



AI-Based Detection of Leaf Diseases in Durian (*Durio zibethinus*) Using Convolutional Neural Networks: Model Development and Performance Evaluation

Supreeya Thepparak¹, Prisana Wonglom¹, Samak Kaewsuksaeng¹, and Anurag Sunpapao^{2*}

¹ Faculty of Agriculture, Thaksin University, Phatthalung Campus, Phatthalung, 93210, Thailand

² Faculty of Natural Resources, Prince of Songkla University, Songkhla, 90110, Thailand

* Correspondence: anurag.s@psu.ac.th

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Abstract: Early detection of durian leaf diseases using artificial intelligence (AI) plays an important role in supporting effective plant disease management within digital agriculture systems. This study aimed to develop an AI-based system for the preliminary detection and classification of common durian leaf diseases using image analysis. Diseased leaf samples were collected from durian orchards in Pa Phayom District, Phatthalung Province, and Chang Klang District, Nakhon Si Thammarat Province, southern Thailand. Associated microorganisms were isolated using the tissue transplanting technique, and morphological characteristics indicated the presence of *Colletotrichum* spp. in leaf spot samples and *Fusarium* spp. in leaf blight samples. In contrast, the algal leaf spot pathogen could not be cultured on standard fungal media. A Convolutional Neural Network (CNN) was employed to classify three disease categories: leaf spot, leaf blight, and algal leaf spot. The image dataset was divided into training, validation, and testing sets, and the model was trained and evaluated accordingly. The results demonstrated that the proposed AI model effectively classified durian leaf disease images, particularly leaf spot and leaf blight. However, this study used a relatively limited dataset, and the proposed system should therefore be considered a preliminary disease-detection tool. The developed AI-based system shows potential for deployment on mobile devices or online platforms to support early disease recognition and decision-making by farmers, thereby improving disease management strategies in durian cultivation.

Keywords: Artificial intelligence; durian leaf disease; image processing; neural networks

1. Introduction

Durian (*Durio zibethinus*) is one of Thailand's most economically significant fruit crops, often referred to as the "King of Fruits." Thailand is the world's largest exporter of durian, with major markets in China, Malaysia, and Hong Kong. Fruit plays a vital role in Thailand's agricultural economy, supporting thousands of farmers, traders, and exporters. Besides its economic value, durian is also culturally significant, often featured in festivals and local markets. However, durian cultivation faces challenges, including pest infestations and fungal diseases, which can significantly affect yield and fruit quality. One of the major challenges affecting durian production and quality is plant diseases, particularly foliar diseases that impact tree growth and fruit

development. Common leaf diseases in durian include leaf spot, leaf blight, Rhizoctonia leaf blight, and algal leaf spot [1–3]. Traditionally, diagnosing these diseases relies on visual observation of symptoms or laboratory analysis, which is time-consuming and requires expert knowledge.

In recent years, artificial intelligence (AI) technology has played a crucial role in digital agriculture, particularly in the classification and diagnosis of plant diseases through image processing and machine learning [4]. This technology helps overcome the limitations of traditional disease diagnosis by accurately and rapidly detecting disease characteristics from plant leaf images. The application of lightweight AI for durian leaf disease classification offers a practical approach for the agricultural sector, especially for farmers who lack expertise in plant pathology and need user-friendly, accessible tools. The application of artificial intelligence (AI), particularly deep learning and convolutional neural networks (CNNs), to plant disease diagnosis has attracted substantial attention in recent years [5]. Numerous studies have demonstrated the effectiveness of image-based models for automated disease classification, including the detection of *Phytophthora* blight [6], classification of foliar diseases in various crops [7], and rice disease identification systems [8]. However, research on AI applications for durian disease classification remains limited. Developing an AI system capable of accurately identifying durian leaf diseases is an essential step toward enhancing plant disease management efficiency and reducing unnecessary chemical use in disease control.

