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DEVELOPMENT OF AUTOMATED ROSE MONITORING SYSTEM WITH DEEP LEARNING-BASED GROWTH STAGE CLASSIFICATION

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ABSTRACT

In cut-flower cultivation, effective production planning is essential to accommodate seasonal fluctuations in market demand. Precise rose growth stage monitoring is critical for cultivation schedule, environmental control, and harvest timing, yet current practices rely on manual observations, which are time-consuming and prone to subjectivity, limiting consistency and scalability. This study presents an automated monitoring system integrating computer vision and deep learning for objective and accurate classification of flower growth stages. Two rose cultivars 'Beehive' and 'Laventine' were evaluated across four reproductive growth stages: visible bud formation (B1), bud enlargement (B2), petal exposure (B3), and harvest maturity (H). A ceiling-mounted rail platform with RGB camera and distance sensor was developed for systematic data collection. Approximately 900 high-resolution top-view images were collected.
A YOLOv11-based classification model was implemented for four-stage growth identification. Cross-cultivar evaluation revealed significant performance differences: cv. 'Beehive' achieved mAP50 of 0.882 with the later stages (B2-H) exceeding 0.91 accuracy, while cv. 'Laventine' showed the lower performance (0.805), indicating cultivar-specific adaptation requirements. Most misclassifications occurred in B1, where limited visual contrast and small object size posed challenges to detection accuracy. Additionally, cv. 'Laventine' showed confusion between B3 and H stages, likely due to the low proportion of H-stage samples. These findings suggest the need to strengthen early-stage representation and increase H-stage sample availability. Preliminary results demonstrate the feasibility of automated monitoring across four reproductive growth stages. The information provides potential for yield prediction, harvest scheduling, and precision greenhouse management crucial for meeting fluctuating market demands. Future work will focus on expanding the dataset to enhance early-stage detection accuracy and developing cultivar-adaptive models to improve system generalizability.

Keywords: Rose phenotyping, Computer vision, Deep learning, Automated monitoring, Precision horticulture

INTRODUCTION

Roses (*Rosa rugosa*) production in Taiwan faces declining due to labor shortages, rising costs, and import competition. Current greenhouse cultivation relies on manual growth monitoring, creating limited, difficult-to-track records, insufficient for establishing reliable relationships between environmental parameters, yield, and quality. Advances in Internet of Things (IoT) and artificial intelligence (AI) enable automated monitoring solution. This study develops a rail-mounted imaging framework integrating RGB sensing with deep learning for objective rose growth stage classification. The YOLOv11-based system enables systematic and scalable monitoring with potential for yield prediction, harvest scheduling, and precision greenhouse management crucial for meeting fluctuating market demands.

MATERIALS AND METHODS

SYSTEM DESIGN

Experiments were conducted at the Idyll Floral Greenhouse (24°00'05.6"N 121°04'14.4"E) in Central Taiwan using two representative rose cultivars, 'Beehive' and 'Laventine'. Approximately 900 overhead images were captured between January and May 2025, covering different developmental stages. The imaging system utilized Raspberry Pi 4 with Camera Module for RGB capture and a LiDAR sensor (TFmini-S; Benewake Co., Ltd.; Beijing, China) for canopy height measurement. Rail-mounted configuration maintained 2.8 to 3.0 m height above the rose beds, capturing aerial-view images at 4608 × 2592 pixels resolution (Fig. 1). This setup enabled consistent viewpoints and systematic coverage of the cultivation area. The LiDAR sensor simultaneously provided segmented average canopy height, offering complementary indicators of vegetative vigor.

