Improved Accuracy of Stomata Micrograph Classification Using YOLOv11 with Gamma Correction and CLAHE

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Abstract: This study aims to improve the accuracy of stomata classification in micrograph images through the You Only Look Once version 11 (YOLOv11) algorithm combined with Gamma Correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) as preprocessing techniques. Microscopic images often suffer from uneven illumination and weak contrast, which hinder automatic stomata detection. Gamma Correction adjusts image brightness non-linearly, while CLAHE enhances local contrast without amplifying noise. Stomata images were captured using a binocular microscope, annotated based on morphology, and divided into training, validation, and test sets for model development. Experimental results show that preprocessing improves YOLOv11 performance, with precision increasing from 0.93 to 0.94, recall from 0.91 to 0.92, and mean Average Precision (mAP) at 50% intersection over union from 0.95 to 0.96. For the Graminoid class, precision increased from 0.84 to 0.86, recall from 0.88 to 0.89, and mAP@50 from 0.82 to 0.83. The Peak Signal-to-Noise Ratio (PSNR) also improved from 27.9–28.35 dB to 28.44–29.40 dB, indicating better image quality. These results demonstrate that the integration of Gamma Correction and CLAHE effectively enhances image clarity and improves stomata detection performance, supporting more reliable and efficient automation in botanical analysis.

1 INTRODUCTION

Stomata are microscopic pores on the surface of plant leaves and stems that play a vital role in gas exchange and the regulation of water loss through transpiration. Their number, size, and morphology are important parameters in plant physiology, ecological adaptation, and taxonomic classification (Haworth et al., 2023). Traditionally, stomata are identified manually using light microscopy, a process that is time-consuming, subjective, and highly dependent on individual expertise. The challenge becomes greater when micrograph images suffer from blurriness, uneven illumination, or low contrast, which significantly hampers accurate morphological analysis (Gibbs & Burgess, 2024). To overcome these limitations, computer vision and deep learning approaches are increasingly applied for automatic stomata classification.

You Only Look Once (YOLO) is a family of one-stage object detection algorithms that perform classification and localization simultaneously, enabling real-time analysis. The latest version, YOLOv11, introduces modules such as C2f, attention mechanisms, and Spatial Pyramid Pooling Fast (SPPF), which improve small-object detection and computational efficiency. Several studies have demonstrated its effectiveness for stomatal analysis Zhang et al. (2021) combined YOLO with superpixel segmentation for stomata recognition, Zhang et al. (2023) proposed the DeepRSD method for randomly oriented stomata, while Yang et al. (2025) developed StomaYOLO for maize stomata detection. Beyond stomata, YOLO has also been applied successfully in plant disease classification (Alhwaiti et al., 2025). These studies confirm YOLO's robustness, supporting its adoption in this research.

However, detection performance with YOLO strongly depends on input image quality. Microscopic images often suffer from uneven lighting, subtle noise, and low contrast that obscure stomatal structures. To address this, image enhancement

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methods were employed before YOLOv11 detection. Gamma Correction was used to normalize illumination by amplifying darker regions without overexposing bright areas, as shown effective in low-light enhancement (Jeon et al., 2024; Wang et al., 2023; Mim et al., 2025). Meanwhile, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance local contrast while controlling noise, a technique widely validated in biomedical and plant imaging (Liu et al., 2021; Gibbs et al., 2021; Narla et al., 2024; Buriboev et al., 2024).

The integration of Gamma Correction and CLAHE has also proven beneficial. For example, Chang et al. (2018) reported that dual gamma correction with CLAHE improved visual quality in low-light images, while Benchabane & Charif (2025) achieved a 6–9% accuracy gain in COVID-19 X-ray classification using this combination. Mim et al. (2025) further confirmed the effectiveness of integrating these techniques for structural clarity and classification performance. Despite these advances, no studies have explicitly incorporated Gamma Correction and CLAHE into the YOLOv11 pipeline for stomatal classification. This research therefore proposes an automatic stomata classification system based on YOLOv11 with integrated Gamma Correction and CLAHE preprocessing, aimed at improving accuracy in tropical leaf micrographs and supporting the automation of botanical analysis and precision agriculture.