This study aims to develop a simple AI-based system for classifying durian leaf diseases using image analysis, enabling farmers to identify diseases and implement appropriate preventive measures quickly. The proposed system utilizes fundamental machine learning techniques, specifically Convolutional Neural Networks (CNN), trained on a dataset of durian leaf images affected by various diseases [9]. Designed for compatibility with mobile devices and online platforms, the system enables practical, real-time field application. This research introduces an approach to developing a lightweight AI system for durian leaf disease classification based on image analysis. The system's performance was evaluated using accuracy, sensitivity, and specificity metrics. The findings will be valuable to both farmers and researchers in developing an accurate and practical AI-based diagnostic tool.

2. Materials and Methods

2.1 Collection of Durian Leaf Disease Samples

Durian leaves exhibiting disease symptoms were collected from Moo 6, Pa Phayom Subdistrict, Pa Phayom District, Phatthalung Province, and Chang Klang District, Nakhon Si Thammarat, Thailand. The collected samples were then brought to the Plant Science Laboratory, Faculty of Agriculture, Thaksin University, Phatthalung Campus, for further analysis.

2.2 Isolation of Pathogenic Fungi and Preliminary Morphological Study

Fungal pathogens were isolated using the tissue-transplanting method as previously described by Daengsuwan et al. [10]. Infected leaf samples were cut into small sections (3×3 mm), surface-disinfected with 1% sodium hypochlorite (NaOCl), and rinsed three times with sterilized distilled water to remove excess NaOCl for 1 minute each. The samples were then blotted dry with sterile filter paper before being placed onto 17% water agar (WA, 17% agar and distilled water) medium and incubated at room temperature ($28 \pm 2^\circ\text{C}$) for three days. Following incubation, hyphal tips emerging from the samples were cut and transferred to potato dextrose agar (PDA, HiMedia, Mumbai, India). The fungal isolates were then examined under a Leica S8AP0 stereomicroscope (Leica Microsystems, Wetzlar, Germany) and a Leica DM750 compound microscope (Leica Microsystems, Wetzlar, Germany) to assess their preliminary morphological characteristics.

2.3 Preparation of Plant Disease Dataset

In this study, a dataset of 1,600 red-green-blue images of durian leaves affected by different leaf diseases was collected from a smartphone (iPhone 16, iOS version 18.6) with a resolution of $8,064 \times 6,048$ pixels. The digital images were taken using a photography box (40 cm wide $\times$ 40 cm deep $\times$ 40 cm high) with a light-emitting diode, with the object-to-camera distance about 45 cm. The image processing technique was coded in Python on Google Colaboratory (Google, California, USA). The images were categorized into four district groups (four classes): healthy leaf, leaf spot, leaf blight, and algal leaf spot, with 400 images per class. Sixty

percent (60%) of the dataset was allocated for training the model, ensuring that it learned patterns and disease characteristics effectively. Twenty percent (20%) of the data was set aside for validation, which was used to fine-tune the model's parameters and prevent overfitting. The remaining 20% was reserved as a test set, allowing an unbiased evaluation of the model's performance in classifying durian leaf diseases (Figure 1).

2.4 Development of the AI Model for Durian Leaf Disease Classification

The image processing technique and AI model were implemented in Python on Google Colaboratory (Google, California, USA). The image was resized to 224 x 224 pixels before being input to the model. Image augmentation, such as horizontal flipping, 90-degree rotation, brightness, and hue adjustment, was used to generate additional training examples to alleviate overfitting. This study employed a Convolutional Neural Network (CNN) to develop an AI model using a transfer-learning architecture based on MobileNetV2 for disease diagnosis. Model development began by defining the CNN architecture, consisting of three convolutional layers with 32 filters and a stride of 2, using the ReLU activation function. Additionally, average pooling layers were incorporated to reduce data size and computational complexity, thereby improving efficiency. The extracted features were then passed through a fully connected layer with 256 neurons. A 0.5 dropout rate was used to prevent overfitting, and the final classification was performed using a Softmax function that categorized the input images into different disease classes. The model was trained on the prepared dataset using Categorical Cross-Entropy as the loss function, which is well-suited to multi-class classification. The Adam optimizer was selected to efficiently optimize the model parameters. The training process was configured to run for 200 epochs with a batch size of 4 and a learning rate of 0.001, ensuring stable learning while minimizing the risk of overfitting (Figure 1). The first training period lasted about 26 seconds, and each of the next two to three epochs lasted about 2 to 3 seconds. This amounts to about 6–7 minutes in total across 200 epochs.

