The International Society of Data Scientists
Journal of Data Science and Artificial Intelligence
Vol. 4, No. 1. Online ISSN: 2831-4794

Applying deep learning with VGG16 to classify durian leaf diseases

Tran Nhu Y[1], Nguyen Huu Chi[1], Ngo Duong Ha[1*]
[1]Faculty of Information Technology, Ho Chi Minh City University of Industry and Trade, 700000, Vietnam

ABSTRACT

Durian is a high-value tropical fruit widely cultivated in Southeast Asia, particularly in Vietnam, Thailand, Malaysia, and Indonesia. However, durian trees are vulnerable to numerous leaf diseases that can significantly reduce yield and fruit quality. In this study, we propose an artificial intelligence-based approach using the VGG16 convolutional neural network to classify diseases on durian leaves. A dataset of 5,603 images representing 10 common diseases and 1 non-disease class was collected and augmented to enhance model generalization. The model achieved a classification accuracy of 94.12% and a loss value of 0.5419, demonstrating its effectiveness compared to ResNet-50. Furthermore, a web-based application was developed to allow farmers to upload leaf images for instant disease diagnosis and receive treatment recommendations. This approach provides a practical, accessible tool to support early disease detection and precision agriculture, contributing to improved productivity and sustainable farming practices.

Keywords: Durian Leaf Diseases, Deep Learning, VGG16, ResNet-50, Smart Agriculture.

1. INTRODUCTION

Durian (*Durio zibethinus*), commonly known as the "king of fruits," holds immense economic and cultural significance across Southeast Asia. In Vietnam, durian cultivation plays a vital role in the agricultural sector, contributing substantially to both domestic consumption and international export markets. Popular varieties such as Ri6, Musang King, and Monthong are widely favored for their high yield and commercial appeal. The country's tropical climate and fertile soil have further positioned Vietnam as one of the region's leading durian producers [1].

Despite its high economic potential, durian cultivation faces serious challenges due to the prevalence of various leaf diseases, including leaf blight, black spot, powdery mildew, anthracnose, and others [1][2]. These diseases adversely affect leaf health, reduce photosynthetic capacity, and significantly impact fruit quality and yield. If not promptly diagnosed and treated, they can lead to long-term declines in orchard productivity and pose substantial risks to farmers' incomes.

Traditionally, disease diagnosis in agriculture relies heavily on manual inspection by experts, which is often time-consuming, labor-intensive, and impractical for large-scale farming. In response, recent advances in artificial intelligence (AI)—particularly deep learning and computer vision—have opened promising pathways for automated plant disease detection through image-based analysis [3][4].

Among deep learning techniques, convolutional neural networks (CNNs) have demonstrated exceptional performance in image classification tasks and have been effectively applied to identify plant diseases in crops such as rice, maize, tomatoes, and grapes [3][4]. One of the most prominent CNN architectures is VGG16, which offers a strong balance between classification accuracy and architectural simplicity. It uses small 3×3 convolutional kernels to extract multi-level features from images, and has been widely adopted in plant pathology research [5][6]. Studies have reported high accuracy rates using VGG16 for disease detection in different types of fruit and vegetable leaves [5]. While similar approaches have been explored for other crops, there remains limited research focused specifically on the classification of durian leaf diseases using deep learning, particularly within the Vietnamese agricultural context [2].

In addition, although more complex models such as ResNet or Inception have also been employed in related domains, their computational intensity may hinder deployment in real-world agricultural environments where resources are limited [5]. VGG16, by contrast, provides an effective trade-off between performance and efficiency, making it more practical for scalable, field-based applications.

This study aims to address these research gaps by constructing a curated dataset of durian leaf images representing ten common disease types and a non-disease class. A deep learning-based classification model using the VGG16 architecture is developed, trained, and evaluated to identify these conditions accurately. Furthermore, a web-based application is

introduced to facilitate real-time diagnosis and deliver disease-specific treatment recommendations. The proposed solution not only contributes to advancing smart agriculture practices but also provides farmers with accessible tools to support timely and sustainable crop management.

2. METHOD

2.1 VGG network model

VGG16 is a deep convolutional neural network (CNN) architecture introduced by the Visual Geometry Group at the University of Oxford in 2014. It has become a foundational model in the field of computer vision due to its simplicity, uniform layer design, and strong performance in image classification tasks. The architecture is particularly well-suited for tasks requiring rich hierarchical feature extraction from images [6].

