Detection of Pomelo Leaf Miner's Eggs Using Image Processing Technique

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***Abstract*—Pomelo production in Thailand faces significant yield losses due to infestation by the Citrus Leaf Miner (Phyllocnistis citrella). Manual inspection of leaf miner eggs is labor-intensive and prone to human error due to their small size (≈1 mm) and color similarity to leaf surfaces. This study proposes a rule-based image processing pipeline for automated detection of pomelo leaf miner eggs using geometric and color features. The novelty lies in integrating Hough Circle Transform with HSV color matching to detect pomelo leaf miner eggs early, before leaf damage occurs. A dataset of 100 images captured under controlled lighting (using a lighting control box) conditions was used for validation. The proposed method integrates HSV color segmentation, contrast adjustment, Gaussian blur, Canny edge detection, morphological operations, Hough Circle Transform, Circularities, and color matching verification. Experimental results demonstrate that combining shape, size, and color features significantly improves performance compared to using geometric features alone. The proposed approach achieved 96.00% accuracy, 100.00% precision, 92.31% recall, 96.00% F1-score, and 100.00% specificity, with only 4.00% error rate. The results indicate that the method is effective for early pest detection under controlled conditions. However, performance in real-world orchard environments with natural sunlight, shadows, and complex backgrounds remains to be validated. Future work will therefore focus on dataset expansion, real-world orchard validation, and comparison with deep learning approaches to enhance robustness and field applicability.**

Keywords— image processing, pest detection, pomelo leaf miner, agricultural, rule-based, edge detection, pomelo, citrus leaf miner, Hough Circle Transform, Color segmentation

I. Introduction

Pomelo (Citrus maxima) cultivation represents a significant agricultural sector in Thailand, contributing substantially to the national economy. However, Citrus Leaf Miner (CLM) infestations cause annual economic losses exceeding 450 million baht due to reduced yields [1]. Traditional manual inspection methods prove inefficient as CLM eggs measure approximately 1 mm in diameter and exhibit color characteristics similar to leaf veins [2].

This paper presents a novel image processing pipeline for automated Pomelo Leaf Miner egg detection, addressing three key challenges: (1) small target size relative to leaf surface, (2) color similarity between eggs and leaf background, and (3) variable lighting conditions in field environments. Unlike prior studies focusing on leaf damage symptoms, this work detects pest eggs at the pre-damage stage, enabling earlier intervention. Our approach combines multiple image processing techniques to achieve robust detection performance.

Given the well-defined visual characteristics of Pomelo Leaf Miner eggs and the limited dataset available, this study adopts a rule-based image processing pipeline grounded in domain knowledge rather than deep learning. This choice offers advantages with low computational cost, high transparency, and minimal data requirements, making it particularly suitable for initial deployment on low-power devices, where the computational overhead of deep learning models would be too heavy. Future work will compare this approach with machine learning methods to further validate robustness in real-world conditions.

II. Related Works

Recent advances in agricultural image processing have demonstrated promising results for various pest detection applications. Leaf diseases detection, SVM for classification, achieving a 96% accuracy rate in identifying apple leaf diseases [3], plant disease detection and proposed an integrated deep learning based on a combination of AlexNet, ResNet50 and VGG16, the maximum detection accuracy of the proposed method for binary dataset is 100% and for multi-class dataset is 99.53%. [4]. Ahsan et al. [5] repurposed the large-scale IP102 dataset by adding detailed annotations for four insect life stages egg, larva, pupa, and adult. Using deep learning models based on ResNet50 and EfficientNetV2M, they achieved high performance in life-stage classification, with EfficientNetV2M reaching 96.5% precision and 96.1% F1-score for stage identification. While deep learning methods such as CNN have shown strong performance in pest detection, this study establishes a rule-based baseline method, which will be compared against learning-based approaches in future work

III. Methodology

The methodology adopts a rule-based pipeline for three primary reasons: (1) Pomelo Leaf Miner egg visual characteristics are well-defined and distinguishable through geometric and color features, eliminating the need for data-driven learning; (2) the rule-based system operates with lower computational cost suitable for resource-constrained devices; and (3) it requires significantly less training data than deep learning, which is practical given the limited dataset available.

