvest decision-making scenarios.

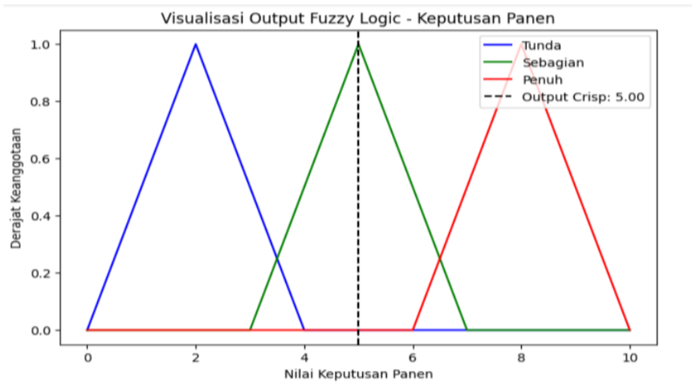


Figure 7. Visualization of fuzzy logic output - harvest decisions

## 4. CONCLUSION

This study successfully designed and implemented an automated system based on YOLOv8 integrated with fuzzy logic to detect the ripeness level and physical condition of chili peppers to support harvesting decisions. Evaluation on laboratory test data showed high detection performance with mAP@0.5 of 0.888 and an optimal F1-score of 0.86 at a threshold of 0.453. In general, the average classification accuracy of the model reached 91.2%, while the highest accuracy of 98% was obtained specifically for the Ripe and Physical Damage classes which have more contrasting visual characteristics, so this figure does not represent the overall performance across all classes. Practical validation showed that the fuzzy system produced harvest recommendations that agreed with expert decisions in 88% of cases and achieved 85% accuracy when tested on field data. Key challenges identified included misclassification in classes with high visual similarity (such as Unripe and Diseased) and sensitivity to lighting variations, necessitating dataset strengthening through further data augmentation, minority class balancing, and the application of training strategies such as hard negative mining. The main contributions of this research include the development of a local chili dataset, the development of fuzzy rules based on agronomic principles, and the design of an interactive dashboard as a supporting tool for more adaptive and visual data-based precision agriculture.

## REFERENCES

Aishwarya, M.P., & Reddy, A.P. (2024). Dataset of chilli and onion plant leaf images for classification and detection. *Data in Brief*, ***54***, 110524. https://doi.org/10.1016/j.dib.2024.110524

Archana, R., & Jeevaraj, P.S.E. (2024). Deep learning models for digital image processing: A review. *Artif Intell Rev*, ***57***, 11. https://doi.org/10.1007/s10462-023-10631-z

Badgujar, C.M., Poulose, A., & Gan, H. (2024). Agricultural object detection with You Only Look Once (YOLO) algorithm: A bibliometric and systematic literature review. *Computers and Electronics in Agriculture*, ***223***, 109090. https://doi.org/10.1016/j.compag.2024.109090

Benos, L., Tagarakis, A.C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*, ***21***(11), 1–55. https://doi.org/10.3390/s21113758

Camacho, J.C., & Morocho-Cayamcela, M.E. (2023). Mask R-CNN and YOLOv8 comparison to perform tomato maturity recognition task. In *Communications in Computer and Information Science* (Vol. 1885, pp. 382–396). Springer. https://doi.org/10.1007/978-3-031-45438-7_26

Chen, Y., Xu, H., Chang, P., Huang, Y., Zhong, F., Jia, Q., Chen, L., Zhong, H., & Liu, S. (2024). CES-YOLOv8: Strawberry maturity detection based on the improved YOLOv8. *Agronomy*, ***14***(7), 1353. https://doi.org/10.3390/agronomy14071353

Cordeiro, L.dos-S., Nääs, I.de-A., & Okano, M.T. (2025). Smart postharvest management of strawberries: YOLOv8-driven detection of defects, diseases, and maturity. *AgriEngineering*, ***7***(8), 246. https://doi.org/10.3390/agriengineering7080246

Gamani, A.-R.A., Arhin, I., & Asamoah, A.K. (2024). Performance evaluation of YOLOv8 model configurations, for instance segmentation of strawberry fruit development stages in an open field environment. *arXiv*. https://doi.org/10.48550/arXiv.2408.05661

Gao, X., Ding, J., Zhang, R., & Xi, X. (2025). YOLOv8n-CA: Improved YOLOv8n model for tomato fruit recognition at different stages of ripeness. *Agronomy*, ***15***(1), 188. https://doi.org/10.3390/agronomy15010188

Gómez, A.C., Bejarano, L.A., & Espitia, H.E. (2025). Model for agricultural production in Colombia using a neuro-fuzzy inference system. *Computers*, ***14***(5), 168. https://doi.org/10.3390/computers14050168

He, L., Wu, D., Zheng, X., Xu, F., Lin, S., Wang, S., Ni, F., & Zheng, F. (2025). RLK-YOLOv8: Multi-stage detection of strawberry fruits throughout the full growth cycle in greenhouses based on large kernel convolutions and improved YOLOv8. *Frontiers in Plant Science*, ***16***, 1552553. https://doi.org/10.3389/fpls.2025.1552553

Joshi, H. (2024). Edge-AI for agriculture: Lightweight vision models for disease detection in resource-limited settings. *arXiv*. https://doi.org/10.48550/arXiv.2412.18635

Liang, X., Jia, H., Wang, H., Zhang, L., Li, D., Wei, Z., You, H., Wan, X., Li, R., Li, W., & Yang, M. (2025). ASE-YOLOv8n: A method for cherry tomato ripening detection. *Agronomy*, ***15***(5), 1088. https://doi.org/10.3390/agronomy15051088

