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Research Article

Rice Maturity Level Segmentation in Paddy Fields Based on UAV Aerial Imagery Using the YOLOv8 Algorithm

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Abstract: Accurate identification of rice maturity is an important factor in determining the optimal harvest period and maintaining grain quality. Conventional field observations are often influenced by subjective judgment and may produce inconsistent results across different observers. This study proposes an automated approach for rice maturity segmentation by integrating Unmanned Aerial Vehicle (UAV) imagery with the YOLOv8 deep-learning model. A dataset consisting of 682 aerial images was collected from paddy fields and categorized into three classes: unripe, ripe, and unhealthy rice. The images were annotated using bounding boxes and divided into training, validation, and testing subsets. Model training was performed using YOLOv8n for 100 epochs with a batch size of 16. Performance evaluation employed accuracy, precision, recall, and F1-score metrics derived from the confusion matrix. Experimental results showed that the proposed framework achieved an accuracy of up to 93%, demonstrating its capability to identify rice maturity conditions effectively. The findings suggest that UAV-based monitoring combined with deep learning can support precision agriculture by providing a faster, more objective, and scalable alternative to manual field assessment.

Keywords: Computer Vision; Image Segmentation; Rice Maturity; UAV; YOLOv8.

1. Introduction

Indonesia is an agrarian country where rice is one of the main food commodities for the population [5]. The maturity level of rice is an important factor in determining harvest quality and agricultural productivity. Errors in determining the appropriate harvesting time can lead to decreased grain quality, increased crop damage, and reduced economic value for farmers [4].

Traditionally, rice maturity assessment is still conducted through visual observation and farmers' experience [5]. However, this method has several limitations because it is highly influenced by human subjectivity and varying environmental conditions [6]. The advancement of computer vision and deep learning technologies provides opportunities to automatically identify rice maturity levels with higher accuracy and consistency.

One of the most widely used deep learning algorithms for object detection is YOLO (You Only Look Once). YOLOv8, the latest version of the algorithm, offers real-time object detection capabilities with high accuracy and efficient computation. In addition, the use of UAV-based aerial imagery enables data acquisition over large rice field areas with a consistent viewing perspective [2].

Several previous studies have applied YOLOv8 in the agricultural sector, such as plant disease detection, rice growth phase identification, and fruit maturity classification [7]. However, research on rice maturity segmentation based on UAV aerial imagery using YOLOv8 is still relatively limited.

Based on these issues, this study aims to develop a rice maturity segmentation system using UAV aerial imagery and the YOLOv8 algorithm. The proposed system is expected to assist farmers in determining the optimal harvesting time more quickly, accurately, and efficiently [6].

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2. Research Method

This research employed an experimental quantitative design. UAV imagery was collected from rice cultivation areas in Kebumen Regency. The dataset consisted of 682 images, including 558 training images, 82 validation images, and 42 testing images. Images were annotated using the Roboflow platform with three maturity categories: unripe, ripe, and unhealthy.

The YOLOv8n architecture was selected because of its lightweight design and suitability for real-time implementation. Training was conducted using 100 epochs, a batch size of 16, SGD optimization, and an image resolution of 640 × 640 pixels. Model performance was assessed using accuracy, precision, recall, and F1-score metrics. The evaluation process aimed to measure the model's ability to correctly detect and classify rice maturity levels under varying field conditions.

Data Collection

The dataset used in this study consisted of aerial images of rice fields captured using a UAV drone. The dataset contained 682 images, which were divided into:

- 558 training images
- 82 validation images
- 42 testing images

Image acquisition was conducted in rice field areas located in Kebumen Regency under various lighting conditions and image capture angles

Dataset Annotation

Each image was annotated using the bounding box method to identify rice objects based on their maturity levels. The annotation process was carried out using the Roboflow platform with three main classes: unripe, ripe, unhealthy. The annotated dataset was then converted into the YOLOv8 format for model training and evaluation.

Model Architecture

This study employed the YOLOv8n model because of its lightweight architecture and computational efficiency,[12] making it suitable for implementation on devices with limited hardware specifications. YOLOv8 utilizes a single-stage detector approach, enabling real-time object detection with high processing speed and accuracy..

Training Configuration

Table 1. The training configuration used in this study.

Parameter	Value
Model	YOLOv8n
Epoch	100
Batch Size	16
Optimizer	SGD
Image Size	640 × 640

Model Evaluation

The model performance was evaluated using a confusion matrix with the following parameters:

- Accuracy
- Precision
- Recall
- F1-Score

The evaluation metrics are defined as follows:

Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

3. Results and Discussion Proposed Method

The trained model successfully identified rice maturity categories from UAV imagery and demonstrated strong detection performance across different field scenarios. The highest accuracy obtained during testing reached 93%, indicating that the model was capable of distinguishing among ripe, unripe, and unhealthy rice plants with high reliability.