The overall workflow of the proposed system, based on this rationale, is shown in Fig. 1 and consists of four main stages: Data gathering and analysis, Image acquisition, Image pre-processing, and Detection combining geometric and color features to enable accurate identification of pomelo leaf miner eggs.

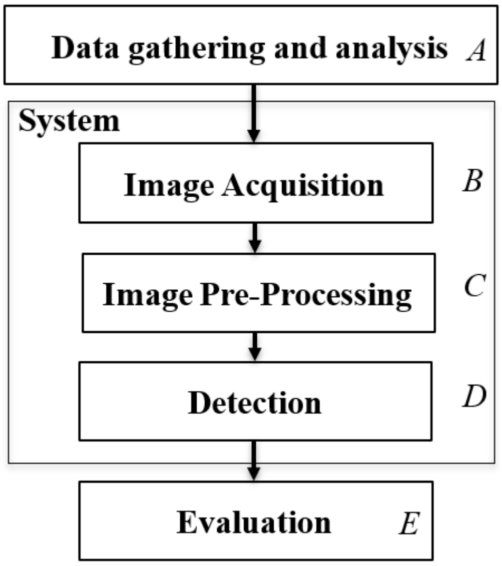


Fig.1 Overall workflow

A. Data Gathering and Analysis

The life cycle of the citrus leaf miner was examined to identify the most suitable detection stage for preventive control. The egg stage was found to be ideal due to its stationary position, consistent shape, and visibility to the naked eye, with a diameter of approximately 1 mm.

This study collected and analyzed pomelo leaf images, focusing particularly on young to middle-aged leaves, as these stages are the most susceptible to citrus leaf miner egg infestation. An analysis was conducted on the color characteristics of both the leaves and the eggs to determine color ranges that could be used for feature extraction. Pomelo leaves were predominantly green, while the eggs ranged from off-white to pale yellow, making color a viable attribute for distinguishing between leaf and egg regions in images.

B. Image Acquisition

Images were captured using a Samsung Galaxy A13 smartphone with camera resolution 50M pixel at a distance of 10 cm under controlled lighting conditions box. The dataset comprises 100 images, randomly split into a training set of 50 images (26 with eggs, 24 without eggs) and a testing set of 50 images (26 with eggs, 24 without eggs). All 100 images were captured under controlled conditions using a lighting box with an illuminance of approximately 125 lux, measured at the leaf surface using a digital lux meter. The setup for image acquisition a sample leaf with eggs and without eggs as shown in Fig.2

C: Leaves with eggs

Fig.2 Image acquisition

C. Image preprocessing

The image pre-processing stage aims to prepare the input images for accurate detection of leaf miner eggs. This stage is organized according to specific objectives.

1) Pomelo leaf region finding to separate the pomelo leaf from the background and identify the segmentation of the leaf from the background by applying **c**olor segmentation [6],[7],[11], [13],[22]. A representative input image is loaded and converted from the RGB color space to the HSV color space. This process results in approximately 1,031,506 pixels corresponding to the leaf region. The HSV thresholds were statistically derived from 50 training images. The lower bound (H=77.87°, S=15.63%, V=21.20%) represents minimum observed values, while the upper bound (H=169.53°, S=100%, V=100%) was intentionally set to maximize coverage of leaf color variations under different lighting conditions.Visualize color as shown in Fig.3

A: Lower bound B: Upper bound

Fig.3 Color segmentation

2) Reduction of light Reflection to reduce the influence of light reflections on original RGB image. Contrast Adjustment [20],[21] is applied using parameters: α, β which controls multiplicative contrast, and γ which adjusts brightness through a power-law transformation. This process helps to diminish the brightness caused by reflections on the pomelo leaf surface and enhances the visibility of circular-shaped objects. As a result, the detection of pomelo leaves and leaf miner eggs is improved. Reflected light can cause certain regions of the image to become excesively bright.

Reducing $\alpha < 1$ and $\beta = 0$ helps decrease the overall image brightness, including overly bright areas. Additionally $\gamma < 1$ increases the brightness in darker regions more than in brighter ones, thereby improving image balance as shown in equation (1) and (2) and before and after image contrast adjustment as shown in Fig. 4. In this study, the exact parameter values used were $\alpha = 0.7$, $\beta = 0$, and $\gamma = 0.8$, determined empirically to optimally suppress specular reflections while preserving egg visibility.