The VGG16 model consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. All convolutional layers use a small 3×3 kernel size, which is the smallest receptive field that can still capture spatial patterns in an image. These layers are accompanied by ReLU (Rectified Linear Unit) activation functions to introduce non-linearity and accelerate training. Between convolutional blocks, 2×2 max pooling layers are used to progressively reduce spatial dimensions and control overfitting.

The model architecture is organized into five main convolutional blocks, each responsible for learning features of increasing complexity:

+ Block 1: Two convolutional layers with 64 filters each, followed by a max pooling layer.
+ Block 2: Two convolutional layers with 128 filters each, followed by a max pooling layer.
+ Block 3: Three convolutional layers with 256 filters each, followed by a max pooling layer.
+ Block 4: Three convolutional layers with 512 filters each, followed by a max pooling layer.
+ Block 5: Three convolutional layers with 512 filters each, followed by a max pooling layer.

After passing through the convolutional blocks, the output feature map is flattened and fed into three fully connected layers:

+ The first fully connected (FC) layer contains 4,096 neurons.
+ The second FC layer with 4,096 neurons.
+ The final output layer with a number of neurons equal to the number of target classes (e.g., 1,000 for ImageNet), followed by a Softmax activation function for multi-class classification.

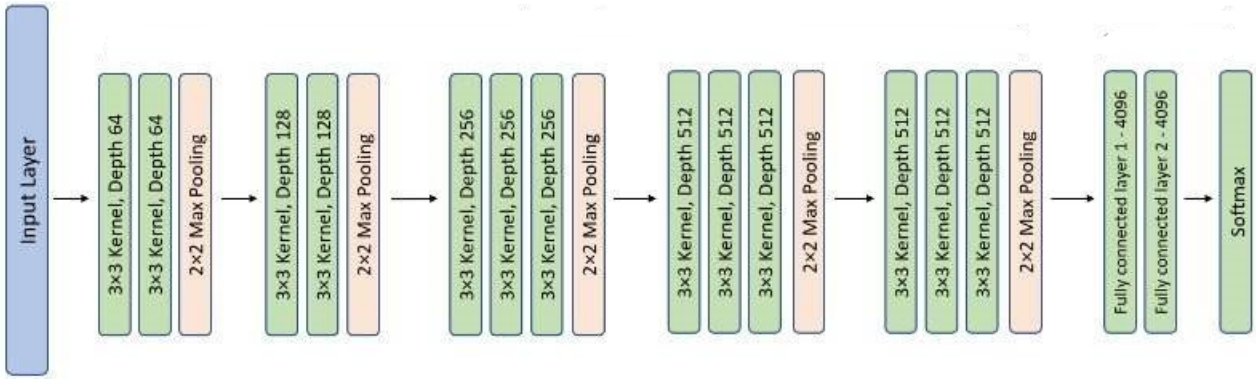


Figure 1. VGG16 network architecture [6].

The overall structure of the VGG16 network is visualized in Figure 1, which demonstrates how the input image is progressively transformed through a sequence of convolution, pooling, and fully connected layers to produce a final class prediction.

Despite its high performance, one limitation of VGG16 is its large number of parameters—approximately 138 million—which leads to high computational and memory demands. However, its straightforward design and robust feature learning capability make it highly compatible with transfer learning, allowing it to be effectively reused in a wide range of tasks such as object detection, image segmentation, and plant disease classification.

2.2 Algorithmic Model

In this study, the VGG16 convolutional neural network (CNN) model is adopted to classify 11 categories of durian leaf conditions, including 10 disease types and 1 non-disease class. The VGG16 architecture is known for effectively extracting hierarchical image features using small 3×3 convolutional filters and max pooling. These characteristics make it especially suitable for detailed tasks such as plant disease classification.

The model training process is designed around the principles of transfer learning. A pre-trained VGG16 model (originally trained on the ImageNet dataset) is used as the base, with its convolutional layers frozen to retain general image feature representations. New fully connected layers are appended and trained specifically for the durian leaf disease dataset, allowing the model to adapt to this domain-specific task while minimizing the risk of overfitting.