Several classification errors were observed in situations involving excessive illumination, shadow effects, or partial occlusion of rice plants. Nevertheless, the overall performance remained competitive compared with related studies employing conventional image-processing approaches. The integration of UAV-based data acquisition and YOLOv8 detection offers practical benefits for large-scale agricultural monitoring because it reduces manual inspection requirements while improving consistency in maturity assessment.

These findings highlight the potential of computer-vision technologies for supporting precision agriculture applications. By enabling automated crop monitoring, the proposed framework can assist farmers and agricultural stakeholders in making more informed harvesting decisions.

Algorithm/Pseudocode

In the implementation of this method, several stages are illustrated in Figure 1. The initial stage begins with research initiation, followed by data collection, labeling process, and dataset preparation. Subsequently, the YOLOv8 model is configured and trained, then the model is tested and evaluated, leading to the final conclusion of the study.

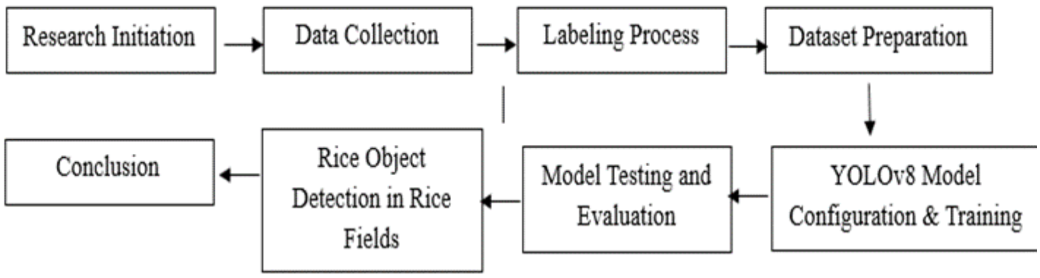

Figure 1. Research Methodology Stages.

Research Initiation

The initial stage involves planning and understanding the research objectives. At this stage, the researcher determines the main focus, which is rice object detection using YOLOv8 to classify rice maturity levels in rice fields.

Database Collection

The database collection process is carried out by gathering image data that will be used for model training. The data may consist of rice plant images taken in paddy fields, which will later be labeled and utilized in the next stage of the process.

Figure 2. The data may consist of rice plant images.

Bounding Box Labeling Process

After the images are collected, the next step is to perform labeling and create bounding boxes around the objects (rice plants) in the images Cláudio et al.. This process aims to help the model recognize and identify objects within the images accurately.

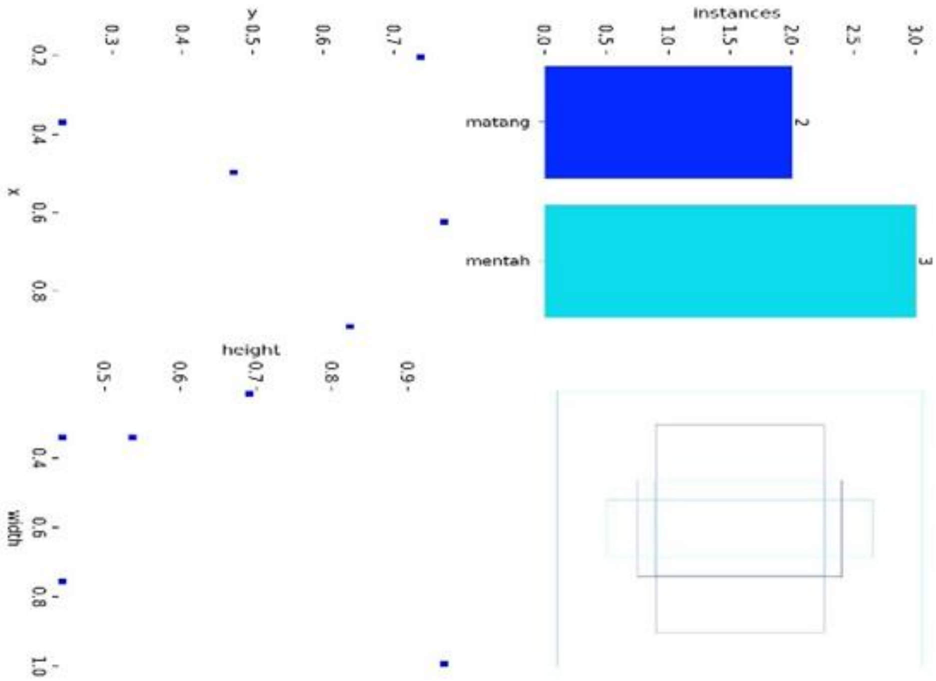

Figure 3. Box Labeling Process.