Contrast Adjustment(alpha)

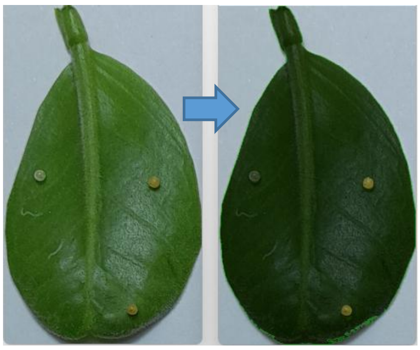
$$g(i,j) = \alpha \times f(i,j) + \beta \tag{1}$$

g(i,j) represents the brightness value of the pixel in the output image at the corresponding position.
f(i,j) represents the brightness value of the pixel in the input image at row i and column j.
α is a parameter that controls the contrast.
β is a parameter that controls the brightness.

Contrast Adjustment(gamma)

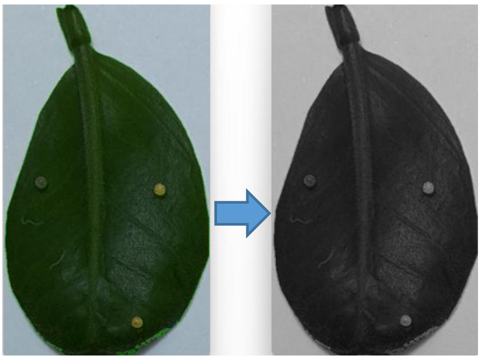
$$O = \left(\frac{I}{255}\right)^{\gamma} \text{x } 255 \tag{2}$$

I represents the intensity value of a pixel in each channel (R, G, or B) of the RGB image.
γ is a parameter that controls brightness adjustment. If $\gamma < 1$, the dark regions of the image will be brightened more than the bright regions; if $\gamma > 1$ the dark regions will be darkened more than the bright regions.
255 is the maximum brightness value of a pixel in an 8-bit image



A: Original B: Contrast adjusted
Fig.4 Contrast adjustment

3) Reduction of Color Complexity to reduce color complexity before further processing by converting RGB to Grayscale. [8], [9], [10],[13], [14], [15]. This simplifies the data and prepares the image for further reduction of residual light reflections that may remain after the contrast adjustment. Before and after contrast adjusted and convert from RGB to Grayscale as shown in Fig.5

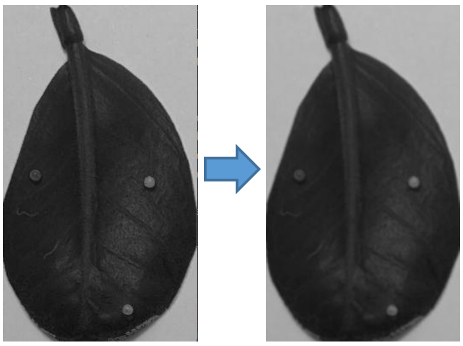


A: Contrast Adjusted B: Grayscale
Fig.5 Convert RGB to Grayscale

4) Reduction of Residual Reflection to further reduce residual reflection remaining after contrast adjustment by using Gaussian Blur [8],[9] with an initial kernel size of 3×3 is applied to the grayscale image. The blurring process indirectly mitigates reflections, which often appear as overly bright regions with sharp boundaries. By blurring the image, these sharp edges become less defined, causing the reflected light to appear more diffused and spread across neighboring pixels. This enhances the performance of subsequent edge detection by reducing noise and smoothing out overly bright regions. As shown in equation (3) and image of Before and after Gaussian Blur as shown in Fig.6

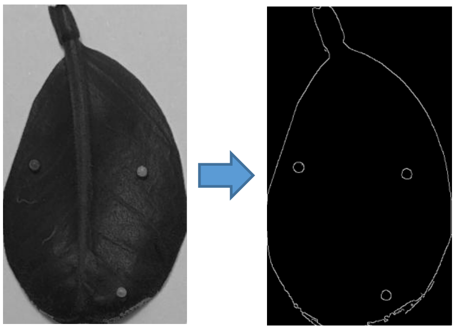
$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

G(x,y) is the value of the Gaussian function at position (x,y).
σ is the standard deviation, controlling the spread (or "width") of the Gaussian kernel.
x and y are the distances from the center of the kernel in the horizontal and vertical directions, respectively.