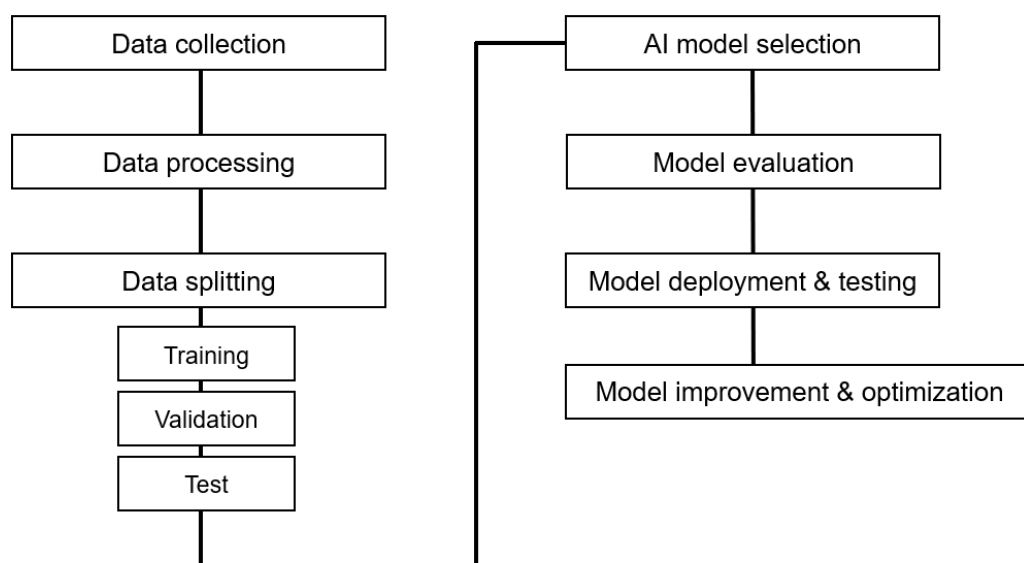


Figure 1. The schematic represents the preparation of the plant disease dataset and the development of the AI model for durian leaf disease classification.

2.5 AI Model Test with Real Sample from the Fields

Unknown durian leaf disease samples were used to test the model's accuracy. The entire evaluation procedure was performed, and the results were expressed to assess the consistency of model performance. The model's accuracy was expressed as a percentage for each sample.

3. Results and Discussion

A survey of durian leaf diseases in Pa Phayom District, Phatthalung Province, and Chang Klang District, Nakhon Si Thammarat, revealed that the most commonly observed diseases were leaf spot, leaf blight, and algal leaf spot. Leaf samples exhibiting disease symptoms were collected and subjected to fungal isolation in the laboratory using the tissue transplanting technique. Preliminary morphological studies of the isolated fungi indicated that *Colletotrichum* sp. was isolated from leaf spot samples, while *Fusarium* sp. was isolated from leaf blight samples (Figure 2). These fungal genera have been previously reported in association with various durian diseases, including foliar diseases such as leaf spot and anthracnose, as well as non-foliar diseases such as twig dieback [11,12]. *Fusarium* species have been widely reported as important pathogens of durian, particularly associated with dieback and canker diseases [11]. For algal leaf spots, fungal cultures could not be established on standard fungal growth media. This finding aligns with the biological characteristics of algae, which typically require specific environmental conditions for growth [13]. Algae must be cultivated on specialized media, such as Bold's Basal Medium [14,15]. Although precise identification of fungal pathogens requires several methods, pathogen isolation and pathogenicity tests are needed to fulfill Koch's postulates, along with morphological characteristics and molecular identification [16,17]. However, this study did not conduct pathogenicity tests or molecular identification of the isolated fungi. Instead, it focused on documenting disease symptoms and identifying the fungal isolates at a preliminary level to support the development of a lightweight AI system for the initial classification of durian leaf diseases.

