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DURIAN DISEASE CLASSIFICATION USING TRANSFER LEARNING FOR DISEASE MANAGEMENT SYSTEM

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Abstract:

Durian fruit is one of the popular fruits in ASEAN countries, even in European countries, making it a high-potential contributor to economic growth in the agricultural sector. However, durian leaf diseases pose significant challenges in most ASEAN countries, such as Malaysia, Indonesia, the Philippines, and Thailand. Traditionally, the identification of leaf diseases relied on manual visual inspection, a labor-intensive and tedious process. To address this issue, we propose a novel approach for durian leaf disease detection and recognition using vision transformers. We employed well-established deep learning models, VGG-19 and ResNet-9, with carefully tuned hyperparameters including epochs, optimizer, and maximum learning rate. Our results indicate that ResNet-9 achieved an impressive accuracy rate of 99.1% when using the Adam optimizer with a maximum learning rate of 0.001. This breakthrough in automated disease recognition promises to significantly reduce labor costs and time for smallholder farmers, enhancing the sustainability of durian cultivation.

Keywords:

Durian Leaf Disease, Detection, Transfer Learning, Disease Management

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Introduction

Durian known as 'king of fruit', plays a pivotal economic role as a fruit crop in several Southeast Asian countries, including Malaysia, Philippines, Indonesia, Vietnam, and notably Thailand, which holds the position of the world's foremost durian exporter (Pongpisutta et al., 2023). According to data from 2016 by Plantations International in Durian Market Report (Plantation International, 2022), Thailand emerged as the dominant global exporter of durian fruit, commanding approximately 95% of the market share, while Malaysia accounted for the remaining 4%. In terms of quantity, Thailand exported a staggering 402.70 million kilograms, whereas Malaysia's exports totalled 17.75 million kilograms.

Despite comprising only 5% of the worldwide durian export volume, Malaysia has made significant strides in developing its durian industry, positioning itself among the leading durian-producing nations globally. Between 2016 and 2020, Malaysia experienced a remarkable 107% surge in the export value of durians. Notably, in September 2020 alone, Malaysia's durian exports found their way into the markets of 22 different countries and regions, generating revenue of US$34.7 million (DHL, 2023). Hong Kong, China, and Singapore consistently emerge as the primary importers of Malaysian durians (DHL, 2023). In our robust growth projection, it is highly plausible that the trade volume will attain 4.5 billion units by the year 2030. This projection entails a substantial increase in trade value, with expectations for it to surge from 15 billion USD in 2016 to well over 35 billion USD by 2030.

Nevertheless, challenges exist in cultivating durians, with the primary concern of diseases, a common issue encountered in various crops. Durian trees can suffer from several diseases. These include spot cancer, base rot, base disease, seedling disease, dead tip disease, fungal infections, leaf spots, leaf blight, and fruit rot. A particularly dangerous ailment is stem rot disease, caused by P. Palmivora. This disease harms the tree's nutrient transport system in the stem. The types of diseases are detailed in the accompanying Table 1. Based on the observation from the Table 1, most of the durian diseases can be observe and portray on the leaves.

Table 1: Types of Durian Diseases

Disease	Causes	Signs
Algal diseases	*Cephaleuros virescens*	orange, rust coloured velutinous spots on the upper surface of leaves, twigs and branches
Anthracnose	*Colletotrichum gloeosporioides*	dark lesions on fruit and premature fruit drop.
Phomopsis leaf spot	*Diplodia theobromae* and *C. gloeosporioides*	Necrotic, brown circular spots, ~1 mm in diameter with dark margins and yellow halos, form on leaves.
Pink disease	*Erythricium salmonicolor*	pinkish-white mycelial threads that envelop branches and shoots.
Postharvest fruit rots	*Phyllosticta* sp. and *Curvularia era- grostidis*	irregular necrotic patches in varying shades of brown
Rhizoctonia leaf blight	*Rhizoctonia solani*	water-soaked spots on leaves that coalesce to form larger, irregular,

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		water-soaked patches that dry into light brown necrotic lesions
Sooty mould and black mildew	Black Mildew fungi	On twigs and leaf petioles, they form a hard-lumpy crust, and on fruit they form a spongy crust on the surface.
Soilborne diseases	*Phytophthora palmivora*	discoloration and exudation of a reddish brown, gummy, resinous substance.
Pythium root rot	*Pythium vexans*	decayed of primary roots and dieback of branches in a portion of the tree
White root disease	*Rigidoporus lignosus*	wilting of foliage, yellow and brown discoloration of leaves, shriveling of leaves
Phytophthora Fruit Rot	Fungal pathogen *Phytophthora palmivora*	rotting and discoloration of fruit and foul odour.
Leaf Blight	*Pestalotiopsis* fungi.	brown lesions and spots on leaves.
Powdery Mildew	Various fungal species.	White powdery substance on leaves and fruit surfaces.
Fruit Splitting	Irregular watering, weather conditions, or genetic factors.	Splitting of fruit skin reduced fruit quality.
Nematode Infestations	Plant-parasitic nematodes.	Stunted growth reduced fruit production.
Yellow Vein Mosaic Virus	Viral infection.	Yellowing and curling of leaves.