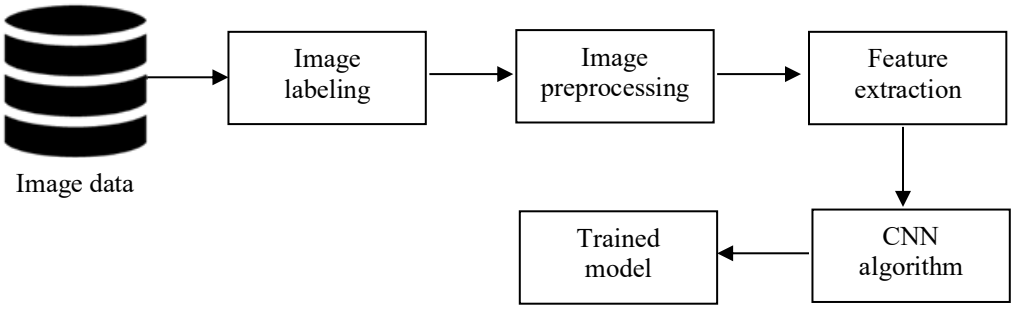


Figure 2. Proposed training pipeline for durian leaf disease classification.

Figure 2 illustrates the five major stages of the proposed system architecture:

Image Data Collection: High-resolution images of durian leaves are collected from multiple sources, including plantations, agricultural research centers, and online databases. Each image is labeled according to one of 11 predefined classes (10 disease types and 1 non-disease class).

Image Labeling: Each image is annotated using expert knowledge and plant pathology references. Labels are used to map images to their respective disease categories for supervised training.

Preprocessing and Augmentation: Images are resized to 224×224 pixels to match the input size required by VGG16. Real-time augmentation techniques such as rotation, flipping, brightness adjustment, and contrast normalization are applied to enhance generalization and reduce overfitting.

Feature Extraction via CNN: A pre-trained VGG16 model (with ImageNet weights) is used as the backbone. Convolutional layers are frozen to retain learned features, while the top layers are replaced and trained on the durian leaf dataset. Deep features are extracted through hierarchical convolutional filters.

Training and Evaluation: The modified model is trained using the Adam optimizer and categorical cross-entropy loss. The dataset is split into training, validation, and test sets (70/10/20). Accuracy and loss are monitored to evaluate performance and fine-tune hyperparameters. The trained model is then deployed for inference.

This algorithmic framework effectively leverages the strength of the VGG16 model and demonstrates how deep learning can be applied in agricultural settings to provide accurate and scalable solutions for disease diagnosis. It supports early detection, enhances decision-making for farmers, and contributes to the advancement of smart farming practices. To achieve this objective, a structured algorithmic framework was developed for classifying of durian leaf diseases using the VGG16 model. The proposed pipeline covers the entire workflow—from data preparation and augmentation to model construction and training—by applying transfer learning techniques to fine-tune a pre-trained VGG16 network for a

domain-specific classification task involving 11 distinct categories (10 disease types and one non-disease class). The key steps of the algorithm are outlined as follows:

Algorithm: Durian Leaf Disease Classification Using VGG16

Input: A dataset comprising 5,603 images of durian leaves, representing 11 categories (10 disease types and 1 non-disease class), with each image resized to 224×224 pixels.

Output: Predicted class label for each input image, corresponding to one of the 11 predefined disease categories.

Step 1: Data Preparation

The image dataset is loaded from the designated directory and organized into labeled categories suitable for training and evaluation.

Split the dataset into two primary subsets:

Training and validation set (80% of the data): used for model training and tuning.

Test set (20%): used to evaluate the model's final performance after training.

Step 2: Data Augmentation and Subset Splitting

Apply data augmentation techniques to enhance dataset diversity and improve generalization. Techniques include:

Random horizontal/vertical flipping

Image rotation

Brightness and contrast adjustment

Utilize lambda functions to implement real-time augmentation during training.

Further split the 80% dataset into:

Training set (70%): used to update model weights.

Validation set (10%): used to monitor the model's performance during training and prevent overfitting.

Step 3: Class Label Initialization

Define an array of class labels representing the 11 durian leaf disease categories. This mapping allows the model's output to be interpreted as meaningful disease names.

Step 4: VGG16 Model Construction

Preprocessing:

Resize and normalize input images to 224×224 pixels.

Integrate data augmentation techniques as part of the input pipeline.

Model Initialization:

Load the pre-trained VGG16 base model with weights from the ImageNet dataset.

