



Automatic Detection of Cabbage Pest Attacks Based on Leaf Images with Machine Learning Approach

Ni Wayan Surya Wardhani¹, Prayudi Lestantyo², Atiek Iriany³, Nur Silviyah Rahmi⁴

Abstract

Early detection of cabbage pest attacks is essential for reducing crop losses and improving agricultural productivity. This paper proposes an automatic cabbage pest detection system based on leaf images by integrating Gray-Level Co-occurrence Matrix (GLCM) texture feature extraction with a Decision Tree Boosting classification approach. The proposed method consists of image acquisition, preprocessing, GLCM feature extraction, and machine learning-based classification to identify pest damage severity. The extracted texture features include contrast, dissimilarity, correlation, homogeneity, angular second moment (ASM), energy, and entropy, which characterize the texture changes caused by pest infestations. Experimental results demonstrate that the proposed approach effectively distinguishes healthy and pest-attacked cabbage leaves and classifies damage into five severity levels: Normal, Low, Moderate, Severe, and Very Severe. The analysis further shows that contrast and entropy increase with increasing damage severity, whereas homogeneity and energy decrease, indicating that GLCM features provide discriminative texture information for pest identification. The Decision Tree Boosting classifier successfully utilizes these features to produce consistent and objective classifications, reducing the reliance on manual visual inspection. Therefore, the proposed framework provides a practical and computationally efficient solution for automatic cabbage pest detection and damage assessment. The developed system has the potential to support precision agriculture by enabling timely pest management decisions, minimizing crop losses, and improving cabbage production. Future research should evaluate the proposed approach using larger field datasets and investigate the integration of advanced deep learning models and multispectral imaging to further improve detection accuracy and robustness.

Keywords:

Cabbage Pest, CART, Classification, Leaf Image, Decision Support System

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1. Introduction

Cabbage is one of the most important vegetable commodities cultivated worldwide because it contributes significantly to food security, household nutrition, and farmers' income. In Indonesia, cabbage cultivation represents a major source of revenue for smallholder farmers and supports the national horticultural sector. However, cabbage productivity continues to fluctuate owing to various production constraints, particularly pest infestations that reduce crop quality and market value. Severe pest attacks damage leaf tissues, inhibit plant growth, and lower harvest yields, resulting in considerable economic losses. Effective pest management therefore becomes an essential component of sustainable cabbage production. Early detection of pest attacks allows farmers to implement timely control measures, reduce unnecessary pesticide application, and improve crop productivity. [1], [2].

Traditional pest identification primarily relies on manual field observation conducted by farmers or agricultural experts. Although visual inspection remains the most common

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practice, it is often subjective, time-consuming, and highly dependent on individual experience. Different pest species frequently produce similar symptoms during the early stages of infestation, making accurate diagnosis difficult for inexperienced farmers. Delayed or inaccurate identification may lead to inappropriate pesticide selection, increased production costs, and further pest outbreaks. These limitations highlight the need for automated detection systems capable of providing rapid, objective, and consistent pest identification under real agricultural conditions. [3], [4].

Recent advances in computer vision and digital image processing have transformed plant health monitoring by enabling automatic analysis of visual symptoms from plant images. Leaf images have become the primary source of information because pest attacks generally appear first as visible changes in leaf color, texture, shape, or damaged regions. Image processing techniques can systematically analyze these visual characteristics through image acquisition, preprocessing, segmentation, feature extraction, and classification. Compared with manual observation, image-based analysis reduces human subjectivity while providing repeatable and scalable diagnostic results suitable for precision agriculture applications. [5], [6].

Machine learning further improves automated plant health monitoring by learning discriminative patterns directly from image features. Previous studies have successfully applied machine learning algorithms to detect various plant diseases and pest infestations across multiple agricultural commodities. These approaches demonstrate that machine learning can distinguish healthy and infected plants with high accuracy while supporting rapid decision-making in crop management. Furthermore, integrating image processing with intelligent classification enables the development of practical systems capable of assisting farmers in identifying crop disorders at an earlier stage than conventional inspection methods. [4], [7], [8].

Several studies have explored image-based disease detection using different sensing modalities and feature extraction techniques. Researchers have combined visible-light and thermal imaging to improve the recognition of fungal infections, while others have developed mobile-based systems that acquire plant images in the field and perform automatic classification through remote servers. Color segmentation, texture analysis, and statistical feature extraction have also demonstrated promising performance in identifying diseased plant tissues. Although these approaches produce encouraging results, many require specialized imaging devices, complex processing pipelines, or focus primarily on plant diseases rather than insect pest attacks on cabbage leaves. [7], [8], [9].