2 METHODOLOGY

This study focuses on the development of a stomata classification and detection system using a deep learning algorithm under uneven lighting conditions in stomata micrograph images. The dataset used in this study consisted of 312 micrograph images of stomata from herbal plant leaves, captured using a biological binocular microscope. These images were distributed across four stomata classes: Anomocytic (76 images), Diacytic (84 images), Graminoid (80 images), and Paracytic (72 images). The dataset was divided into training (218 images, 70%), validation (62 images, 20%), and testing (31 images, 10%).

To enhance the training set and reduce overfitting, data augmentation was applied. For each training image, three additional augmented images were generated by applying 90° clockwise rotation, 90° counter-clockwise rotation, and a flipped orientation. This process expanded the training set from 218 to 588 images. By introducing these geometric variations, the model was exposed to stomata with different orientations, ensuring better class balance and improving robustness in recognizing morphological structures under diverse conditions.

Following the annotation process, bounding boxes and class labels were assigned to each stomata instance. Since a single micrograph may contain multiple stomata, the number of annotated instances exceeds the total number of images. Table 1 summarizes the distribution of labels across the four stomata classes.

After dataset preparation and annotation, the workflow of the proposed system, including preprocessing, model training, and evaluation, is illustrated in Figure 1.

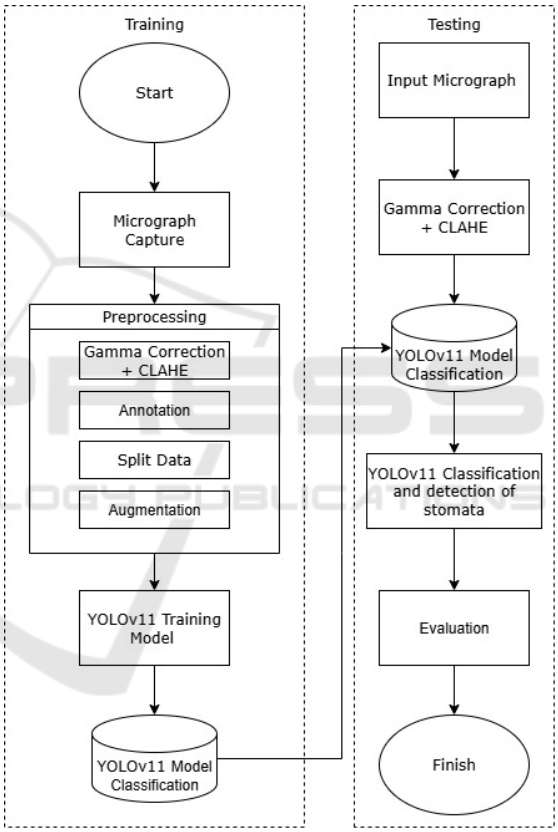


Figure 1: System Design Flow.

2.1 Training Phase

During the training phase, the YOLOv11 model was fine-tuned using the Ultralytics framework. The pre-processed dataset (Gamma Correction and CLAHE applied) consisted of 588 augmented training images, 62 validation images, and 31 test images. Training was performed for 100 epochs with a batch size of 4 and an input resolution of 640 × 640 pixels. The learning rate was initialized at 0.001 with the default

optimizer provided by Ultralytics. All experiments were executed on a workstation equipped with an NVIDIA RTX 4070 GPU (8 GB VRAM). The model checkpoint with the highest validation mAP@50 was saved for subsequent evaluation.

2.1.1 Data Acquisition

Stomata images were acquired using a biological binocular microscope at 3× and 4× magnification, covering the four stomata types analyzed in this study. The samples were obtained from four different herbal plants, with one representative species used for each stomata type. The process of data acquisition as shown in Figure 2.

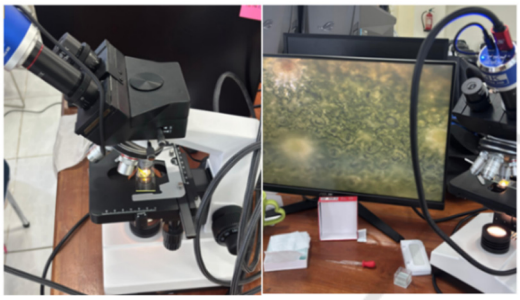


Figure 2: Stomata micrograph data acquisition.