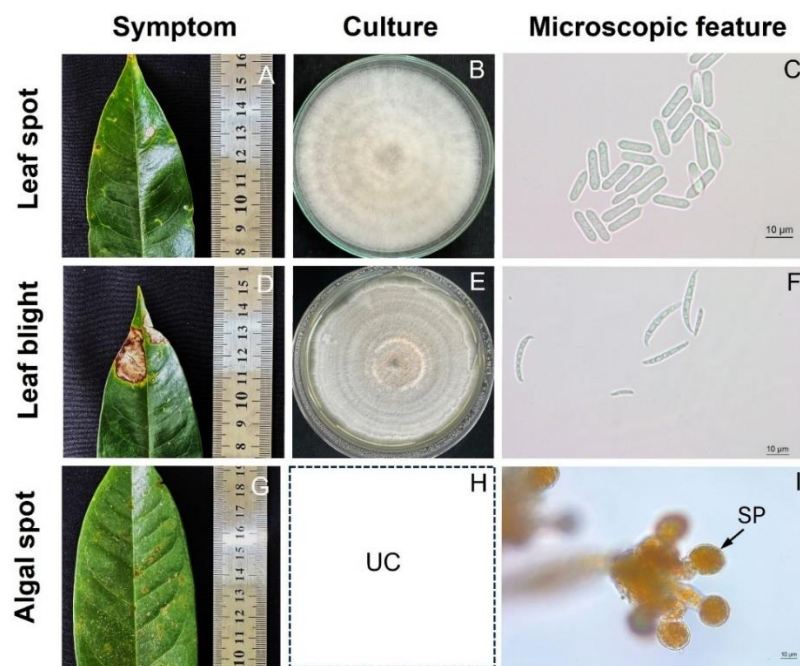


Figure 2. Symptom development of durian leaf disease and culture on potato dextrose agar (PDA), and microscopic features observed by a compound microscope. Durian leaf spot (A), colony of *Colletotrichum* on PDA (B), conidial mass (C), durian leaf blight (D), colony of *Fusarium* sp. on PDA (E), and conidial mass (F), durian algal leaf spot represent orange thalli (G), unculturable (UC) on PDA (H) and structure of parasitic algae (I). The arrow indicates zoosporangia of the plant-parasitic alga *Cephaleuros*, SP = sporangia.

To develop an AI model for classifying durian leaf diseases, the dataset was split into three subsets: training (60%), validation (20%), and test (20%). This division ensures that the model can effectively learn patterns from the training data while being evaluated on separate validation and test sets. The model was developed using a Convolutional Neural Network (CNN), a deep learning technique widely used for image classification tasks. After training the model, its accuracy was analyzed using the model accuracy graph (Figure 3). The graph's X-axis shows the number of training iterations (epochs), while the Y-axis shows the

model's accuracy. The training accuracy curve shows a rapid increase in accuracy during the initial epoch, demonstrating that the model quickly learned distinguishable features of durian leaf diseases. As training progressed, accuracy continued to improve, eventually stabilizing between 98% and 100% in the later epoch. This stabilization suggests that the model effectively captured the dataset's key characteristics and achieved high classification accuracy.

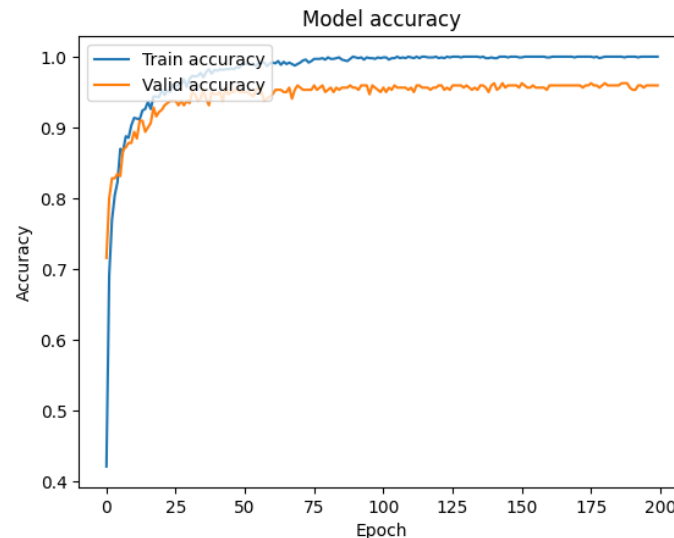


Figure 3. The learning curve from the training and validation datasets shows accuracy (Training accuracy: 1.00; Validation accuracy: 0.96). Training accuracy of the model across different epochs. The x-axis represents the number of epochs, and the y-axis shows the model's accuracy.