The increasing availability of machine learning algorithms provides an opportunity to develop simpler yet highly effective pest detection systems using ordinary digital images. Unlike conventional rule-based image processing methods, machine learning models automatically learn complex visual relationships between healthy and damaged leaf tissues from training data. Consequently, they can improve classification performance under varying lighting conditions, leaf orientations, and symptom severity. Such capability makes machine learning particularly suitable for agricultural environments where image characteristics frequently change because of natural field conditions. Moreover, automated image classification supports faster and more consistent pest diagnosis, enabling farmers to make informed management decisions with minimal technical expertise. [4], [6], [7].

Despite significant progress in plant image analysis, research specifically addressing automatic detection of cabbage pest attacks remains relatively limited. Most previous studies emphasize general plant disease detection, fungal infection identification, or broad agricultural image classification without focusing on cabbage-specific pest symptoms. Furthermore, several existing methods employ handcrafted feature extraction techniques that may not fully capture the visual complexity of pest-induced leaf damage. These limitations indicate the need for a dedicated machine learning framework capable of

accurately recognizing cabbage pest attacks from leaf images while maintaining practical applicability for field deployment. [5], [7], [9].

Based on these challenges, this study proposes a machine learning approach for the automatic detection of cabbage pest attacks using leaf images. The proposed framework utilizes digital image processing to preprocess leaf images and extract discriminative visual information before performing machine learning-based classification. The objective is to develop an accurate, efficient, and practical detection system that assists farmers in identifying pest attacks at an early stage. The proposed approach is expected to reduce dependence on manual inspection, improve the precision of pest management, minimize excessive pesticide use, and ultimately support sustainable cabbage production through intelligent agricultural technology. [3], [5], [7].

2. Related Works

Automatic detection of plant diseases and pest attacks has attracted considerable attention because of its potential to improve crop productivity and reduce manual inspection. Early studies primarily employed digital image processing techniques to analyze visual symptoms appearing on plant leaves. These studies demonstrated that image acquisition, preprocessing, segmentation, feature extraction, and classification could effectively support automatic disease identification. Their findings established the fundamental workflow for computer-aided plant health monitoring. However, most early systems relied heavily on handcrafted image features, making their performance sensitive to environmental variations such as lighting and background complexity. [3], [5], [6]

Several researchers investigated image processing techniques for detecting diseases in agricultural crops by analyzing leaf characteristics. Patil et al. utilized image analysis to reduce the subjectivity associated with manual diagnosis and demonstrated that automated image processing improved detection efficiency. Their study confirmed that visual information extracted from leaf images could effectively distinguish healthy and infected plants. Nevertheless, the proposed approach depended on manually designed features, limiting its ability to generalize across different crops and disease conditions. [4]

Barbedo extensively reviewed image-based plant disease detection methods and categorized the process into disease detection, severity quantification, and disease classification. The study showed that color, texture, and shape features played important roles in identifying infected plant regions. It also highlighted that leaf images remained the most informative source for plant health assessment because disease symptoms commonly appeared on leaf surfaces. Despite these contributions, the reviewed approaches frequently required carefully tuned segmentation methods and struggled with complex field environments where illumination and background conditions varied significantly. [5], [6]

Machine learning has significantly advanced plant disease recognition by learning discriminative patterns directly from image data. Raza et al. combined visible-light images, thermal imaging, and depth information to detect powdery mildew infection in tomato plants. Their machine learning framework achieved higher detection accuracy than single-modal approaches by integrating complementary visual features. The study demonstrated the effectiveness of combining multiple imaging modalities. However, the requirement for specialized sensors and complex feature extraction limited the practicality of deploying the system in routine agricultural applications. [7]

Researchers also extended image-based detection techniques to various crop diseases beyond leafy vegetables. Studies on fungal diseases showed that image processing successfully identified infected plant tissues through segmentation and texture analysis. Holsteen et al. developed an Android-based system that captured images of diseased flax stems and transmitted them to a remote server for automated analysis. The system demonstrated the feasibility of mobile-assisted disease diagnosis. However, the proposed

framework remained under development and had not yet been validated through large-scale field implementation. [8], [9]