Traditionally, the monitoring of plant diseases has relied upon visual inspections carried out by agriculturists or laborers, often with the naked eye(Singh et al., 2017 & Petrellis, 2015). This approach can be labor-intensive and monotonous, particularly given the considerable height of Durian trees. With the emergence of artificial intelligence (AI), various tree diseases, including Durian, have been detected and recognized using AI. In the agricultural sector, disease is a common thing to happen regardless of the type of fruit. In the context of fruit disease monitoring, researchers and practitioners often face the challenge of striking a balance between the accuracy of deep learning models and the computational resources required for efficient monitoring. Various deep learning architectures and techniques have been explored to address this challenge, aiming to optimize accuracy and efficiency. Table 2 provides a brief analysis of the most used models in fruit disease detection.

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Table 2: State of The Arts for Fruits and Plant Monitoring and Detection of Disease Using Deep Learning Algorithm

Deep Learning Network	Fruits/Plants	References
CNN	Amla, papaya, guava, citrus, orange, passion fruits	(Gupta et al., 2023), (Sujatha et al., 2023), (Katumba et al., 2020), (Saha, 2020), (Xie et al., 2020), (Sullca et al., 2019)
GoogleNet	Potato, bell pepper, grape	(Mohanty et al., 2016), (Ji et al., 2020)
YOLO (v2, V5, v7)	Tomatoes, Amla	(Gupta et al., 2023), (Ouyang et al., 2022)
Faster R-CNN	Tomatoes	(Ouyang et al., 2022)
RetinaNet	Tomatoes	(Ouyang et al., 2022)
VGGNet	Grape, blueberry, apple, dates,	(Ji et al., 2020), (Mu et al., 2021), (Khan et al., 2018), (Nasiri et al., 2019), (Mahmood et al., 2022), (Begum et al., 2022)
Resnet	Tomatoes, multiple fruits,	(Ouyang et al., 2022), (Khan et al., 2018), (Wang et al., 2017)
MobileNet	Tomatoes, papaya, guava, citrus, avocado	(Sujatha et al., 2023), (Ouyang et al., 2022), (Thangaraj et al., 2020)
DenseNet	Tomatoes	(Ouyang et al., 2022)
AlexNet	Potato, bell pepper	(Mohanty et al., 2016)

The progress in computer vision and image processing techniques has shifted from traditional machine learning models to deep learning models in fruit disease monitoring (Sullca et al., 2019). Deep learning models, particularly Convolutional Neural Networks (CNNs) and their variants, have demonstrated significantly improved performance. CNN models have achieved around 97% accuracy in fruit disease detection, with some variants surpassing 99% accuracy. However, a drawback of CNN models is their lack of real-time speed. Comparing different models, VGGNet is more accurate than AlexNet, but AlexNet has a lower error rate.

In (Nugraha et al., 2021), an expert system has been developed for diagnosing diseases in Durian plants, utilizing the Naïve Bayes method—a statistical classification technique. This system predicts the disease class by calculating the probabilities associated with each disease based on the observed symptoms in durian plants. The disease with the highest probability is identified as the diagnosis. The study's accomplishment is creating an accurate expert system for diagnosing diseases in durian plants, using the Naïve Bayes method. Experimental results

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indicate an 82% accuracy rate for the system, demonstrating its effectiveness in identifying durian plant diseases based on user-entered symptoms. The primary objective of this expert system is to aid farmers in promptly detecting and treating diseases in durian plants, ultimately enhancing durian fruit production and quality in Indonesia.

While (Al Gallenero et al., 2023), demonstrates the successful implementation of a portable device equipped with the Duri Premium application, powered by a Convolutional Neural Network (CNN) MobileNet model. This system effectively identifies and categorizes various durian leaf diseases, including algal spots, leaf blight, leaf spots, healthy leaves, and unidentified diseases. Leveraging transfer learning and retraining on a substantial dataset, the CNN MobileNet model achieves a commendable overall accuracy rate of 93.333% in disease identification. The study underscores the significance of this technology in promptly recognizing and addressing durian leaf diseases, consequently mitigating the economic losses associated with such ailments. Future research directions include augmenting the dataset, expanding the training data, and optimizing the CNN architecture to enhance the system's performance, particularly for devices with limited computing capabilities.