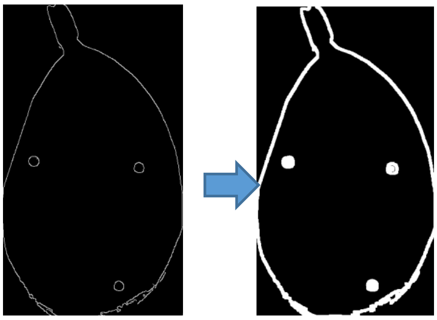
A: Before B: After
Fig.6 Gaussian Blur

5) Detected Edge Refinement to refine the edges detected by the Canny edge detection method, enhancing the clarity, continuity, and roundness of the leaf miner egg boundaries by applied Morphological Operations [9],[12],[15]. After converting the contrast-adjusted image to grayscale and applying Canny edge detection to obtain a binary image as shown in Fig. 7, morphological operations refine the detected edges. Experimentally evaluated multiple dilation kernel sizes and found that a 5×6 kernel yielded the most continuous edge connectivity with minimal shape distortion compared to other kernel configurations. Subsequently, 1×1 erosion kernel was selected to eliminate residual edge artifacts introduced by the dilation process, as larger erosion kernels were found to cause unacceptable shape deformation in circular structures.



A: Grayscale image B: Binary image

Fig.7 Obtained from grayscale to binary



A: Before B: After

Fig.8 Morphological operation

6) Preliminary Finding for Leaf Miner's Eggs to segment the color range of leaf miner eggs and ensure coverage of all possible color conditions by applying Color Segmentation [6], [7], [13] for Leaf Miner's Egg(s), representative pixels from 74 eggs samples (totaling 73,871 pixels) were extracted. The mean (μ) and standard deviation (σ) of the Hue (H) component were calculated, along with the minimum and maximum values of Saturation (S) and Value (V) as shown in TABLE I. These values were then used to define the lower and upper bounds of the HSV color range for each group of egg conditions, serving as the foundation for color-based detection rules.

TABLE I: Leaf Miner Egg Color Range

Egg Group	Mean of Hue (μ)	Std Dev of Hue (σ)	Lower color range			Upper		
			μ-σ(H)	min(S)	min(V)	μ+σ(H)	max(S)	max(V)
Whitish	88.26°	8.98°	79.28°	0.39%	23.53%	97.24°	100.00%	98.04%
Light Yellow	73.90°	13.92°	59.98°	0.39%	23.53%	87.82°	100.00%	98.04%
Dark Yellow	70.08°	11.64°	58.44°	0.39%	23.53%	81.72°	100.00%	98.04%
Dark	76.74°	21.26°	55.48°	0.39%	23.53%	98.00°	100.00%	98.04%
Others	73.90°	14.22°	59.68°	0.39%	23.53%	88.12°	100.00%	98.04%

D. Detection

1) The Hough Circle Transformation [16], [17],[18], [19] is applied to detect circular shapes in the edge-enhanced image, as shown in equation (4) The parameters were configured as param2 = 12, MinRadius = 3, and MaxRadius = 13. The radius bounds were derived from diameter measurements collected from 74 leafminer egg specimens, while param2 was determined empirically through parameter tuning, yielding a value of 12 from experimental study that minimized detection errors. This method identifies circles that match specific size and shape criteria, allowing for the detection of objects such as leaf miner eggs that exhibit circular characteristics.

$$(x - x_{\text{center}})^2 + (y - y_{\text{center}})^2 = r^2 \quad (4)$$

(x,y) represents any point on the circumference of a shape that approximates a circle.
(x_{center},y_{center}) represents the center point of the shape that approximates a circle.
r denotes the radius of the circle.

2) Evaluation.of.Circular.Completeness to assess the likelihood that a detected circle corresponds to a leaf miner egg, the completeness of the circumference is evaluated, as shown in (5). This is done by comparing the actual number of pixels detected along the circular edge with the theoretical circumference calculated using the equation $2\pi r$. If the completeness is greater than or equal to 80%, the circle is considered to have a high probability of representing a leaf miner egg.