Freeze all convolutional layers (trainable = False) to retain the learned low-level features.

To adapt VGG16 to the durian leaf disease classification task, a series of custom layers is appended to the base model to enable classification into the target categories:

Flatten layer to convert feature maps into a 1D vector.

Dense layer with 256 neurons and ReLU activation.

Dropout layer with a rate of 0.5 to reduce overfitting.

Final Dense layer with 11 neurons and Softmax activation to produce class probabilities.

Step 5: Model Training

Compile the model using:

Loss function: categorical_crossentropy, suitable for multi-class classification.

Optimizer: Adam, chosen for its adaptive learning rate and efficient convergence.

Metric: accuracy, to evaluate classification performance.

Train the model using the training set, and validate its performance using the validation set across multiple epochs. Monitor learning curves to adjust parameters or prevent overfitting as needed.

3. DATA COLLECTION

To develop a reliable and accurate deep learning model for durian leaf disease classification, a comprehensive image dataset was constructed based on agricultural research and plant pathology references. Image data were gathered from diverse and credible sources, including on-site photography at durian plantations, documentation provided by agricultural research centers, and reputable online databases. This multi-source collection strategy was essential to ensure both the credibility and diversity of the dataset [7][8].

Table 1. Description of common durian leaf diseases.

No.	Disease Name	Scientific/Common Name	Key Symptoms	Number of images	Figure
1	Leaf blight	Blight disease	- Leaves appear silvery, dry, and underdeveloped. - Premature leaf drop and reduced photosynthesis.	416	
2	Leaf scorch	Leaf scorch disease	- Brown burn spots start at leaf margins and spread inward. - Leaves become dry, brittle, and fall off early.	415	
3	Leaf rot	Leaf rot disease	- Soft, water-soaked lesions appear on the leaf surface. - Infected areas darken and rot over time. - Leaves may emit a foul odor and fall prematurely.	480	
4	Black spot	Black spot disease	- Necrotic dark brown spots with yellow halos form on the leaf surface. - Spots expand and reduce photosynthesis, causing yellowing and early leaf drop, particularly harmful during flowering and fruiting stages.	538	

No.	Disease Name	Scientific/Common Name	Key Symptoms	Number of images	Figure
5	Leaf spot	Leaf spot disease	- Small, scattered spots form on the leaves. - Gradual loss of green color and photosynthetic ability.	640	
6	Powdery mildew	Powdery mildew	- White powdery layer appears on the leaf surface. - Leaves weaken, lose green color, and fall off easily.	420	
7	Algal disease	Algal disease	- Green or black spots appear. - Leaves become weak and show reduced photosynthesis.	504	
8	Anthracnose	Anthracnose	- Brown spots develop on the leaves. - Can lead to rapid leaf death if untreated.	500	
9	Anthill leaf blight	Anthill leaf blight disease	- Oily, shiny patches with irregular shapes appear. - Fungal filaments form, causing leaves to stick like ant nests. - In severe cases, burnt spots and a foul odor develop as branches dry out and bark blackens.	400	
10	Leaf curl	Leaf curl disease	- Young leaves become deformed and pale. - Leaf edges curl inward; leaves harden and thicken. - Color changes from light green to yellow, followed by leaf drop. - Burn spots may develop on the margins or surface.	655	
11	NotDurianDisease			635	

The dataset includes images of ten distinct durian leaf diseases, each exhibiting characteristic symptoms and varying visual appearances. For each disease type, between 416 and 655 images were collected, ensuring adequate representation across categories. The images were captured under different lighting conditions, angles, and backgrounds to reflect real-world scenarios and enhance the model's robustness and generalizability.

During data preparation, emphasis was placed on ensuring high image quality, clear symptom visibility, and balanced class distribution. Each image was labeled according to the disease it represented, based on expert knowledge, plant pathology literature, and visual verification. The final dataset thus provides a reliable foundation for training deep convolutional neural networks.

A detailed overview of the ten disease categories is presented in Table 1, including disease names, scientific or common references, key visual symptoms, image counts per class, and example illustrations. This reference table was used to guide the labeling process and serves as the basis for constructing a robust, well-labeled dataset for the classification model.