2.1.2 Preprocessing

The image was pre-processed using Gamma Correction ($\gamma = 0.9$) to non-linearly adjust brightness, making fine stomatal structures more visible in darker regions. In addition, CLAHE was applied with a clip limit of 3.0 and a tile grid size of 8×8 to enhance local contrast while preventing excessive noise. These enhancements ensured that the input images preserved morphological details critical for stomata recognition. Figure 3 illustrates one of preprocessing result.

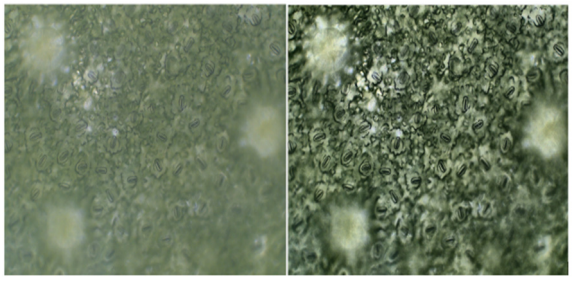


Figure 3: Preprocessing results.

2.1.3 Annotations

Stomata are given bounding boxes and morphological labels to train the YOLOv11 model to recognize and distinguish stomata types.

2.1.4 Split Data

The dataset was split into training, validation, and testing subsets for model training and evaluation as shown in Table 1.

Table 1: Distribution of stomata labels.

Class	Labels Train	Labels Validation	Labels Testing	Label count
Anomocytic	3679	339	230	4248
Diacytic	4925	770	141	5836
Graminoid	3532	520	217	4269
Paracytic	4618	266	355	5239
Total	16754	1895	943	19592

2.1.5 Data Augmentation

In the Figure 4, each original stomata image was augmented into three variations: one rotated 90° clockwise, one 90° counterclockwise, and one kept unchanged. This increased the dataset from 219 to 590 images, helping the YOLOv11 model generalize better by simulating different microscope orientations.

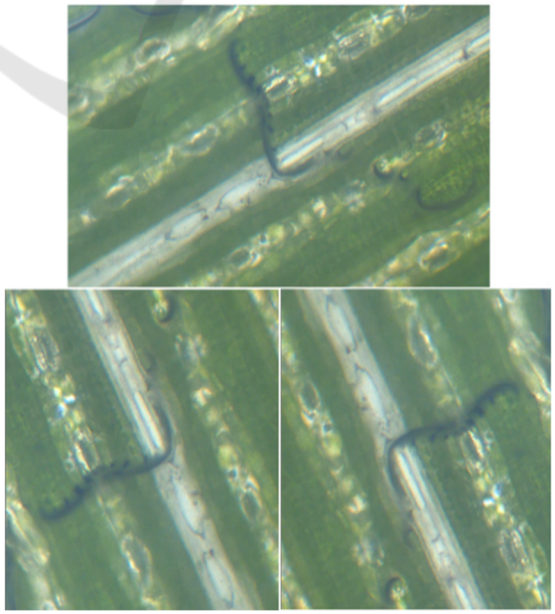


Figure 4: Data augmentation results.

2.1.6 Training Model YOLOv11

The pre-processed and annotated images were then used to train YOLOv11. This integration allowed the model to learn more discriminative visual features from images with improved lighting and contrast, leading to better stomata classification performance.

2.1.7 Build Model

The model is stored after validation and is ready to be used for classification and detection of stomata in test data.

2.2 Testing Phase

In the testing phase, the trained YOLOv11 model was evaluated on the held-out test set of 31 images, which had been preprocessed with Gamma Correction and CLAHE. No augmentation or annotation was applied during testing to ensure fairness. The model predictions were compared with ground-truth labels using precision, recall, mAP@50, mAP@50–95, and F1-score as evaluation metrics.

2.2.1 Input Data

The images tested are images that have never been used before and are entered into the system to evaluate the final performance of the model. The results of this stage provide an overview of the extent to which the model is capable of working on completely new data.

2.2.2 Preprocessing (Testing)

In the testing phase, only Gamma Correction and CLAHE were applied to the images. Unlike the training phase, no annotation or augmentation was performed, as the goal was to evaluate the model on unseen images with enhanced visibility and contrast, ensuring a fair and unbiased evaluation.