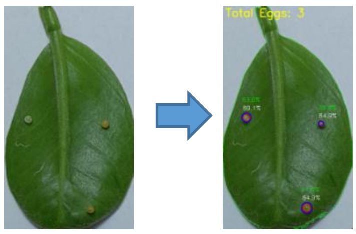
$$completeness = \left(\frac{contour\_perimeter}{circumference}\right) \times 100 \quad (5)$$

contour_perimeter represents the no. of pixels detected along the circle contour drawn on the image.
circumference represents the perimeter of the circle, calculated using the formula $2\pi r$ where r is the radius of the circle.

Matched Color of Eggs to further validate whether a detected circle corresponds to a leaf miner egg, the percentage of pixels within the defined color range specific to leaf miner eggs is calculated for each detected circular region (based on shape and size), as shown in equation (6). If the percentage of matching color pixels is greater than or equal to 20%, an additional circle is drawn to mark it, and the circle is counted as a valid leaf miner egg as shown in Fig.10

$$color\_percentage = \left(\frac{total\_color\_pixels}{pixel\_count}\right) \times 100 \quad (6)$$

total_color_pixel represents the total no. of pixels within the circular region that match the specified color range.
pixel_count represents the total number of pixels inside the drawn circular region.



A: Before B: After

Fig.10 Detection

E. Evaluation

To quantitatively evaluate and compare the detection performance between the two proposed methods are using only shape, size features and using shape, size, color range features. Confusion matrix was employed for each method. The matrix categorizes predictions into four outcomes: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), as shown in TABLE II. Key performance metrics, including Accuracy, Error Rate, Precision, Recall, Specificity, and F1-score, were calculated using equations (7) – (12) for both experimental setups.

TABLE II. CONFUSION MATRIX OUTCOMES

	Predicted	
Actual	**With Egg**	**Without Egg**
No. of pomelo leaf with egg	True Positive (TP)	False Negative (FN)
No. of pomelo leaf without egg	False Positive (FP)	True Negative (TN)

Accuracy: Overall correctness of predictions.

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{7}$$

Error: Proportion of incorrect predictions.

$$Error = \frac{\text{FP+FN}}{\text{TP+TN+FP+FN}} \tag{8}$$

Precision: Reliability of positive detections.

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{9}$$

Recall: Ability to detect all actual positives.

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \tag{10}$$

Specificity: Ability to reject false negatives.

$$Specificity = \frac{\text{TN}}{\text{TN+FP}} \tag{11}$$

F1-score: Harmonic mean of precision and recall.

$$F1 = 2 \times \frac{\text{Precision x Recall}}{\text{Precision + Recall}} \tag{12}$$

IV. EXPERIMENTAL RESULTS

A. Leaf Miner Egg Detection Using Shape and Size

Egg detection using shape and size was evaluated on 50 young pomelo leaf images. The model achieved 92.00% accuracy and 92.31% recall but produced false positives in two non-egg images, resulting in 92.31% precision, 91.67% specificity, and an F1 score of 92.31% in TABLE III. These results suggest that further improvement is needed to reduce false detections.

TABLE III. CONFUSION MATRIX DETECTING RESULT BY USING SHAPE AND SIZE

Actual / Predicted	**Predicted: With Egg**	**Predicted: Without Egg**
No of pomelo leaf with egg	True Positive(TP)	False Negative(FN)
26	24	2
No of pomelo leaf without egg	False Positive(FP)	True Negative(TN)
24	2	22

B. Leaf Miner Egg Detection Using Shape, Size, and Color Range

Egg detection using shape, size, and color range was evaluated on 50 images of young pomelo leaves. The model achieved 96.00% accuracy with a 4.00% error rate and a recall of 92.31%. It obtained 100.00% precision and 100.00% specificity, with an F1 score of 96.00%, as shown in TABLE IV. These results demonstrate the model's strong effectiveness in detecting leaf miner eggs and distinguishing between images with and without eggs.