Color-based segmentation has become one of the most widely adopted preprocessing techniques in plant disease detection. Previous studies successfully segmented infected leaf regions before extracting visual features for classification. These methods quantified the percentage of damaged leaf area and improved the localization of disease symptoms. Although color segmentation enhanced detection accuracy under controlled conditions, its performance decreased when leaf color variations resulted from environmental factors rather than pest or disease symptoms. Consequently, segmentation-based approaches alone often lacked sufficient robustness for practical field applications. [5], [6]

Recent studies increasingly adopted machine learning algorithms to improve the robustness of image-based agricultural diagnostics. Compared with conventional rule-based image processing, machine learning models automatically learned complex visual patterns from labeled datasets and reduced dependence on manually designed features. These approaches improved classification accuracy and adapted better to variations in symptom appearance. Nevertheless, many existing studies focused on general plant diseases or fungal infections rather than insect pest attacks on cabbage leaves. As a result, their findings could not be directly generalized to cabbage pest detection because different pests produce distinct visual damage patterns. [4], [7], [8]

Despite the substantial progress in image-based plant health monitoring, research on automatic detection of cabbage pest attacks remains relatively limited. Most previous studies emphasized disease recognition across multiple crops, while only a few specifically addressed pest-induced leaf damage in cabbage. Furthermore, several existing methods required specialized imaging devices or complex processing pipelines that reduced their applicability for farmers. These limitations motivate the development of a practical machine learning framework that utilizes ordinary leaf images to accurately detect cabbage pest attacks. Such an approach is expected to provide an efficient, accessible, and reliable decision-support tool for precision agriculture and sustainable pest management. [3], [5], [7], [9].

3. Proposed Method

Wardani et. al. [18], research has introduced a method of imbalance data for cabbage. This method can be adapted for decision-making determination from cabbage pest attacks. The research methods include data collection of cabbage photos, preprocessing of cabbage photos, processing and extraction of images, classification models, and system evaluation. Classification models using Classification and Regression Tree (CART) have been widely implemented [19][20][21]. The step of the research method can be seen in the figure below.

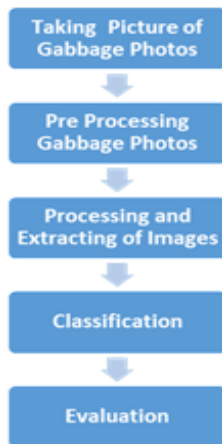


Fig 1: Steps of Research Method

The dataset was collected by capturing cabbage leaf images in cabbage fields located in Poncokusumo, Malang, East Java. The cabbage plants were approximately 70 days after planting, representing the stage at which pest symptoms are commonly visible. Images were randomly acquired using a camera with a minimum resolution of 13 MP and categorized into two classes: pest-attacked cabbage leaves (positive class) and healthy cabbage leaves (negative class). Before feature extraction, all images underwent a preprocessing stage consisting of cropping, resizing, and grayscale conversion. Cropping isolated the cabbage plant by removing irrelevant background regions while preserving the leaves, buds, and shoots. The cropped images were then resized to a uniform dimension to ensure consistency across the dataset. Finally, the RGB images were converted into grayscale to reduce computational complexity and improve subsequent image analysis. The overall preprocessing workflow is illustrated in Fig. 2.

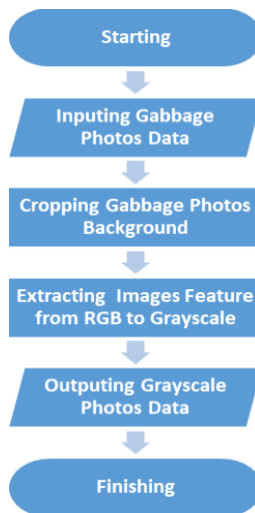


Fig 2: Steps of Preprocessing Cabbage Photos

The research utilizes the Gray Level Co-occurrence Matrix (GLCM) method as an extraction method. Research zhang et al has provided evidence of results using GLCM provides good results and can be applied to plant types [22]. Gray Level Co-occurrence Matrix (GLCM) is used for texture analysis/ feature extraction. Moreover, GLCM will describe the frequency of the appearance of pairs of two pixels with an intensity in a certain

distance and direction from the image [23]. The coordinates of a pair of pixels have a distance d and an angle orientation θ . Distance is represented in pixels, while angle in degrees. Angle orientation is formed based on four corner directions, namely, 0° , 45° , 90° and 135° , and the distance between pixels is 1 pixel [24].