Therefore, this study introduces the detection of durian diseases through the utilization of transfer learning techniques, offering an enhancement to conventional farm disease management procedures. The diseases to be identified are specifically algal spot, leaf blight, and leaf spot. In addition to these diseases, we will also correlate healthy leaves with detection and evaluate images of other parts of the durian tree, including fruit, twigs, and branches, as unknowns.

Methodology

Dataset Preparation

In this experimental study, our objective was to develop and train a robust deep learning model for the precise classification of diseases affecting durian plants. Our dataset comprised a total of 1,344 images distributed across four distinct classes. The primary aim was to create a high-performing model with the capability to accurately classify the following diseases: 'durian_leaf_spot', 'durian_leaf_blight', 'durian_algal_leaf_spot', and 'durian_healthy'. The total of images of each of the class is presented in Table 3 and portrayed in Figure 1.

Table 3: Durian Disease Dataset Extracted From (Roboflow, 2022)

Dataset	Description	Total number of images
'durian___leaf_spot'	Images of durian leaves with leaf spot disease.	336
'durian___leaf_blight'	Images of durian leaves with leaf blight disease	336
'durian___algal_leaf_spot'	Images of durian leaves with algal leaf spot disease	336
'durian___healthy'	Images of healthy durian leaves	336

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Data augmentation techniques were employed to enhance training data diversity and boost model generalization. Utilizing the 'ImageDataGenerator' class from Keras, the training data underwent various augmentations, including random rotations (up to 40 degrees), horizontal and vertical shifting (up to 20% of image dimensions), shearing transformations (up to 20%), random zooming (in or out by up to 20%), and horizontal flipping (mirror images). The 'nearest' method was applied to fill newly created pixels, resulting in four augmented versions of each original image, effectively expanding the training dataset size.

The original dataset has been split into training and validation sets using a validation split ratio of 20%. This ensures that 80% of the data is used for training, while the remaining 20% is reserved for validation.

(a) algae_leaf_spot (b) leaf_blight (c) leaf_spot (d) healthy leaf

Figure 1. Sample of Durian Leaf Diseases Images

Durian Diseases (DD) Detection using Transfer Learning

The utilization of VGG9-19, a streamlined and efficient IMAGENET model, as a pre-trained network is a key aspect of this research. This transfer learning approach facilitates the automated detection of Durian disease. This is primarily attributed to the convolutional layers within the VGG-19 model, which excel at capturing micro features by employing a compact receptive field of *3x3*. Moreover, the VGG-19 model comes equipped with the rectified linear unit (ReLU) activation function and optimizer, eliminating the need for adjustments during training and model generation. The initial phase involves loading all DD dataset into the model and subjecting them to pre-processing, which includes data augmentation to artificially expand the training dataset. Subsequently, the pre-trained model is invoked to import its pre-trained weights. Figure 2(a) provides an overview of the proposed VGGNet-16 model for DD detection. Throughout the training process, the model iteratively refines and converge its understanding of the DD dataset, with hyperparameters fine-tuned to achieve optimal model performance.

The incorporation of a dropout layer featuring a dropout probability of 0.5, strategically positioned before applying the sigmoid activation function within the fully connected layer (FCL). This introduction of the dropout layer serves a crucial role in mitigating potential overfitting concerns. It's essential to note that this layer is thoughtfully configured to maximize its regularization impact, with the regularization parameter $p(1-p)$ reaching its zenith at $p = 0.5$. Empirical evidence from the Tensorflow and Keras frameworks confirms that a dropout layer set at 0.5 is particularly well-suited for larger network architectures. As for optimization, Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam) are chosen optimization algorithms commonly used in deep learning. SGD updates model weights using gradients of the loss function computed on mini-batches of training data. It employs a fixed

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learning rate or learning rate schedules to adjust the step size during training. While SGD is simple and memory-efficient, it may require more manual tuning and can converge slowly. In contrast, Adam dynamically adapts learning rates for each parameter, incorporates momentum, and is robust to noisy gradients. These features often lead to faster convergence and make it a popular choice for various deep learning tasks.