TABLE IV: CONFUSION MATRIX DETECTING RESULT BY USING SHAPE, SIZE, COLOR RANGE

Actual / Predicted	**Predicted: With Egg**	**Predicted: Without Egg**
No of pomelo leaf with egg	True Positive(TP)	False Negative(FN)
26	24	2
No of pomelo leaf without egg	False Positive(FP)	True Negative(TN)
24	0	24

A False Negative example is shown in Fig.11. The model failed to detect the egg because the test image's heavy shadows were not well-represented in the training dataset.

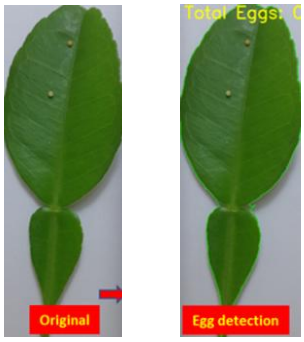


Fig. 11 False Negative

C. Comparison of experimental result

To further assess the effectiveness of the proposed approach, the performance of two detection methods between shape, size and shape, size, color range was compared using confusion matrices, including accuracy, error rate, precision, recall, specificity, and F1-score based on confusion matrix, evaluation result as shown in TABLE V

TABLE V: COMPARISION EGG DETECTION RESULTS

Detection Criteria	Accuracy	Error Rate	Precision	Recall	Specificity	F1 Score
Shape & Size	92.00%	8.00%	92.31%	92.31%	91.67%	92.31%
Shape, Size & Color range	96.00%	4.00%	100.00%	92.31%	100.00%	96.00%

V. DISCUSSION

Combining shape, size, and color range significantly enhanced detection performance over using shape and size alone. Color verification improved precision, specificity, and F1-score by reducing false positives, but recall remained unchanged (92.31%) because eggs under heavy shadows failed shape detection before color verification could be applied. Occasional misclassification of similarly shaped and colored objects highlights the need for better feature discrimination. Overall, the model shows strong potential for early-stage pest monitoring in agriculture.

Future work will investigate shadow removal and illumination normalization techniques such as adaptive histogram equalization to improve recall.

All parameters were manually tuned on the training set (50 images) via trial-and-error to maximize F1-score. Selected values: α=0.7, γ=0.8, Gaussian kernel 3×3, Canny (50,205), dilation 5×6, erosion 1×1, Hough param2=12, minRadius=3, maxRadius=13

The study was conducted under controlled lighting with a limited dataset, which may not fully represent real orchard conditions. Rule-based thresholds may be sensitive to natural light variation, shadows, and leaf backgrounds, and circular objects such as water droplets or debris may be misclassified. Future work will address these limitations by: (1) expanding the dataset with diverse real-orchard images, including variations in lighting conditions, temperature, particles and water droplets, (2) benchmarking against lightweight deep learning models such as YOLOv8s selected for their suitability for deployment on mobile and low-power devices, (3) integrating adaptive thresholding, and (4) developing a mobile/IoT-enabled application for real-time farmer use.

VI. Conclusion

This study proposed an image processing approach for detecting pomelo leaf miner eggs based on shape, size, and color range. Experimental results showed that the integration of color features significantly improved detection performance compared to using only shape and size. The proposed model achieved high accuracy (96.00%), with strong precision, specificity, and F1 score, indicating its potential for agricultural pest monitoring. This performance is comparable to related works, such as Chakraborty et al. [3] (96% accuracy) and Ahsan et al. [5] (96.5% precision), demonstrating that the proposed rule-based approach achieves competitive results without requiring large training datasets.

The current study demonstrates the feasibility of a rule-based image processing approach for detecting leaf miner eggs under controlled conditions. However, the method's performance in real orchard environments with natural light, shadows, and complex backgrounds remains to be

References

[1] S. Meecharoen, *Pomelo*, Phichit: Phichit Horticultural Research Center,Agricultural Research and Development Office Region 2, 2009.

[2] Information and Communication Technology Center, *Pomelo*, (Report), Bangkok: Department of Agricultural Extension, 2020.

[3] Chakraborty et al., "Prediction of apple leaf diseases using multiclass support vector vachine," 2nd International Conference on Robotics, Electrical and Signal Processing Techniques, (ICREST'21), Dhaka, Bangladesh, January 5-7, 2021, pp. 147 - 151.

