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## **INTRA-ROW MECHANICAL CABBAGE WEEDING BASED ON MACHINE VISION**

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### **ABSTRACT**

Cabbage production is strongly influenced by environmental factors such as weather, soil, weeds, and pests, which can reduce both yield and quality. Chemical weeding is efficient and inexpensive but restricted due to environmental and food safety concerns, while manual weeding is safe yet labor-intensive. To address these issues, this study proposes a machine vision-based in-row weeding system that integrates a belt-driven sliding module with an embedded computing platform. Using the YOLOv9-tiny model, the system performs real-time cabbage-weed recognition and weeding control. Experimental results showed high performance, with precision and recall of 0.955 and 0.972, respectively. Grayscale augmentation improved robustness by reducing color dependence and visual noise. In simulation tests, the system achieved a weed removal rate of 77.5% and maintained a crop damage rate of 11.1%. These results demonstrate a feasible and efficient solution to support weed management, reduce herbicide use, and advance smart agriculture.

**Keywords:** cabbage, weed management, machine vision, deep learning, Image processing

### **INTRODUCTION**

Cabbage production is affected by environmental factors such as weather, soil, weeds, and pests, which reduce yield and quality. Chemical weeding is efficient but restricted due to environmental and food safety concerns, while manual weeding is safe but labor-intensive. To address these issues, machine vision and deep learning have been increasingly applied in precision agriculture. This study focuses on developing an in-row weeding system for cabbage, combining a belt-driven sliding module with an embedded computing platform. Using the YOLOv9-tiny model and grayscale image augmentation, the system aims to improve recognition accuracy and support efficient weed management.

### **MATERIALS AND METHODS**

This study presents a machine vision–based in-row weeding system with three components. First, cabbage images of common Taiwanese varieties were collected, annotated with Roboflow, and divided into training, validation, and testing sets (8:1:1), with grayscale augmentation to improve robustness. Second, the YOLOv9-tiny model was applied for real-time detection, generating bounding boxes for crop avoidance and weeding area planning. Third, a hardware system integrating a camera, NVIDIA Jetson Nano, and Arduino Uno controlled stepper motors for tool actuation. System performance was evaluated using weed removal and crop damage rates, confirming the system’s effectiveness and feasibility for smart agriculture.

$$\eta_1 = \frac{Q_1 - Q_2}{Q_1} \times 100\% \quad (1)$$

where:

$\eta_1$  = weed removal rate

$Q_1$  = total number of weeds before weeding

$Q_2$  = total number of weeds after weeding

$$\eta_2 = \frac{M_2}{M_1} \times 100\% \quad (2)$$

where:

$\eta_2$  = represents the crop damage rate

$M_1$  = total number of crops

$M_2$  = total number of damaged crops after weeding

## RESULTS & DISCUSSION

The training results with grayscale images are shown in Table 1 and Figure 1. The model achieved its best performance at G-1, and the augmented model outperformed the unprocessed model overall, enhancing its practicality in field operations. In system simulation tests, the crop damage rate was controlled at 0.111, while the weed removal rate reached 0.775. The weeding tool effectively avoided cabbage and reduced crop damage, confirming the feasibility of this approach.

Table 1 Comparison of model performance with grayscale-enhanced images at different ratios

Model	Training Set Ratio (Original : Grayscale)	Precision	F1-score	mAP@0.5
G-1	1:1	0.968	0.975	0.990
G-2	1;3	0.950	0.967	0.971
G-3	3:1	0.957	0.970	0.975
G-4	control group	0.955	0.972	0.988

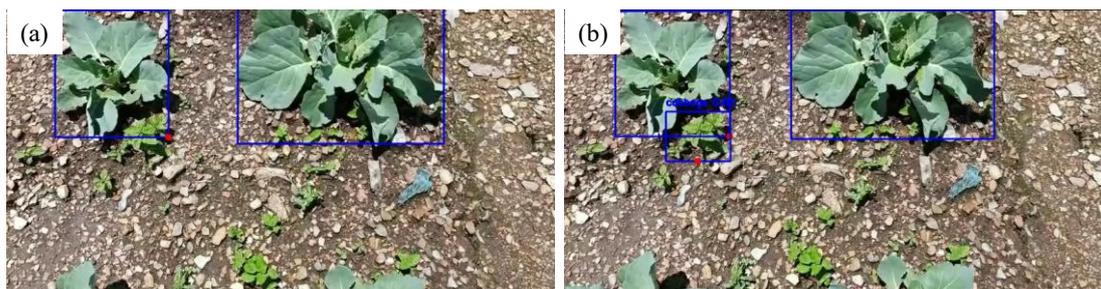


Figure 1. (a) Application of the grayscale-enhanced model (no weed misclassification)

(b) Application of the baseline model (with weed misclassification).

## **CONCLUSIONS**

This study developed a machine vision–based in-row weeding system for cabbage. By applying data augmentation techniques and grayscale processing, the model's recognition accuracy in field environments was effectively improved. In addition, a weeding-area algorithm was integrated with the hardware system, enabling precise cabbage recognition and effective crop avoidance, thereby enhancing the efficiency of weeding operations.

## **REFERENCES**

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