4. RESULTS AND APPLICATION DEVELOPMENT

4.1 Experiment results

To evaluate the performance of the proposed classification model, both the VGG16 and ResNet-50 architectures were trained and tested on the same durian leaf disease dataset. The experiments were conducted under identical training conditions, with each model trained for 30 epochs, using a learning rate of 0.0001 and a batch size of 32. The dataset was split into training, validation, and test sets according to a 70/10/20 ratio, respectively.

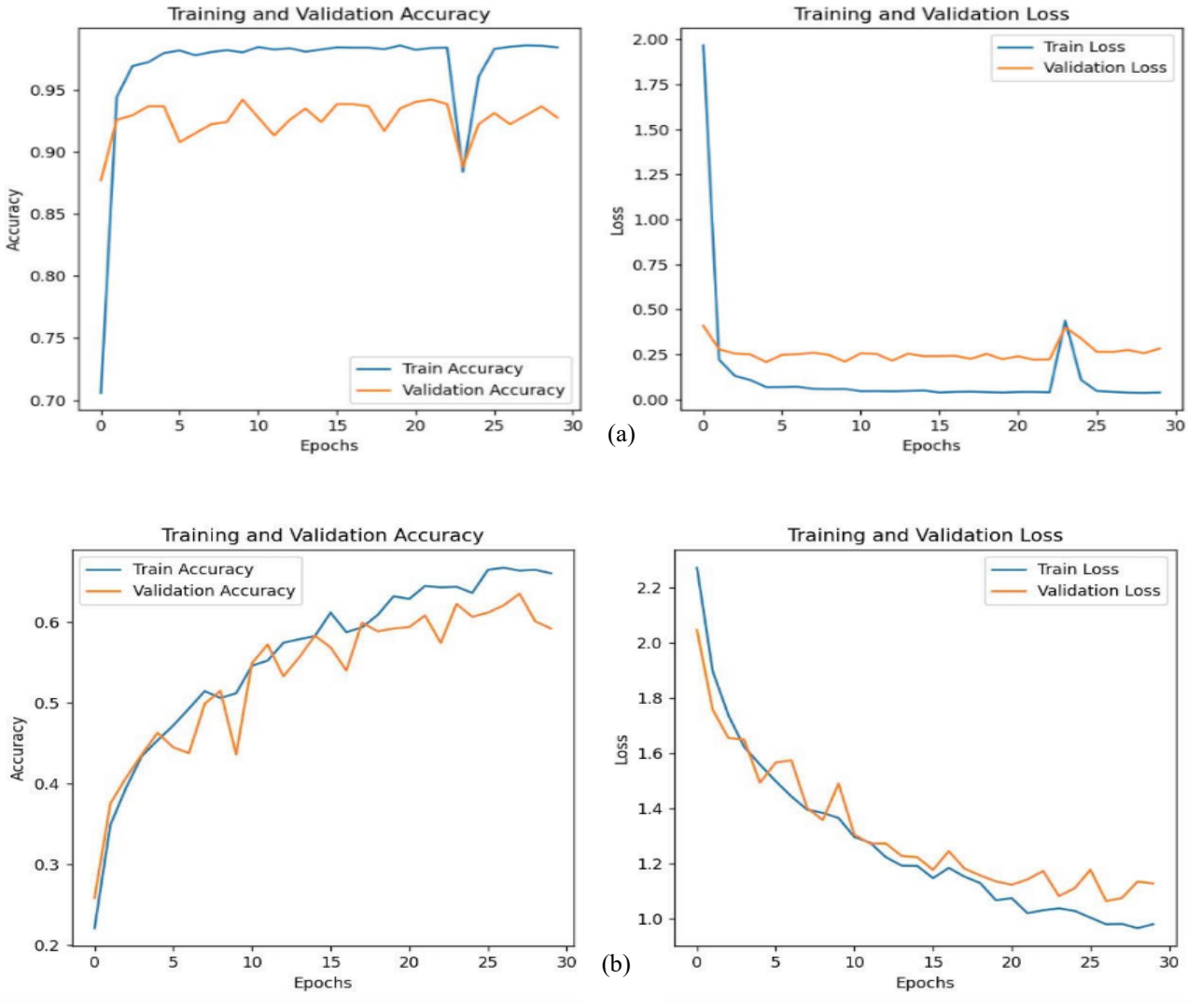


Figure 3. (a) Accuracy and loss of VGG16 during training. (b) Accuracy and loss of ResNet-50.