[4] C. Sunil et al., "Binary Class and Multi-Class Plant Disease Detection using Ensemble Deep Learning-Based Approach," *researchgate.net* [Online]. Available: https://www.researchgate.net/publication/365251408_Binary_class _and_multi-class_plant_disease_detection_using_ensemble_deep_learning- based_approach. [Accessed: February 20, 2026].

[24] F. F. Ahsan et al., "Deep Learning-Based Analysis of Insect Life Stages Using a Repurposed Dataset," *Ecological Informatics*, vol. 90, 2025.

[6] S. Phatchuay et al., "Coffee Ripeness Classification Using Color Space Image Processing," *Journal of Industrial Technology and Engineering, Pibulsongkram Rajabhat University*, vol. 4, no. 3, pp. 369–381, Sep.–Dec. 2022.

[7] A. Kale et al., "Cotton leaf disease detection using Image processing," *Journal of Emerging Technologies and Innovative Research,* vol. 8, no. 6, pp. a718 - a723, June 2021.

[8] S. Wangchuen et al., "Development of Egg Size Sorting System Using Image Processing Techniques," *Khon Kaen Agriculture Journal*, vol. 51, suppl. 1, pp. 14–21, Mar.–Apr. 2023.

[9] S. Itnal et al., "Pest detection using Image processing," International Journal of Innovative Technology and Exploring Engineering, vol. 9, no. 2, pp. 1496 – 1498, December 2019.

[10] L. Johnny et al., "Pest detection and extraction using image processing techniques," International Journal of Computer and Communication Engineering, vol. 3, no. 3, pp. 189 - 192, May 2014.

[11] S. Phatchuay et al., "Coffee Ripeness Classification Using Color Space Image Processing," *Journal of Industrial Technology and Engineering, Pibulsongkram Rajabhat University*, vol. 4, no. 3, pp. 369–381, Sep.–Dec. 2022.

[12] S. Unkaew, "Detection of White Mold on Rubber Sheet Surface Using Image Processing," *Thaksin University Journal*, vol. 10, no. 2, pp. 50–61, Jul.–Dec. 2007.

[13] K. Khaeso et al., "Rice Grain Quality Inspection Using Image Processing Techniques," *Khon Kaen Agriculture Journal*, vol. 51, no. 4, pp. 756–768, Jul.–Aug. 2023.

[14] A. Putthiphiphatkajorn and P. Phromsurin, "Detection of Egg Cracks under Vacuum System Using Image Processing Techniques," *Journal of Science and Technology*, vol. 25, no. 3, pp. 509–519, May–Jun. 2017.

[15] G. P. Prathibha et al., "Early pest detection in tomato plantation using image processing," *International Journal of Computer Applications* (0975 – 8887), vol. 96, no.12, pp. 22 - 24, June 2014.

[16] V. Sawasdee and N. Wangkeeree, "Finding Suitable and Secure Threshold Values for Iris Authentication," *J Sci Technol MSU*, vol. 40, no. 1, pp. 40–49, Jan.–Feb. 2021.

[17] P. Boonmawasanasong and S. Sodsri, "Detection of Alcohol Drinkers from Images Using Cheek Color and Eye Width Recognition," *Journal of Science and Technology*, vol. 27, no. 3, pp. 539–549, May–Jun. 2019.

[18] U. Birange et al., "Circle detection using circular hough transform," International Journal of Scientific Research and Engineering, vol. 2, no. 5, pp 1070 - 1072, September – October 2019.

[19] L. Chen and L. Chen, "Adaptive image enhancement method based on gamma correction,"*Academic Journal of Computing & Information Science*, vol. 5, no. 4, pp. 65 - 70, May 2022.

[20] W. Wang et al., "Weak-Light image enhancement method based on adaptive local gamma transform and color compensation," *Hindawi Journal of Sensors*, vol. 2021, Article ID 5563698, pp. 1 - 18, June 2021.

[21] H. Sayin et al., "Optimization of CBCT data with image processing methods and production with fused deposition modeling 3D printing," *Medical & Biological Engineering & Computing*, vol. 63, no 8, pp. 2235 – 2246, July 2025.

[22] Y. Min Oo and N. Htun, "Plant leaf Disease detection and classification using image processing," International Journal of Research and Engineering, vol. 5, no. 9, pp. 517 -523, September - October 2018.