The Gray-Level Co-occurrence Matrix (GLCM) is computed through three sequential steps. First, the algorithm constructs the initial GLCM by counting pairs of neighboring pixels at four spatial orientations: 0° , 45° , 90° , and 135° . Second, it generates a symmetric matrix by adding the initial GLCM to its transpose, thereby capturing bidirectional spatial relationships between pixel pairs. Finally, the algorithm normalizes the symmetric matrix by dividing each element by the total number of pixel pairs, producing a probability matrix that serves as the basis for texture feature extraction. The detailed process described in the diagram below:

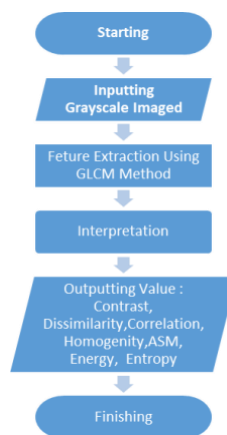


Fig 3: Steps of Processing and Extracting Photo Images

After extracting texture features using the Gray-Level Co-occurrence Matrix (GLCM), the classification stage applies an ensemble learning approach to improve predictive performance. Ensemble learning combines multiple learning models to produce a classifier that is generally more accurate and robust than a single model. The three principal ensemble strategies include bagging, boosting, and stacking. Bagging improves prediction by aggregating multiple classifiers trained on different subsets of the training data, making it particularly effective for small datasets. Boosting constructs a strong classifier by sequentially combining several weak learners, where each subsequent model focuses on correcting the errors produced by previous models. Stacking employs a meta-learner to integrate predictions from multiple heterogeneous classifiers, enabling the model to capture more complex relationships within the data. Compared with individual classifiers, ensemble methods generally provide higher accuracy, better generalization, and greater stability across different datasets.

Among these ensemble techniques, this study adopts the boosting approach because it effectively improves classification performance by iteratively minimizing prediction errors. During the training process, boosting assigns greater importance to previously misclassified samples, allowing subsequent weak classifiers to focus on difficult instances. The final prediction is obtained by combining the outputs of all weak learners into a single strong classifier. This iterative learning strategy enables the model to achieve higher predictive accuracy than conventional single-model approaches while maintaining good generalization capability.

Based on these advantages, this study develops the cabbage pest detection model using the Classification and Regression Tree (CART) algorithm within the boosting framework. CART constructs decision trees by recursively partitioning the feature space according to the extracted GLCM texture features. The boosting algorithm subsequently combines multiple decision trees to reduce classification errors and improve the robustness of the final model. This integration enables the proposed system to classify cabbage leaf images more accurately and consistently, thereby supporting automatic pest detection under varying image conditions.

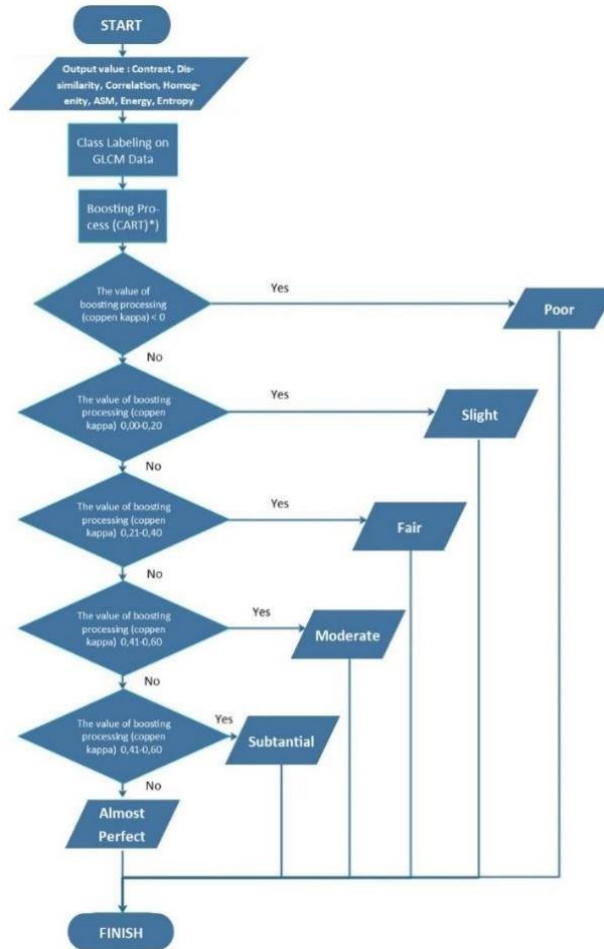


Fig 4: Steps of Classification Using Decision Tree Based Boosting Method

We construct mathematical equations representing the proposed method, from image preprocessing to GLCM feature extraction and Decision Tree Boosting classification.