2.2.3 Yolov11 Stomata Detection & Classification

The trained YOLOv11 model directly received the pre-processed test images and performed stomata detection and classification. By using enhanced images, the model was able to achieve higher precision and recall in identifying small stomatal structures.

2.2.4 Evaluation

To assess the performance of the proposed YOLOv11 model, detection results were compared against the ground truth annotations using widely adopted evaluation metrics, including Accuracy, Precision, Recall, mean Average Precision (mAP), and Peak Signal-to-Noise Ratio (PSNR).

To evaluate the performance of the YOLOv11 model in detecting various types of stomata under different image processing scenarios (without preprocessing, with Gamma Correction, and with CLAHE), a confusion matrix was employed as the primary evaluation technique (Figure 5). The confusion matrix provides a detailed summary of classification outcomes by categorizing predictions into four main groups: True Positive (*TP*), representing stomata objects that were correctly detected and classified by the model; False Negative (*FN*), referring to stomata objects that were missed and not detected by the model; False Positive (*FP*), representing non-stomata regions that were incorrectly classified as stomata; and True Negative (*TN*), indicating non-stomata regions that were correctly identified as not belonging to the stomata class.

		Predicted	
		True	False
Actual	True	*TP*	*FN*
	False	*FN*	*TN*

Figure 5: Confusion Matrix.

Where *TP* (True Positive) denotes the number of correctly detected stomata, *TN* (True Negative) denotes the number of correctly rejected non-stomata regions, *FP* (False Positive) represents the number of incorrectly detected regions, and *FN* (False Negative) represents the number of missed stomata.

Precision (1) measures the proportion of correctly predicted stomata among all detected regions.

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

Recall (2) measures the proportion of correctly detected stomata with respect to all actual stomata in the ground truth.

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

Where AP_i represents the Average Precision for class *i*, and N is the total number of classes. The mAP (3) is widely used in object detection to evaluate the overall detection performance across all classes.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (3)$$

Where MAX_I is the maximum possible pixel value (255 for 8-bit images), and MSE is the Mean Squared Error between the original image and the processed image. PSNR (4) quantifies the quality of image enhancement during preprocessing and detection.

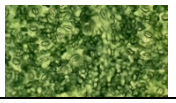
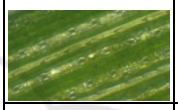
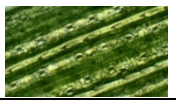
$$PSNR = 10 \cdot log_{10}(\frac{MAX_I^2}{MSE}) \quad (4)$$

3 RESULTS AND DISCUSSION

3.1 Peak Signal-to-Noise Ratio (PSNR) Evaluation

The PSNR values in all three images showed an increase after preprocessing using Gamma Correction and CLAHE. In Table 2, the initial PSNR was in the range of 27.9–28.35 *dB* and increased to 28.44–29.40 *dB* after preprocessing. This increase indicates an improvement in the visual quality of the image, especially in terms of lighting and local contrast, without compromising important details. This proves that the preprocessing technique used is effective in clarifying the structure of the stomata, thus supporting the automatic detection process by the YOLOv11 model more accurately.

Table 2: PSNR evaluation.

Gamma	PSNR (*dB*)	Gamma + CLAHE	PSNR (*dB*)
	27.96		28.33
	28.01		28.69
	27.88		28.63
	28.43		29.32

3.2 YOLOv11 Training Results with Gamma Correction + CLAHE

The training was conducted on an NVIDIA RTX 4070 GPU (8 GB VRAM) using the Ultralytics YOLO framework. Each epoch required ~2.5 minutes, with a total training time of 4.2 hours for 100 epochs, and inference reached 45 FPS (≈22 ms per image), showing near real-time suitability. As shown in Table 3, preprocessing improved YOLOv11 performance compared to the baseline (P = 0.93, R = 0.91, mAP@50 = 0.95, mAP@50–95 = 0.54). Gamma Correction slightly raised recall and mAP@50–95, CLAHE increased precision, and their combination gave the best results (P = 0.94, R = 0.92, mAP@50 = 0.96, mAP@50–95 = 0.55). Accuracy was calculated as.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

The proposed method achieved 95% accuracy, higher than Zhang et al. (2021) with 91.6%, Gibbs et al. (2021) with 90.2%, Zhang et al. (2023) with

94.3%, and Utiarahman (2025) with 93.5%. These results confirm that Gamma + CLAHE preprocessing enhances YOLOv11 as shown in Figure 7, providing the better balance of precision, recall, and accuracy rather than without Gamma + CLAHE (Figure 6)..