Dataset Preparation in Roboflow

Roboflow is a computer vision development framework used for better data collection, preprocessing, and model training techniques. Roboflow provides public datasets that are available to users and also allows users to upload their own custom datasets Pokhrel. Roboflow is used to manage image datasets, perform labeling, train models, and automatically detect diseases. Its workflow includes converting labeled datasets into a format compatible with YOLOv8 for model training and implementation

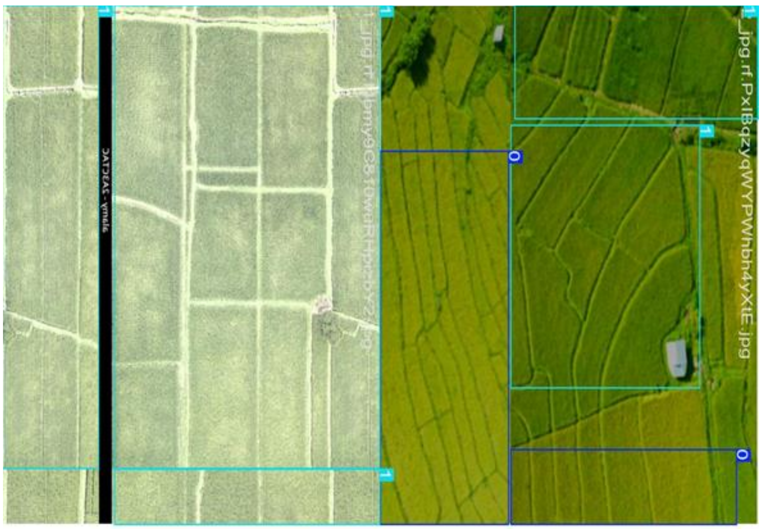

Figure 4. Manage Image Datasets.

YOLOv8 Model Configuration and Training

This stage is the core part of the research, where the YOLOv8 model is configured and trained using the prepared dataset. YOLOv8 is used for object detection to recognize and classify rice plants in images based on their maturity level.

Figure 5. Model Configuration and Training.

Model Testing and Evaluation

After the model has been trained, the next stage is testing and evaluating the model's performance. The model is tested using previously unseen data (test data) to assess how well it performs in detecting objects and classifying the maturity levels of rice plants in paddy fields

Figure 6. Model Testing and Evaluation.

Model Success? (Decision)

After the evaluation stage, if the model achieves an adequate level of accuracy, the next step is to perform object detection on rice plants in paddy fields to produce the desired output. However, if the model does not achieve satisfactory results, improvements and retraining processes are carried out on the model.

Figure 7. Model Success.

Successful Rice Field Object Detection

If the model is considered successful, this stage represents the functional deployment of the system. It demonstrates that the model is able to accurately localize rice plants in paddy field images (object detection) while simultaneously assigning the appropriate label from the predefined maturity categories (unripe, ripe, or unhealthy) [6].

Figure 8. Unripe, Ripe, or Unhealthy.

Conclusion

The final stage is drawing conclusions from the research, where the detection results and model performance are analyzed and summarized. This provides further insights into the effectiveness of the developed rice maturity detection system in paddy fields.

Result Analysis

The results of this study demonstrate that the YOLOv8 [15] algorithm is capable of effectively detecting and classifying rice maturity levels. The use of UAV aerial imagery provides significant advantages in the data acquisition process, particularly for monitoring large-scale rice field areas efficiently.

The model was able to distinguish between ripe, unripe, and unhealthy classes based on the color and texture characteristics of rice objects. However, several misclassifications were still observed under excessively bright lighting conditions or when the objects were partially occluded.

Compared to previous studies, the proposed method offers advantages in real-time object segmentation capabilities while maintaining a relatively high level of accuracy. These findings indicate that the integration of UAV aerial imagery and YOLOv8 has strong potential for supporting intelligent and automated agricultural monitoring systems.

4. Conclusions

This study presented a rice maturity segmentation framework based on UAV aerial imagery and the YOLOv8 algorithm. The proposed model achieved promising performance, with a maximum accuracy of 93% in classifying rice maturity conditions. The results demonstrate that combining UAV technology with deep-learning methods provides an effective solution for automated agricultural monitoring..

Future research should consider expanding the dataset, incorporating additional environmental variations, and evaluating more advanced augmentation strategies to improve model robustness. Further optimization of the detection model may also enhance generalization performance under diverse real-world conditions.

Author Contributions: Amin Ma'aruf[1] contributed to the research on rice maturity level segmentation in paddy fields based on UAV aerial imagery using the YOLOv8 algorithm. Akhmad Fadjeri[2] supervised the research process, developed the research methodology, and conducted technical validation and evaluation of the system.

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