After multiple rounds of fine-tuning and retraining, the VGG16 model demonstrated significantly better performance compared to ResNet-50. As shown in Table 2, VGG16 achieved an accuracy of 94.12% and a loss value of 0.5419, whereas ResNet-50 reached only 63.55% accuracy with a higher loss of 1.2459. These results were also confirmed through visualizations of the training and validation metrics presented in Figure 3, which illustrate the learning curves of both models over the 30 training epochs.

The superior performance of VGG16 can be attributed to its simpler and more consistent architectural design, which allows for efficient feature extraction even on relatively limited datasets. In contrast, the deeper and more complex ResNet-50 model may require a larger and more diverse dataset to fully exploit its residual learning capabilities.

Table 2. Comparison of ResNet-50 and VGG16 model evaluation results on the test and training sets.

Algorithm	Accuracy	Loss
ResNet-50	0.6355	1.2459
VGG16	0.9413	0.5419

		Predicted label											
	Classify	Leaf blight	Leaf scorch	Leaf rot	Black spot	Leaf spot	Powdery mildew	Algal disease	Anthracnose	Anthill leaf blight	Leaf curl	Not Durian Disease	**SUM**
True label	Leaf blight	80	0	0	1	0	1	1	0	0	1	0	84
	Leaf scorch	0	79	1	0	0	1	0	2	0	0	0	83
	Leaf rot	2	0	90	0	0	0	0	0	3	0	1	96
	Black spot	0	1	2	100	0	2	1	1	1	0	0	108
	Leaf spot	0	1	0	1	120	1	0	2	0	2	1	128
	Powdery mildew	0	0	0	1	0	80	1	2	0	0	2	86
	Algal disease	0	3	0	0	1	1	92	0	0	2	2	101
	Anthracnose	1	1	2	0	0	1	1	93	0	1	0	100
	leaf blight	0	0	0	1	0	0	0	1	78	0	0	80
	Leaf curl	0	0	0	0	0	0	0	2	2	127	0	131
	Not Durian Disease	1	0	2	1	0	2	0	1	1	0	117	125
Precision		95.2	92.9	92.8	95.2	99	89.9	95.8	89.4	91.8	95.5	95.1	93.9
Recall		95.2	95.2	93.8	92.6	93.8	93.0	91.1	93.0	97.5	96.9	93.6	94.2
F1 score		95.2	94.0	93.3	93.9	96.4	91.4	93.4	91.2	94.5	96.2	94.4	94.0
Accuracy		94.12											**Average**

Figure 4. Confusion matrix and class-wise evaluation metrics (precision, recall, and F1-score) for the VGG16 model on the durian leaf disease classification task.

The performance of the VGG16 model was further examined using a confusion matrix and detailed evaluation metrics for each class, including precision, recall, and F1-score across all 11 categories (10 disease types and 1 non-disease class). The results are presented in Figure 4 and indicate that the model achieves high and consistent accuracy across the dataset. The model achieved an overall classification accuracy of 94.12%, with an average F1-score of 94.0% across all classes. Categories such as Leaf spot, Leaf curl, and Not Durian Disease recorded precision and recall values exceeding 95%, indicating strong performance in identifying distinct visual symptoms like leaf deformation, spotting, or the absence of disease.

Leaf rot was occasionally misclassified as Anthill leaf blight (3 instances), and vice versa. This is likely due to visual similarities in symptoms such as darkened or rotting leaf patches. Algal disease and Anthracnose showed some level of confusion (F1-scores between 91% and 93%), possibly because both manifest as dark lesions or necrotic areas that are difficult to differentiate under variable lighting conditions. Powdery mildew had the lowest precision (89.9%), as it was sometimes misclassified into multiple categories. This may be due to its subtle, white powder-like texture, which is easily mistaken for other types of discoloration or fungal growth.

Based on this comparative evaluation, the VGG16 model was selected as the core architecture for the durian leaf disease classification system. Its high accuracy, stable convergence, and compatibility with transfer learning make it an effective and practical solution for real-world agricultural applications, particularly in environments with limited computational resources.

4.2 Application Development

To support practical deployment of the proposed classification model, a web-based application was developed using the VGG16 deep convolutional neural network, which had been fine-tuned to accurately classify 11 categories of durian leaf conditions (10 disease types and one non-disease class). This application is intended to assist farmers in early disease detection, thereby improving orchard productivity, fruit quality, and overall crop management efficiency.