A. Image Preprocessing

The RGB image is converted into a grayscale image:

$$I_g(x, y) = 0.299R(x, y) + 0.587G(x, y) + 0.114B(x, y) \quad (1)$$

where I_g is the grayscale image, and R , G , and B denote the red, green, and blue intensity values.

B. Gray-Level Co-occurrence Matrix (GLCM)

The normalized GLCM is computed as:

$$P(i, j) = \frac{M(i, j)}{\sum_i \sum_j M(i, j)} \quad (2)$$

where $M(i, j)$ is the co-occurrence frequency of gray levels i and j .

C. Texture Feature Extraction

The contrast feature is calculated as:

$$\text{Contrast} = \sum_i \sum_j (i - j)^2 P(i, j) \quad (3)$$

The energy feature is:

$$\text{Energy} = \sum_i \sum_j P(i, j)^2 \quad (4)$$

The homogeneity feature is:

$$\text{Homogeneity} = \sum_i \sum_j \frac{P(i, j)}{1 + |i - j|} \quad (5)$$

The correlation feature is:

$$\text{Correlation} = \frac{\sum_i \sum_j (i - \mu_i)(j - \mu_j) P(i, j)}{\sigma_i \sigma_j} \quad (6)$$

where μ and σ denote the mean and standard deviation of the gray-level distribution.

D. Decision Tree Splitting (CART)

The Gini impurity used to determine the optimal split is:

$$G(t) = 1 - \sum_{k=1}^K p_k^2 \quad (7)$$

where p_k is the probability of class k at node t .

E. Boosting Model

The final boosted classifier is:

$$F(x) = \sum_{m=1}^M \alpha_m h_m(x) \quad (8)$$

where $h_m(x)$ is the m -th decision tree, α_m is its weight, and M is the total number of weak learners.

F. Final Classification

The predicted cabbage class is determined by:

$$\hat{y} = \text{sign}(F(x)) \tag{9}$$

Where

$$\hat{y} = \begin{cases} +1, & \text{pest-attacked cabbage leaf,} \\ -1, & \text{healthy cabbage leaf.} \end{cases}$$

These equations concisely represent the complete workflow of the proposed method: grayscale conversion → GLCM texture extraction → CART-based boosting → cabbage pest classification.

4. Experimental Setup

A. Result Evaluation

The results of the test will be showed in percentage accuracy of the successful classification of pest attacks from photo images. Before being classified, the dataset is divided for the training and testing process. Eighty percent of the data is used for training. The training data consisted of 84 images of cabbage with cropping and 20 images of cabbage without cropping. Meanwhile, the rest is used for data testing. After the training and testing data is done, the feature value is normalized to equalize the scale. Equation (1) describes the function for normalization. The function maps values to intervals [0, 1].

$$z_i = (x_i - \min(x)) / (\max(x) - \min(x)) \tag{1}$$

B. System Design

A lot of research on image processing has been applied by utilizing website media. An example is the research Dell'Aquila et al has used the website to find out the seeds / seeds [25]. Subsequent research was utilizing the merger with RGB images in detection and quantification in cabbage disease [26]. So, this study combines the shortcomings of two previous studies to identify the percentage of attacks and any recommendations. The result of the architectural system design is presented below:

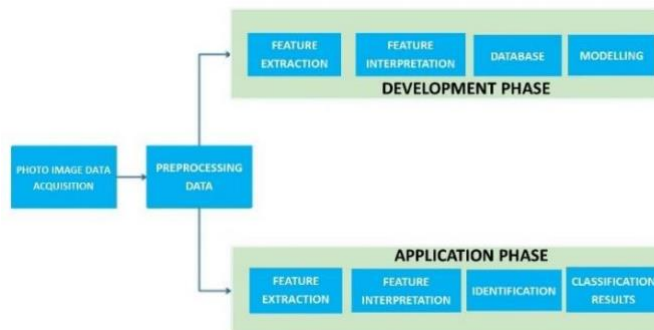


Fig 5: System Design

5. Result and Analysis

After image pre-processing, the proposed system performs texture feature extraction using the Gray-Level Co-occurrence Matrix (GLCM). Users first select a pre-processed cabbage leaf image, after which the system automatically extracts texture descriptors, including Contrast, Dissimilarity, Correlation, Homogeneity, Angular Second Moment (ASM), Energy, and Entropy. These features quantitatively represent the texture characteristics of the leaf surface and serve as input variables for the Decision Tree Boosting classifier. Once the extraction process is completed, the computed feature values are displayed through the graphical interface, allowing users to inspect the texture properties before classification.