Table 3: Results of YOLOv11 Original and YOLOv11 Training with Gamma + CLAHE.

Study / Method	Dataset / Target	Approach	Reported Performance
Zhang et al., 2021	Stomata micrographs (various plants)	YOLO + entropy rate superpixel segmentation	Accuracy = 93%
Zhang et al., 2023	Corn leaves	DeepRSD	Accuracy= 94.3%
Gibbs et al., 2021	Wheat stomata micrographs	CNN-based	Accuracy > 90%
Utiarahman, 2025	Herbal plants	Benchmark YOLOv8–v11	YOLOv11: Precision = 0.933, Recall = 0.886, mAP@50 = 0.951, mAP@50–95 = 0.515
This study (YOLOv11 baseline)	Herbal plant stomata (4 types)	YOLOv11 without preprocessing	Accuracy = 94% Precision = 0.93, Recall = 0.91, mAP@50 = 0.95, mAP@50–95 = 0.54
This study (YOLOv11 + Gamma)	Herbal plant stomata (4 types)	YOLOv11 with Gamma	Accuracy = 95% Precision = 0.93, Recall = 0.92, mAP@50 = 0.95, mAP@50–95 = 0.55
This study (YOLOv11 + CLAHE)	Herbal plant stomata (4 types)	YOLOv11 with CLAHE	Accuracy = 94% Precision = 0.94, Recall = 0.91, mAP@50 = 0.94, mAP@50–95 = 0.54
This study (YOLOv11 + Gamma + CLAHE)	Herbal plant stomata (4 types)	YOLOv11 with Gamma Correction + CLAHE	Accuracy = 95% Precision = 0.94, Recall = 0.92, mAP@50 = 0.96, mAP@50–95 = 0.55

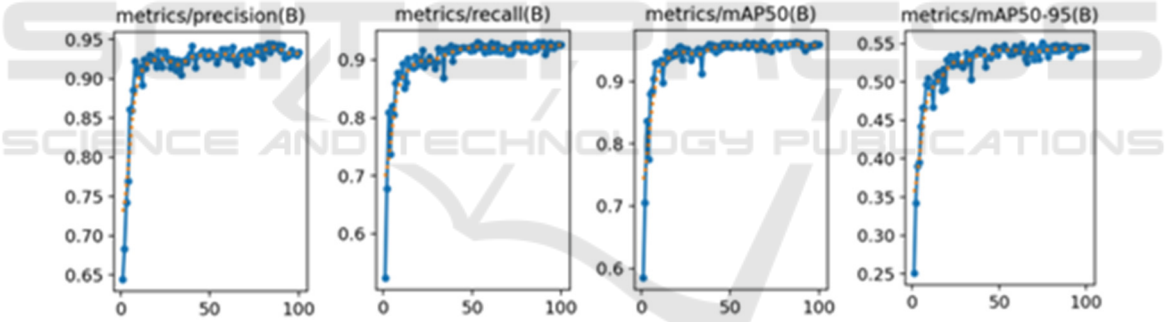


Figure 6: Graph of the results of the original YOLOv11 training (mAP 50, mAP 50-95, precision, and recall).

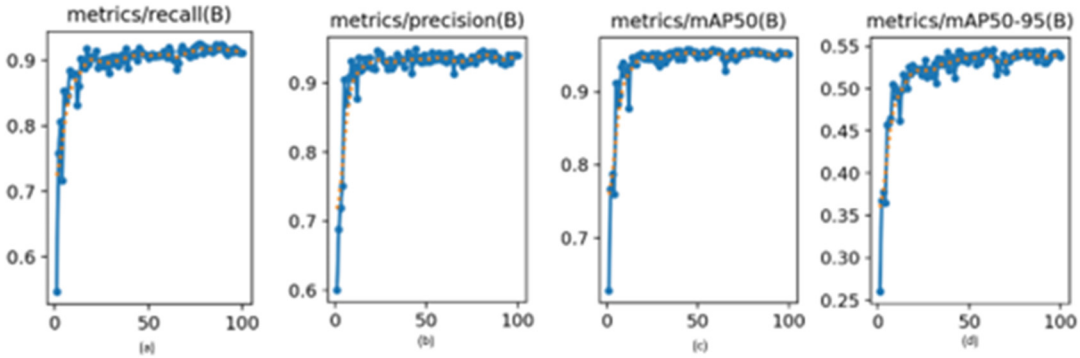


Figure 7: Graph of YOLOv11 training results with Gamma Correction + CLAHE (mAP 50, mAP 50-95, precision, and recall).