The disease identification process begins with image acquisition, where farmers capture leaf samples directly from the orchard. These images are then analyzed by the system based on key visual features such as shape, color, lesion size, and abnormal symptoms including spots, discoloration, curling, and signs of fungal infection. Leveraging the VGG16 model, the system processes the uploaded image and returns a prediction of the most likely disease class.

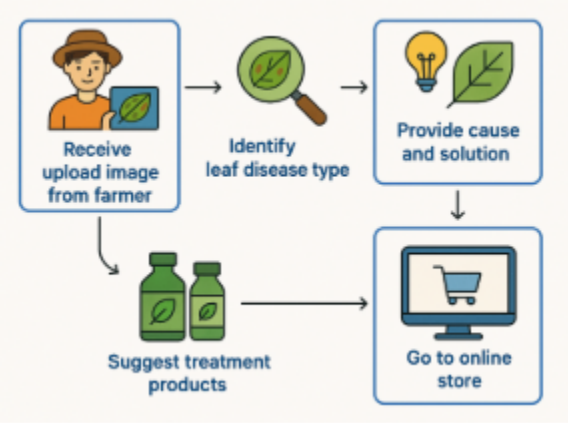


Figure 5. Developed application

Upon classification, the application displays detailed information about the detected disease, including its scientific name, visual symptoms, likely causes, and recommended treatments. To further enhance usability, the platform integrates links to relevant agricultural products, enabling farmers to easily purchase plant protection agents or treatment solutions.

Beyond disease recognition, the application also incorporates a user-friendly online store with core e-commerce functionalities. These include product listing pages, detailed descriptions, and a shopping cart feature—designed to streamline the acquisition of necessary tools and materials for plant care directly through the system.

An overview of the application's key functions—such as image-based disease identification, knowledge delivery, and treatment recommendation—is illustrated in Figure 5.

5. CONCLUSIONS

This study demonstrates the effectiveness of the VGG16 convolutional neural network model in classifying durian leaf diseases with high accuracy. The proposed application, built upon the VGG16 architecture, achieved a classification accuracy of 94.12% across 11 categories, including 10 common disease types and a non-disease class. Practical testing shows that the system can provide users with rapid disease identification by uploading leaf images through a web interface. Alongside classification results, the application offers detailed information on disease symptoms, causes, and suggested treatment solutions. Additionally, it integrates direct links to relevant plant protection products, offering a convenient platform for farmers to access both knowledge and agricultural supplies. This represents a significant advancement in supporting the adoption of smart farming technologies in durian cultivation.

Despite its promising results, the system still faces several limitations. The model performs optimally with high-quality, close-up images of individual leaves; however, its accuracy declines when processing images containing multiple leaves, background noise, or distant perspectives. This performance drop is largely attributed to limitations in the training dataset, which currently lacks sufficient variability and real-world complexity.

To address these shortcomings, future work should focus on expanding the dataset to include a broader range of high-resolution images captured under diverse environmental conditions and from various geographical regions. A more comprehensive and representative dataset will enhance the model's generalization ability and reliability in real-world scenarios. Ultimately, such improvements will contribute to the development of a more robust and impactful disease diagnosis tool for farmers and agricultural practitioners.

REFERENCES

[1] N. T. Mai, "Ảnh hưởng của các yếu tố môi trường đến sự phát triển bệnh nấm trên cây sầu riêng," *Tạp chí Bảo vệ Thực vật*, 2021.
[2] H. V. Phuc, "Ứng dụng trí tuệ nhân tạo trong quản lý bệnh cây trồng: Trường hợp cây sầu riêng," *Luận văn tốt nghiệp, Đại học Bách Khoa TP.HCM*, 2022.
[3] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, p. 1419, 2016.
[4] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
[5] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.
[6] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," vol. abs/1409.1556, 2014. [Online]. Available: http://arxiv.org/abs/1409.1556
[7] S. Subhadrabandhu and S. Ketsa, *Durian: King of Tropical Fruit*, Bangkok: Office of the University Press, Kasetsart University, 2001, pp. 93–115.
[8] P. Keerati and C. Wongkaew, "Diseases of durian (*Durio zibethinus*) in Thailand: occurrence, diagnosis, and management," *Journal of Tropical Plant Protection*, vol. 30, no. 2, pp. 125–134, 2018.