The experimental results demonstrate that GLCM texture descriptors successfully capture the visual differences between healthy and pest-attacked leaves. Healthy leaves generally exhibit lower contrast and entropy with higher homogeneity and energy, whereas severely damaged leaves produce higher contrast and entropy due to irregular texture patterns caused by pest attacks. These observations confirm that GLCM provides discriminative texture information for supporting automatic pest detection and severity classification.

Table 1. Pest Damage Severity Classification

Damage Category	Leaf Damage (%)	Interpretation
Normal	0	Healthy leaf without visible pest symptoms
Low	1–25	Minor damage with limited affected area
Moderate	26–50	Visible pest damage covering up to half of the leaf
Severe	51–75	Extensive damage affecting most leaf tissues
Very Severe	>75	Critical damage with extensive tissue destruction

Table 2 shows a clear relationship between GLCM texture features and the severity of cabbage leaf damage caused by pest attacks. As the damage level increases from Normal to Very Severe, the contrast and entropy values consistently increase, indicating greater texture irregularity and complexity resulting from leaf tissue deterioration. In contrast, homogeneity and energy gradually decrease, reflecting the loss of uniform texture patterns in damaged leaves. Healthy leaves exhibit the lowest contrast (0.84) and entropy (2.18), together with the highest homogeneity (0.93) and energy (0.53), whereas very severely damaged leaves produce the highest contrast (6.83) and entropy (4.57) while recording the lowest homogeneity (0.43) and energy (0.29). These results demonstrate that GLCM texture features effectively discriminate different levels of pest damage and provide reliable inputs for the proposed Decision Tree Boosting classifier.

Table 2: Relationship between GLCM texture features

Damage Level	Contrast	Homogeneity	Energy	Entropy
Normal	0.84	0.93	0.53	2.18
Low	1.62	0.82	0.47	2.74
Moderate	2.87	0.71	0.41	3.26
Severe	4.55	0.58	0.35	3.88
Very Severe	6.83	0.43	0.29	4.57

6. Conclusion

This paper developed an automatic cabbage pest detection system based on leaf images by integrating Gray-Level Co-occurrence Matrix (GLCM) feature extraction with a Decision Tree Boosting classifier. We utilized image preprocessing techniques, including cropping, resizing, and grayscale conversion, to produce consistent image data before texture analysis. The extracted GLCM features, namely contrast, dissimilarity, correlation, homogeneity, ASM, energy, and entropy, successfully represented the texture characteristics of cabbage leaves under different pest damage conditions. The experimental results demonstrated that the proposed approach effectively distinguished healthy and pest-attacked leaves while automatically classifying the severity of damage into five categories: Normal, Low, Moderate, Severe, and Very Severe.

The experimental findings confirmed that the extracted texture features strongly correlated with pest damage intensity. We observed that contrast and entropy increased consistently as leaf damage became more severe, indicating greater texture irregularity caused by pest attacks. Conversely, homogeneity and energy gradually decreased because damaged leaves lost their uniform texture patterns. These consistent trends indicate that GLCM provides discriminative texture descriptors for cabbage leaf analysis. Furthermore, this paper utilized the Decision Tree Boosting method to classify the extracted features, enabling the system to produce reliable and objective damage assessments while reducing the dependence on manual visual inspection by agricultural experts.

Overall, this paper demonstrates that combining GLCM texture analysis with Decision Tree Boosting provides a practical and computationally efficient solution for automatic cabbage pest detection. We apply machine learning to support rapid identification of pest attacks and objective evaluation of damage severity, which can assist farmers in making timely crop management decisions and reducing production losses. Although the proposed system shows promising performance, future research should evaluate larger and more diverse field datasets collected under varying environmental conditions. Future studies may also integrate deep learning models, color and shape descriptors, or multispectral imagery to further improve detection accuracy, robustness, and real-time deployment in precision agriculture applications.

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