Liu, K.E., Ma, J., Lai, E.M.-K., Data Science, & Artificial Intelligence. (2018). A dynamic fuzzy rule and attribute management framework for fuzzy inference systems in high-dimensional data. *Artificial Intelligence*, ***1***(1), 1–23. https://doi.org/10.48550/arXiv.2504.19148

Ma, Y., & Zhang, S. (2025). YOLOv8-CBSE: An enhanced computer vision model for detecting the maturity of chili pepper in the natural environment. *Agronomy*, ***15***(3), 537. https://doi.org/10.3390/agronomy15030537

Moya, V., Quito, A., Pilco, A., Vásconez, J.P., & Vargas, C. (2024). Crop detection and maturity classification using a YOLOv5-based image analysis. *Emerging Science Journal*, ***8***(2), 496–512. https://doi.org/10.28991/ESJ-2024-08-02-08

Nagpal, R., Long, S., Jahagirdar, S., Liu, W., Fazackerley, S., Lawrence, R., & Singh, A. (2023). An application of deep learning for sweet cherry phenotyping using YOLO object detection. *arXiv,* 1-18. https://doi.org/10.48550/arXiv.2302.06698

Rohaeti, E., Muzayanah, K., Septaningsih, D.A., & Rafi, M. (2019). Fast analytical method for authentication of chili powder from synthetic dyes using UV-Vis spectroscopy in combination with chemometrics. *Indonesian Journal of Chemistry*, ***19***(3), 668–674. https://doi.org/10.22146/ijc.36297

Saatchi, R. (2024). Fuzzy logic concepts, developments and implementation. *Information (Switzerland)*, ***15***(10), 656. https://doi.org/10.3390/info15100656

Saktriawindarta, R., & Kusrini, K. (2024). Metode klasifikasi tingkat kematangan buah dan sayuran: Tinjauan sistematis. *G-Tech: Jurnal Teknologi Terapan*, ***8***(4), 2344–2354. https://doi.org/10.70609/gtech.v8i4.5067

Sapkota, R., Ahmed, D., & Karkee, M. (2024). Comparing YOLOv8 and Mask R-CNN for instance segmentation in complex orchard environments. *Artificial Intelligence in Agriculture*, ***13***, 84–99. https://doi.org/10.1016/j.aiia.2024.07.001

Schneider, F., Swiatek, J., & Jelali, M. (2024). Detection of growth stages of chilli plants in a hydroponic grower using machine vision and YOLOv8 deep learning algorithms. *Sustainability*, ***16***(15), 6420. https://doi.org/10.3390/su16156420

Shorten, C., & Khoshgoftaar, T.M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, ***6***(1), 60. https://doi.org/10.1186/s40537-019-0197-0

Shrivastava, A., Pfister, T., Tuzel, O., Susskind, J., Wang, W., & Webb, R. (2017). Learning from simulated and unsupervised images through adversarial training. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 2242–2251). IEEE. https://doi.org/10.1109/CVPR.2017.241

Sun, H., Zheng, Q., Yao, W., Wang, J., Liu, C., Yu, H., & Chen, C. (2025). An improved YOLOv8 model for detecting four stages of tomato ripening and its application deployment in a greenhouse environment. *Agriculture*, ***15***(9), 1–33. https://doi.org/10.3390/agriculture15090936

Terven, J., Córdova-Esparza, D.M., & Romero-González, J.A. (2023). A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS. *Machine Learning and Knowledge Extraction*, ***5***(4), 1680–1716. https://doi.org/10.3390/make5040083

Vincent, D.R., Deepa, N., Elavarasan, D., Srinivasan, K., Chauhdary, S.H., & Iwendi, C. (2019). Sensors driven AI-based agriculture recommendation model for assessing land suitability. *Sensors*, ***19***(17), 3667. https://doi.org/10.3390/s19173667

Wang, L., Zhao, Y., Xiong, Z., Wang, S., Li, Y., & Lan, Y. (2022). Fast and precise detection of litchi fruits for yield estimation based on the improved YOLOv5 model. *Frontiers in Plant Science*, ***13***, 965425. https://doi.org/10.3389/fpls.2022.965425

Wang, S., Xiang, J., Chen, D., & Zhang, C. (2024). A method for detecting tomato maturity based on deep learning. *Applied Sciences*, ***14***(23), 1–24. https://doi.org/10.3390/app142311111

Xu, D., Ren, R., Zhao, H., & Zhang, S. (2024). Intelligent detection of muskmelon ripeness in greenhouse environment based on

YOLO-RFEW. *Agronomy*, ***14***(6), 1091. https://doi.org/10.3390/agronomy14061091

Zophie, J., & Triharminto, H.H. (2020). Implemetasi algoritma You Only Look Once ( YOLO ) menggunakan web camera untuk mendeteksi objek statis dan dinamis. *JurnalTNIAngkatan Udara*, ***1***(1), 98-109.

Zheng, S., Jia, X., He, M., Zheng, Z., Lin, T., & Weng, W. (2024). Tomato recognition method based on the YOLOv8-Tomato model in complex greenhouse environments. *Agronomy*, ***14***(8), 1764. https://doi.org/10.3390/agronomy14081764

Zhu, L., & Spachos, P. (2021). Support vector machine and YOLO for a mobile food grading system. *Internet of Things*, ***13***, 100359. https://doi.org/10.1016/j.iot.2021.100359