However, one critical aspect to consider in training deep learning models is overfitting. Suppose the model's accuracy on the training set is significantly higher than on the validation or test sets. In that case, it may indicate that the model has overfit the training data and struggles to generalize to new, unseen data. Without validation accuracy as a reference, there is a risk that the model may overfit the training data. To ensure the model's generalizability, it is essential to monitor validation accuracy and validation loss throughout training. These metrics help assess whether the model effectively classifies new data rather than memorizing the training dataset.

The model loss graph provides valuable insights into the AI model's learning process. This graph shows the loss values across different training epochs, helping assess whether the model is improving over time (Figure 4). The X-axis (Epochs) represents the number of training iterations, where each epoch refers to a complete pass through the training dataset. The Y-axis (Loss) indicates how far the model's predictions deviate from the expected values, with lower loss values suggesting better learning. The train loss curve shows a continuous decline as the number of epochs increases, indicating that the model is progressively learning from the data and reducing errors. The learning curve from the training and validation datasets shows a loss of 0.002 (Training loss) and 0.10 (Validation loss). This steady downward trend suggests that the model effectively captures the patterns in the dataset. Additionally, the absence of significant fluctuations in the graph indicates that the learning process is stable and free from erratic changes. If the loss continues to decrease without sudden increases, it implies that the model is learning efficiently and has not yet overfitted to the training data. However, to ensure optimal model performance, it is crucial to monitor both the validation and training losses. If the validation loss decreases alongside the training loss, it suggests the model is generalizing well. Conversely, if the validation loss begins to rise while the training loss continues to decline, this may indicate overfitting, where the model memorizes the training data but fails to perform well on new, unseen data (Figure 4).

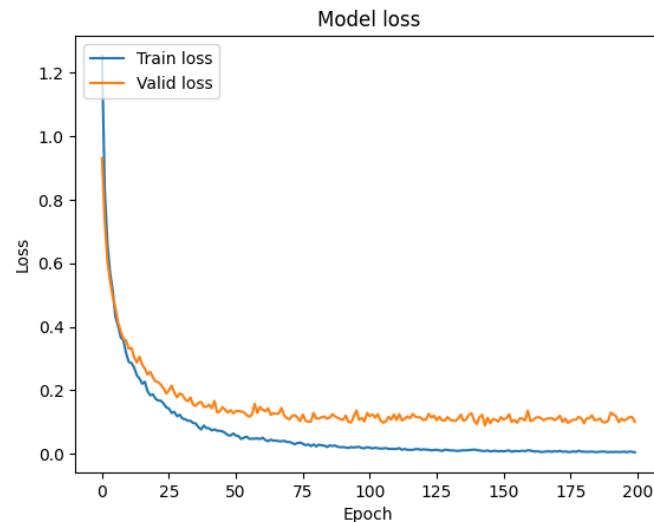


Figure 4. The learning curve from the training and validation datasets represents the loss. (Training loss 0.002, and Validation loss 0.10) Training loss of the model across different epochs. The x-axis represents the number of epochs, and the y-axis shows the loss.

Table 1 presents the performance of the proposed AI-based model for durian leaf disease classification, comparing predicted results with expert observations across four classes: healthy leaf, algal leaf spot, leaf blight, and leaf spot. The evaluation metrics include precision, recall, and F1-score, which provide a comprehensive assessment of the model's classification capability for each disease class. The model demonstrated strong performance across all classes, with precision values ranging from 0.96 to 0.98. The healthy leaf class achieved a precision of 0.96 and a recall of 0.98, indicating that the model accurately distinguished healthy leaves from diseased ones with minimal misclassification. Similarly, the algal leaf spot class achieved the best performance, with a precision of 0.98 and perfect recall of 1.00, resulting in an F1-score of 0.99. This suggests that the model was highly effective in identifying algal leaf spot symptoms. For the leaf blight class, the model achieved a precision of 0.96 and a recall of 0.97, yielding an F1-score of 0.96, indicating balanced and reliable classification performance. The leaf spot class exhibited slightly lower recall (0.91) compared to other classes, which may be attributed to visual similarities with other disease symptoms. Nevertheless, the precision remained high at 0.96, and the F1-score reached 0.94, reflecting satisfactory predictive capability. Overall, the macro-averaged F1-score of 0.96 and an overall accuracy of 0.97 confirm that the proposed model performs consistently well across all disease categories. These results demonstrate the model's robustness and its potential for practical durian leaf disease diagnosis in real-world agricultural settings.