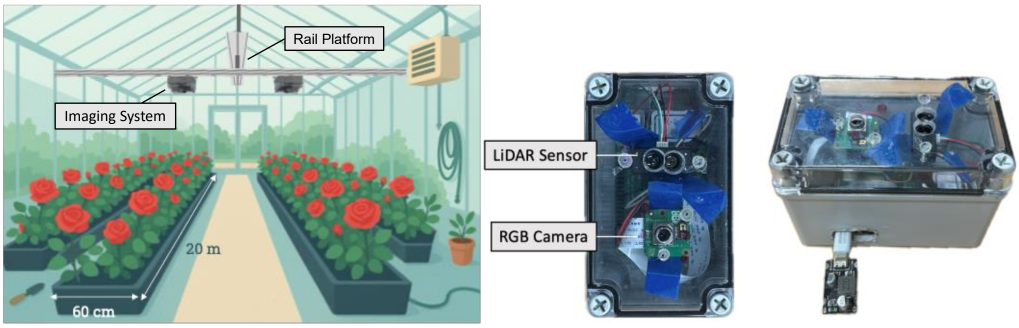

Fig. 1 Rail-mounted imaging system: greenhouse installation schematic and monitoring system design.

GROWTH STAGE CLASSIFICATION FRAMEWORK

The phenotypic traits for image analysis were determined in consultation with researchers at the Flower Experiment Station, focusing on visually identifiable features relevant to commercial rose production. Based on this evaluation, the developmental process of cut roses was divided into four stages: B1 (visible bud formation, initial emergence without enlargement), B2 (bud enlargement, rapid increase in bud size without opening), B3 (petal exposure, partial opening with visible pigmentation), and H (harvest maturity, fully expanded petals reaching marketable standards) (Fig. 2). The visibility-based staging approach has also been demonstrated to be physiologically and practically valid in rose 'Red Naomi' studies (Costa et al., 2016).

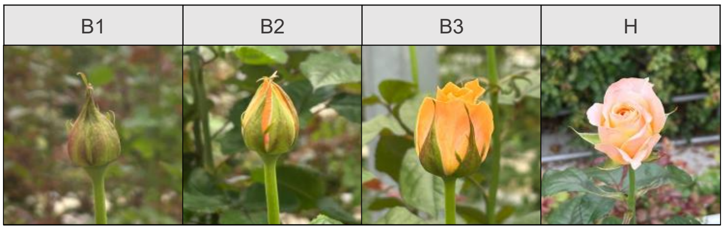

Fig. 2 Growth stage classification of roses based on visible bud development (B1–H).

DEEP LEARNING MODEL

YOLOv11-m was adopted for multi-object detection and classification. The model handles multiple roses per image while outputting both class and bounding box coordinates. Medium-scale architecture balanced computational efficiency with detection accuracy for the collected image resolution. Initial images were collected using two approaches prior to rail-based deployment. An RGB camera mounted on a handheld fixture and a mobile phone with a selfie stick captured top-view images at approximately 2.6 m, yielding 620 samples (350 of cv. ‘Laventine’ and 270 of cv. ‘Beehive’). Labelme (Wada, 2017) was used for annotation. These annotated datasets formed the basis for YOLOv11 training generated bounding box labels across growth stages (Table 1). Model performance was evaluated using standard metrics: mean Average Precision (mAP) for overall detection accuracy, Precision and Recall for class-specific performance, and F1-score for balanced assessment of detection quality.

Table 1. Distribution of bounding boxes across cultivars and growth stages.

Growth Stages / Cultivars	Number of Bounding Boxes				
	B1	**B2**	**B3**	**H**	**Total**
cv. ‘Laventine’	1590	2387	1422	269	5668
cv. ‘Beehive’	983	1023	634	245	2885

RESULTS & DISCUSSION

MODEL PERFORMANCE

Data augmentation was applied to improve model training with limited and imbalanced samples. Standard methods (resizing, rotation, translation, scaling, flipping, and brightness adjustment) improved generalization, while Mosaic and cutout-based strategies reduced small-object accuracy. After excluding the latter, mAP for ‘Laventine’ improved by 2.6%.

Evaluation of the fine-tuned YOLOv11-m model revealed varying accuracies across developmental stages and cultivars. ‘Beehive’ demonstrated strong later-stage identification with mAP of 0.911, 0.968, and 0.982 for B2, B3, and H, respectively. F1-scores exceeded 0.83 for these stages. B1 performance remained limited with 0.668 F1-score, reflecting challenges in detecting small buds. ‘Laventine’ showed generally lower performance. B2–H mAP ranged 0.774 to 0.928, while B1 achieved 0.598, highlighting cultivar-specific training requirement (Table 2).