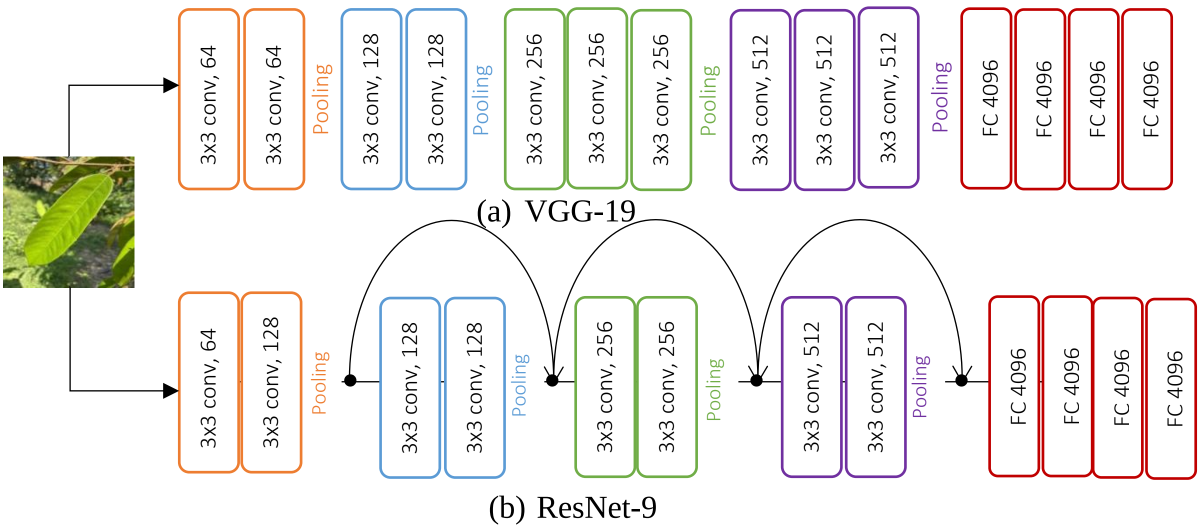

Figure 2. Deep Learning Architecture

ResNet-9 belongs to the ResNet (Residual Network) family, which introduced the concept of residual connections which shows in Figure 2(b). These connections enable the network to effectively train very deep models by mitigating the vanishing gradient problem. ResNet-9 follows a basic architecture pattern where each residual block consists of convolutional layers, batch normalization, activation functions (usually ReLU), and skip connections. The skip connections allow the output of one layer to be added to the output of a deeper layer. ResNet-9 is a relatively shallower network with only nine weight layers, making it computationally more efficient and faster to train than VGG-19. Its advantage lies in its ability to capture complex features and patterns even with reduced depth. This makes ResNet-9 a favorable choice for scenarios where computational resources are limited, or when working with smaller datasets.

Results and Discussion

In the conducted experiments, two prominent deep learning architectures, VGG-19 and ResNet-9, were employed for the task of DD detection, with Adam and SGD optimizers applied to each. The results showcased the model's performance under various hyperparameter configurations such as epochs, learning rate and optimizer. The experiment design was started with the maximum learning rate 0.001, 0.005 and 0.01 with epochs 20, 30 and 40.

Table 4 and Table 5 has demonstrated the results of VGG-19 with Adam optimizer, achieved validation accuracy ranging from 82.71% to 88.12%, while VGG19 with SGD optimizer provided consistent and competitive results, with validation accuracy ranging from 85.42% to 88.75%. While the model performs well, there are some fluctuations in performance with different hyperparameter settings, such as learning rates 0.001 with epoch 40 using Adam. This

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might be due to overfitting. Thus, we performed dropout and early stopping condition, the results accuracy of 0.8896 outperform for model VGG-19 with Adam.

Table 4: Results of VGG-19 with an Adam Optimizer

Max Learning Rate	Epochs	Train Loss	Validation Loss	Validation Accuracy
0.001	20	0.3053	0.3538	0.8271
0.001	30	0.3067	0.4302	0.8500
0.001	**40**	**0.0007**	**0.0129**	**1.0000**
0.005	20	0.3028	0.3597	0.8438
0.005	30	0.3023	0.5185	0.8708
0.005	**40**	**0.2825**	**0.4971**	**0.8812**
0.01	20	0.4239	0.4565	0.8500
0.01	**30**	**0.4385**	**0.5425**	**0.8604**
0.01	40	0.4081	0.6616	0.8438

Table 5: Results of VGG-19 with SGD Optimizer

Max Learning Rate	Epochs	Train Loss	Validation Loss	Validation Accuracy
0.001	20	0.3606	0.6550	0.8542
0.001	30	0.3909	0.6632	0.8542
0.001	**40**	**0.2453**	**0.5595**	**0.8875**
0.005	20	0.4351	0.6310	0.8708
0.005	**30**	**0.3400**	**0.5985**	**0.8771**
0.005	40	0.2758	0.5750	0.8708
0.01	20	0.4400	0.6371	0.8542
0.01	30	0.3336	0.6181	0.8542
0.01	**40**	**0.2577**	**0.4881**	**0.8812**