Table 1. The comparison of leaf diseases in durian between the observer and the predictive model.

		Predicted leaf disease				Precision	Recall	F1-score
		Healthy leaf	Algal leaf spot	Leaf blight	Leaf spot			
Observers	Healthy leaf	82	0	0	2	0.96	0.98	0.97
	Algal leaf spot	0	86	0	0	0.98	1.00	0.99
	Leaf blight	0	1	68	1	0.96	0.97	0.96
	Leaf spot	3	1	3	73	0.96	0.91	0.94
Macro F1-score						0.96		
Accuracy						0.97		

To further evaluate the model's performance, it was tested for classifying three durian leaf diseases: leaf spot, leaf blight, and algal leaf spot in unknown samples. Figure 5 shows the predictions of the trained AI model on unseen durian leaf images. For each input image, the model outputs the probability distribution across four classes: healthy leaf, algal leaf spot, leaf blight, and leaf spot. For the image "Unknown1.jpg", the model classified the leaf as an algal leaf spot with a confidence of 100%, while assigning 0% probability to the healthy leaf, leaf blight, and leaf spot classes. This result indicates highly confident, correct classification, demonstrating the model's strong ability to recognize algal leaf spot symptoms. Similarly, for the image "Unknown2.jpg", the model again predicted algal leaf spot with 100% probability, with no confusion observed among the remaining disease classes. This further confirms the model's consistency and robustness in identifying algal leaf spot under different visual conditions. For the image "Unknown3.jpg", the model predicted algal leaf spot with a probability of 98.70%, assigning small probabilities to leaf blight (1.29%) and leaf spot (0.01%). Although minor confusion was observed between algal leaf spot and leaf blight, the dominant prediction remained correct, indicating that the model can effectively distinguish algal leaf spot even when visual features overlap with those of other disease symptoms. Overall, these results demonstrate that the proposed model provides high-confidence predictions and exhibits strong discriminatory power among durian leaf disease classes. The probability output also provides transparency into model decision-making, which is particularly valuable for practical applications, as users can assess prediction confidence when diagnosing diseases in real-world conditions.

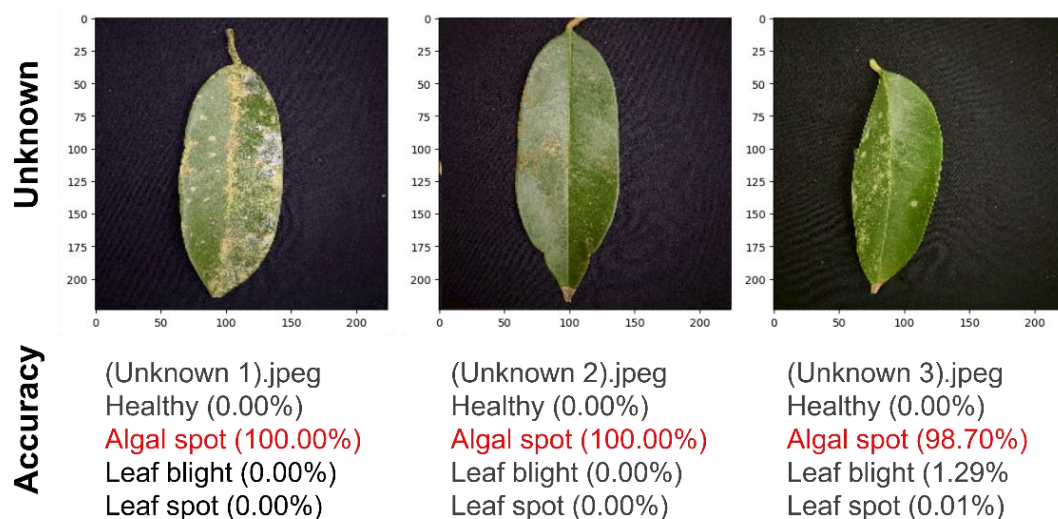


Figure 5. Classification results of durian leaf diseases using an artificial intelligence-based system. The left panel displays the predicted disease class and its associated probability for each test image.

