Classification of Durian Foliar Diseases by Xception and Mask R-CNN Models

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ABSTRACT

Durian is an important export product in Thailand, with demand steadily increasing. However, durian farmers still face significant challenges in increasing productivity due to foliar diseases. This study applied deep learning methods to classify durian leaves into four categories: agal spot leaf, blight leaf, other diseased leaf, and healthy leaf. A dataset of 12,960 images was compiled from local farms and public sources, reflecting real-world field conditions. Two efficient image classification models, Xception and Mask R-CNN, were employed with carefully tuned hyperparameters. The ResNet-9 model was compared with the two proposed models. The results showed that both the Mask R-CNN and Xception models outperformed ResNet-9 on the same dataset. The Mask R-CNN achieved a high accuracy of 99.61%, precision of 97.80%, recall of 98.81%, F1 score of 98.30%, and a loss of 0.0987, when using the Adam optimizer with a maximum learning rate of 0.001 over 6,740 iterations. However, the training time of the Mask R-CNN was 377 seconds higher than the Xception model. The proposed models offer a capable tool for early disease detection and smart monitoring of durian leaf diseases, potentially supporting yield improvement and reducing dependency on manual diagnosis.

Keywords-Durian leaf diseases; Xception model; Mask R-CNN model; durian leaf classification

I. INTRODUCTION

Thailand's durian market has experienced rapid growth, primarily driven by the increasing popularity of durian consumption in China over the past five years. This increased demand has significantly raised the value of Thai durian exports [1]. Durian leaf diseases are an essential factor in the growth of the durian tree, which impacts the yield of durian fruits. Common durian leaf diseases include algal spot and blight leaves, psyllid infestation, and asterolecanium ungulatum. The algal leaf spot is one of the most severe durian diseases in Thailand, spreading rapidly through wind, rain, and insects [2]. The motivation for this research stems from farmers in Yala Province, Thailand, who need tools to help diagnose durian leaf diseases instead of relying on skilled human labor. Visual evaluation is the primary diagnostic method commonly utilized by experts to identify durian leaf diseases, and early detection is crucial as it can significantly reduce their spread.

Currently, image technology has advanced significantly with the development of Artificial Intelligence (AI) techniques. Machine Learning (ML) and Deep Learning (DL) are now widely applied for the detection of plant diseases with impressive accuracy. Traditional ML techniques such as Artificial Neural Networks (ANN), K-means, and Support Vector Machines (SVM) were initially used to classify images of plant diseases [3-5], but recent studies showed that DL approaches significantly outperform these conventional methods [6-9]. Techniques such as Convolutional Neural Networks (CNN), Deep Belief Networks (DBNs), and models such as VGG16, VGG19, and ResNet have demonstrated superior abilities in extracting features autonomously from input images, making them ideal for plant disease detection [10-13]. Various studies have used CNN as the primary method in solving computer vision problems [3, 4]. Xception is a DL model with depthwise separable convolutions that replace the

Inception modules [5]. The Xception model has been successfully implemented for plant classification, scene image classification, and diagnosis of COVID-19 [6, 7]. Although CNN approaches have already gained distinction for image classification, image segmentation is also an interesting solution with high performance. The Mask Region-based Convolutional Neural Network (Mask R-CNN) has been effectively applied for image segmentation and is suitable for multi-object detection in durian leaf images [8-10]. Mask R-CNN extends Faster R-CNN by adding a mask prediction branch, making it perform well for both detection and segmentation [11, 12].

Although some studies have focused on the classification of durian leaf diseases, the advancement of DL models continues. The high performance of recent DL models should be investigated for durian leaf disease classification as an improved detection tool for farmers. Thus, this study compared two effective classification methods, the Xception model and the Mask R-CNN technique, to find the most accurate model to help farmers classify and prevent diseases. The Xception model was selected because of its efficient architecture utilizing depthwise separable convolutions, making it suitable for lightweight, high-accuracy classification tasks. It is especially effective in extracting subtle features from leaf texture and color variations. In contrast, the Mask R-CNN model extends its capability beyond classification, enabling pixel-wise segmentation, which is crucial for detecting the spatial distribution of lesions. The contributions of this work are as follows:

- Few studies have focused specifically on tools to detect durian leaf diseases. This study introduces an appropriate classification technique for durian leaf diseases by testing a dataset collected from real-world conditions in Thailand, demonstrating its applicability in practical field settings.
- Presents the first comparative application of these two state-of-the-art DL models, Xception and Mask R-CNN, for durian leaf disease classification and instance segmentation. By evaluating their performance, this study provides insight into their relative strengths for smart agricultural use. To the best of our knowledge, these models have not previously been applied to this problem, although their unique capabilities and performances. The comparison and evaluation of both models provides a practical reference for future work in plant disease diagnosis.
- Introduces a novel DL-based approach to support the early diagnosis of durian foliar diseases by integrating classification and instance segmentation methods. The Xception model, known for its efficiency in extracting fine-grained features through depthwise separable convolutions, is applied for image classification. Meanwhile, the Mask R-CNN enables precise object detection and segmentation of disease-affected regions. These two models represent a new contribution to the detection of agricultural diseases, particularly durian leaves, where little work has been done. This study fills a gap in agricultural AI applications for durian leaf diseases, especially under real-world conditions.

This study not only evaluates model performance using accuracy, precision, and Intersection over Union (IoU), but also provides insight into the real-world applicability of these models in smart agriculture. The findings indicate that both models yield promising results, with Mask R-CNN demonstrating potential for real-time implementation due to its segmentation capabilities. Future implications include deploying the proposed system on a mobile or IoT-based platform to assist farmers in remote areas with instant disease diagnosis and mitigation strategies.

II. METHODOLOGY

A. *Research Framework*

This research adopts two DL image classification and instance segmentation techniques for diagnosing durian foliar diseases. The framework consists of five key stages: (i) Dataset acquisition and labeling; (ii) Image preprocessing and data augmentation; (iii) Image segmentation for Mask R-CNN; (iv) Configuration and classification, including training and validation; (v) Performance evaluation. The Xception model is employed for classification tasks, while the Mask R-CNN model is used for both classification and precise localization through segmentation. This research enables a comprehensive comparison between two state-of-the-art DL techniques in the context of tropical plant disease detection.

Figure 1 illustrates the workflow for classifying durian leaf disease using both Xception and Mask R-CNN models. Figure 2 shows representative images of the four durian leaf classes in this study.

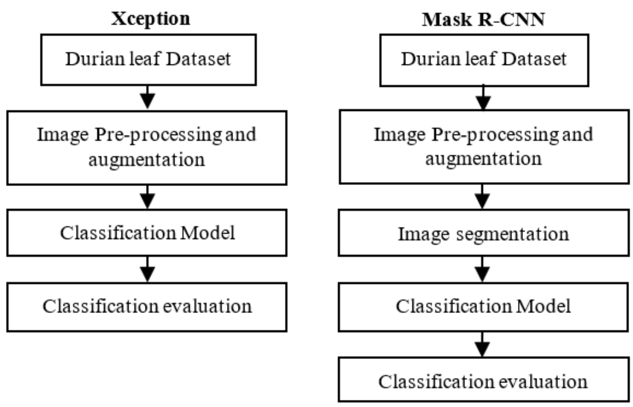

Fig. 1. Research workflow for durian leaf disease classification using Xception and Mask R-CNN models.

Fig. 2. Example images of durian leaf classes used in this study. From left to right: algal spot leaf, blight leaf, other diseased leaf, and healthy leaf.

B. Durian Leaf Disease Dataset

The dataset used in this study was collected from two main sources: (i) Field data, 228 images of durian leaves collected through interviews and direct observations with durian farmers in Yala province, Thailand, between March and May 2024 [14] (this field survey also recorded farm management practices and environmental conditions); (ii) Open-source data: 420 images obtained from a publicly available dataset of durian leaf diseases hosted on Roboflow [15], originally published on official agricultural websites. All online resources were screened for reliability and image quality before inclusion. All images were preprocessed, including duplicate removal, expert validation of labels, and normalization of image sizes, before being used for model training.

C. Image Preprocessing and Augmentation

The durian leaf dataset was preprocessed according to the procedure illustrated in Figure 3.