3.3 YOLOv11 Testing Results with Gamma + CLAHE

The test results in Table 4 showed that the YOLOv11 model with Gamma Correction and CLAHE preprocessing outperformed the original model. In the Anomocytic and Paracytic (AD) classes, there was an increase in precision, mAP, and accuracy. For the Graminoid class, recall increased from 0.88 to 0.89 and precision from 0.84 to 0.86, indicating improved detection. Meanwhile, the Diacytic class achieved consistently high results on both models (precision 0.95–0.96; accuracy 0.99), indicating optimal detection even without preprocessing.

Table 4: YOLOv11 Testing Results with Gamma + CLAHE.

Method	Class	TP	FP	FN	TN	Precision	Recall	Accuracy	mAP 50	mAP 50-95
YOLOv11 Original	Anomocytic	202	28	32	787	0.91	0.83	0.94	0.93	0.52
	Diacytic	138	3	7	901	0.95	0.97	0.99	0.98	0.57
	Graminoid	200	17	44	788	0.84	0.88	0.93	0.82	0.43
	Paracytic	352	3	23	671	0.95	0.98	0.98	0.99	0.59
YOLOv11 + Gamma Correction	Anomocytic	201	29	30	797	0.90	0.83	0.94	0.93	0.53
	Diacytic	138	3	9	907	0.95	0.97	0.99	0.99	0.58
	Graminoid	200	17	50	790	0.85	0.90	0.94	0.83	0.44
	Paracytic	350	5	26	676	0.95	0.98	0.97	0.99	0.60
YOLOv11 + CLAHE	Anomocytic	199	31	33	795	0.92	0.83	0.94	0.92	0.52
	Diacytic	138	18	47	794	0.96	0.98	0.99	0.99	0.57
	Graminoid	199	18	47	794	0.86	0.87	0.94	0.82	0.43
	Paracytic	351	4	27	676	0.95	0.98	0.97	0.99	0.59
YOLOv11 + Gamma Correction + CLAHE	Anomocytic	204	26	32	793	0.91	0.85	0.95	0.94	0.52
	Diacytic	138	3	10	904	0.96	0.98	0.99	0.99	0.58
	Graminoid	201	16	10	790	0.86	0.89	0.94	0.83	0.43
	Paracytic	351	4	22	678	0.95	0.98	0.98	0.99	0.60

3.4 Results of Gamma+CLAHE Application

Figure 8 presents the results of stomata detection on micrograph images processed with Gamma Correction and CLAHE. The YOLOv11 model successfully detects stomata, as indicated by the bounding boxes labeled "diacytic" and "paracytic" in the relevant regions. CLAHE enhances local contrast, making stomatal structures clearer even in previously blurry or dim areas, while Gamma Correction balances overall illumination across the image.

Figure 8: Comparison of the application of Gamma Correction + CLAHE.

4 CONCLUSIONS

This study developed a YOLOv11-based automatic stomata classification system with Gamma Correction and CLAHE preprocessing. The results showed improved image quality (higher PSNR) and better detection performance in terms of precision, recall, and mAP. The model provided more stable and accurate detection of different stomata types, confirming the benefit of combining image enhancement with deep learning for botanical analysis.

However, the study has limitations, including a relatively small dataset restricted to four stomata types and moderate performance gains from preprocessing. Although YOLOv11 achieved acceptable inference speed, further optimization is needed for large-scale or real-time use.

Future work should involve real-time experiments, the integration of attention mechanisms to enhance feature extraction, and expansion of the dataset with additional plant species to improve robustness and generalizability. These efforts are expected to increase both the efficiency and accuracy of automatic stomata detection for broader applications in plant science and precision agriculture.

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