The loss values significantly decreased after 200 epochs, further indicating that the model was well-trained and capable of distinguishing between different disease types with high reliability (Figure 5). The experimental results demonstrate that the CNN model effectively classifies durian leaf diseases with high accuracy, particularly for leaf spot and leaf blight. This aligns with previous studies on the application of CNNs in plant disease classification [18,19]. For example, Mohanty et al. [20] reported that CNN models could achieve up to 99% accuracy in identifying plant diseases from images. However, the classification accuracy for algal leaf spot was lower than that for the other two diseases. This may be attributed to unclear disease characteristics or to the visual similarity between infected and non-infected leaves, which makes classification more challenging [21]. Several factors could influence the model's performance, including dataset quality and data augmentation techniques used to enhance image diversity. Since deep learning models require large datasets to reduce the risk of overfitting, the effectiveness of data augmentation is crucial for improving model generalization [22]. Additionally, hyperparameter selection, such as learning

rate and batch size, significantly affects the training speed and model efficiency. Further optimization of these parameters may be required to achieve even better classification performance.

Although the developed system effectively classifies durian leaf diseases, it cannot identify the exact causal pathogens. For accurate pathogen identification, morphological characterization is required to distinguish algal species [23,24], while both morphological and multi-locus DNA analyses are necessary for fungal species identification [17,25]. The current system serves as a preliminary plant disease classification tool, but its real-world application requires consideration of external factors, such as lighting conditions and camera angles during image capture. This finding would help farmers manage their durian fields early using appropriate methods, such as chemical control [26], biological control [27], or integrated pest management [28]. Additionally, integrating the system into mobile devices or online platforms would enhance accessibility for farmers, making disease diagnosis more practical in the field. Future research should focus on expanding the model's ability to classify a broader range of durian diseases and on enhancing real-time disease analysis via mobile applications. These improvements would contribute to more efficient, user-friendly disease-detection systems for agricultural use.

In this study, a CNN-based model was developed to demonstrate the feasibility of image-based preliminary detection of durian leaf diseases. The primary focus was on model development and performance evaluation within a cloud-based environment (Google Colab), rather than on deployment-level optimization or hardware-specific benchmarking. Consequently, inference time, memory consumption, and computational efficiency on mobile devices were not directly evaluated in this study. The Google Colab environment is designed for model training and validation and does not support direct measurement of real-time inference performance on mobile hardware. Evaluating mobile deployment performance would require exporting the trained model and testing it on actual mobile devices under specific hardware conditions, which was beyond the scope of this study. Nevertheless, the proposed model demonstrates potential for future integration into mobile or web-based platforms to support field-level disease detection. Further work will focus on optimizing the model architecture, comparing it with established lightweight networks (e.g., MobileNet or EfficientNet), and benchmarking performance on mobile devices to enable practical, efficient deployment for real-world agricultural applications.

4. Conclusions

This study successfully developed an AI-based system using Convolutional Neural Networks (CNNs) for the preliminary detection and classification of common durian leaf diseases, namely leaf spot, leaf blight, and algal leaf spot, based on image analysis. The model demonstrated strong classification performance, particularly for leaf spot and leaf blight, consistent with previous studies highlighting the effectiveness of CNNs for image-based plant disease detection. The relatively lower accuracy observed for algal leaf spot may be attributed to the disease's subtle visual characteristics and its similarity to other leaf symptoms. It is important to note that the proposed system is intended as an initial screening tool rather than a definitive diagnostic method. Future work should focus on expanding the range of durian diseases included in the model, optimizing its deployment efficiency, and evaluating its performance under field conditions. These advancements would support early disease recognition and informed decision-making, ultimately contributing to more effective disease management and improved durian production.

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