On the other hand, ResNet-9 demonstrated exceptional performance, with Adam optimizer delivering validation accuracy ranging from 95.21% to 99.11% (refer Table 6), showcasing remarkable convergence. The SGD optimizer also performed well, achieving validation accuracy between 79.34% and 88.96%, as presented in Table 7. The choice of optimizer significantly impacted the model's stability and overall accuracy, with Adam generally yielding stable and higher accuracy for ResNet-9, while SGD remained a robust performer for both models. It is essential to consider resource constraints and the risk of overfitting when fine-tuning hyperparameters to achieve optimal results. These experiments highlight the potential of deep learning models, particularly ResNet-9, in durian leaves disease detection, emphasizing the importance of selecting the appropriate optimizer to optimize performance.

Table 6: Results of ResNet-9 with an Adam Optimizer

Max Learning Rate	Epochs	Train Loss	Validation Loss	Validation Accuracy
0.001	20	0.0007	0.1483	0.9521
0.001	30	0.0110	0.0149	0.9797
0.001	**40**	**0.0001**	**0.0003**	**0.9911**
0.005	20	0.0226	0.0396	0.9667
0.005	30	0.0158	0.0189	0.9792
0.005	**40**	**0.0154**	**0.0176**	**0.9792**

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0.01	20	0.0543	0.0548	0.9729
0.01	30	0.0446	0.0458	0.9896
0.01	**40**	**0.0225**	**0.0235**	**0.9896**

Table 7: Results of ResNet-9 with SGD Optimizer

Max Learning Rate	Epochs	Train Loss	Validation Loss	Validation Accuracy
0.001	20	0.0082	0.0253	0.8113
0.001	30	0.0364	0.0364	0.8447
0.001	**40**	**0.0001**	**0.0296**	**0.8896**
0.005	20	0.0001	0.0394	0.8081
0.005	30	0.0001	0.0298	0.8447
0.005	**40**	**0.0001**	**0.0324**	**0.8792**
0.01	20	0.0001	0.0400	0.7934
0.01	30	0.0002	0.0243	0.8073
0.01	**40**	**0.0001**	**0.0298**	**0.8358**

ResNet outperforms VGG-19 due to its effective handling of the Vanishing Gradient Problem encountered in deep neural networks. As neural networks become deeper, gradients can diminish significantly during backpropagation, hampering training. This occurs because gradients are multiplied as they propagate backward through the layers. When gradients become excessively small, early layers' weight updates are ineffective, leading to slow convergence and suboptimal training.

ResNets tackle the vanishing gradient issue by introducing residual connections. Instead of learning the direct output, ResNets learn residual functions, representing the difference between the desired output and the current layer output. In mathematical terms, if $H(x)$ signifies the intended mapping, ResNets learn $F(x) = H(x) - x$. They then add this learned residual back to the original output, resulting in $F(x) + x$. These residual connections allow even layers learning to be the identity function to still enable useful transformations by modifying residuals. Consequently, ResNets facilitate training very deep networks without suffering from the vanishing gradient problem. In contrast, VGG-19, though deeper, lacks these skip connections, making ResNet-style architectures preferable due to their training stability. Furthermore, ResNet-9 offers a shallower alternative to VGG-19 with only nine weight layers. This characteristic enhances computational efficiency and accelerates training, particularly beneficial for smaller datasets, as is the case here. In such scenarios, ResNet-9 becomes a more practical choice, striking a balance between model depth and computational resources.

Conclusion

This research represents a significant advancement in the field of durian leaf disease detection and recognition, addressing a critical issue faced by durian farmers in ASEAN countries and beyond. The traditional manual identification of leaf diseases has been a labor-intensive and time-consuming process, posing substantial challenges to the agricultural sector's sustainability. Through the application of cutting-edge deep learning techniques and the utilization of well-established models like VGG-19 and ResNet-9, we have successfully developed an automated system capable of accurately detecting and recognizing durian leaf diseases. Notably, our results demonstrate the remarkable performance of the ResNet-9 model, achieving an impressive accuracy rate of 99.1% when utilizing the Adam optimizer. By

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automating disease detection, we aim to significantly reduce the labor costs and time invested by smallholder farmers, ultimately improving their livelihoods and ensuring the sustainability of durian farming. Moreover, this technology promises to mitigate the impact of leaf diseases on crop yield, thereby contributing to food security and economic stability in the ASEAN region.

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