Table 2. Fine-tuned YOLOv11-m performance across cultivars and growth stages.

Class / Index	cv. ‘Beehive’					cv. ‘Laventine’				
	B1	**B2**	**B3**	**H**	**Total**	**B1**	**B2**	**B3**	**H**	**Total**
Precision	0.698	0.749	0.939	0.728	0.778	0.634	0.867	0.898	0.622	0.755
Recall	0.629	0.937	0.854	1.000	0.885	0.63	0.861	0.804	0.806	0.775
F1 score	0.662	0.833	0.894	0.843	0.815	0.632	0.864	0.848	0.702	0.765
mAP	0.668	0.911	0.968	0.982	0.882	0.598	0.928	0.92	0.774	0.805

To further investigate the sources of misclassification, the confusion matrix was analyzed. It indicates frequent misclassification between B1 and vegetative backgrounds, primarily due to limited visual contrast and the small size of early buds, while later stages were more distinctly separated (Fig. 3). In addition, 'Laventine' exhibited confusion between B3 and H stages, likely attributable to the proportionally fewer H-stage samples. These observations highlight the importance of reinforcing early-stage representation and expanding H-stage datasets to improve classification stability and ensure consistent performance across cultivars.

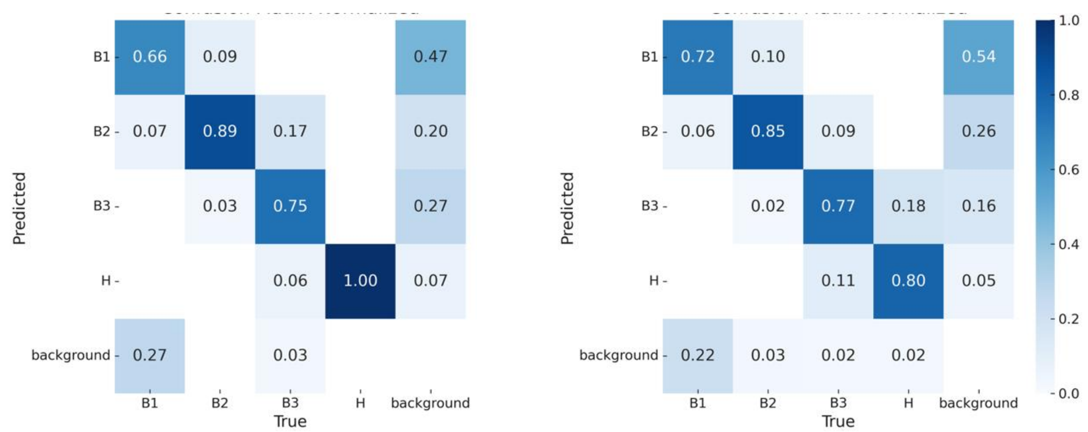

Fig. 3 Confusion matrices for 'Beehive' (left) and 'Laventine' (right).

CONCLUSIONS

This study successfully developed an AI-based rose monitoring system achieving mAP values of 0.882 and 0.805 for 'Beehive' and 'Laventine', respectively. Strong mid- to late-stage bud identification was achieved, while early-stage detection remained improvement due to size and contrast limitations. Cultivar-specific performance variations provide insights for developing adaptive models in precision floriculture. The system demonstrates feasibility for replacing manual monitoring with automated image-based assessment, establishing a scalable foundation for intelligent greenhouse management. Future developments will focus on enhanced early-stage detection accuracy and real-time deployment optimization for commercial applications.

Cultivar-specific performance variations provide insights for developing adaptive models in precision floriculture. The system demonstrates feasibility for replacing manual monitoring with automated image-based assessment, establishing a scalable foundation for intelligent greenhouse management. Future developments will enhance early-stage accuracy and optimize real-time deployment for commercial applications.

ACKNOWLEDGEMENTS

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