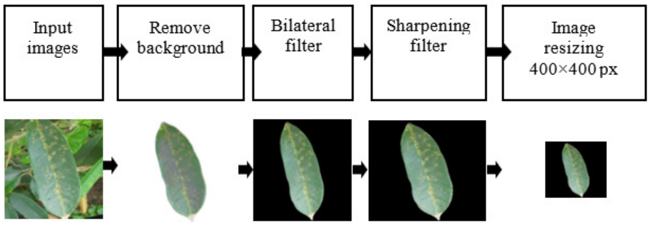

Fig. 3. Image preprocessing process.

The background was removed. Then, a bilateral sharpening filter was applied in OpenCV by adjusting the kernel. The images were resized to 400×400 pixels. Python version 3 with Visual Studio Code version 1.83.1 was used on a Lenovo LEGION 5 computer with an AMD RYZEN 5 4000 Series CPU, a NVIDIA GeForce RTX 2060 GPU, and 16 GB of RAM. The total number of images in the dataset was 648. This dataset was divided into two sets: the first, consisting of 540 images, for training and validation, while the second, with 108 images, was reserved for testing. However, this number of images was not sufficient for training and testing. Thus, data augmentation was performed using the image data generator function in the Keras library. By generating 20 new images for each original image, the number of images increased to 10,800. Then, these images were divided into the four categories equally.

TABLE I. DURIAN DISEASE DATASET

Dataset	Description	Total images for training and validation	Total images for testing
Agal spot leaves	Images of durian leaves with agal spot leaves.	2,700	540
Blight leaves	Images of durian leaves with blight leaves.	2,700	540
Disease leaves	Images of other durian leaf diseases.	2,700	540
Healthy leaves	Images of healthy durian leaves.	2,700	540

Eighty percent of all images (8,640 images) in the dataset were labeled for training, and twenty percent of them (2,160 images) were used for validation (80:20) [10]. The second set of 108 images was augmented to 2,160 images for testing. These were further divided into 540 images of algal spot leaf, 540 images of blight leaf, 540 images of other durian leaf diseases, and 540 images of healthy durian leaves, as shown in Table I.

D. Image Segmentation

Image segmentation is a critical step in the Mask R-CNN model, enabling it to locate and outline disease-affected regions on durian leaves. This technique allows the system to distinguish between healthy and infected areas at the pixel level, offering more precise classification than models relying on whole-image analysis. Unlike the Xception model, which performs only image-level classification, Mask R-CNN integrates segmentation into its architecture. This study used the Roboflow platform to manage the segmentation dataset, as it provides a user-friendly interface to annotate, convert, and export datasets in formats suitable for DL models, particularly in the COCO (Common Objects in Context) format. The annotated datasets were then used to train the Mask R-CNN model, significantly improving its performance in detecting and localizing durian foliar diseases.

E. Classification by the Xception model

The tools for classification in this research consisted of two parts: The first part was software, which included Google Colab, Python version 3, and various libraries and open-source tools such as Tensorflow2 and Keras. The second part was hardware, specifically a GPU (T4 model) with 51 GB RAM. These tools were used to classify durian diseases from images. Transfer learning techniques were also used. The initial values of the network weights were taken from ImageNet [16].

The Xception model is a linear stack of depthwise separable convolution layers and residual connections, implemented in the TensorFlow framework. This model was used to extract features and classify diseases on plant leaves. The structure of the model is divided into three parts: The Entry flow, responsible for finding feature maps that are then sent to the second part, the Middle flow, which extracts the outstanding features, and the Exit flow, which extracts the final features. The most appropriate feature configuration is connected to the Fully Connected (FC) or dense layer to classify durian leaf diseases. Figure 4 shows the structure of the model. RGB images were used for training the Xception model [6], with training details shown in Table II.

TABLE II. TRAINING DETAILS FOR XCEPTION

Hyperparameter	Detail
Epochs (Ep)	60, 70, 80
Optimizer	Adam, SGD
Momentum	0.9 for SGD
Learning rate (LR)	0.01, 0.005, 0.001
Batch size per image	128

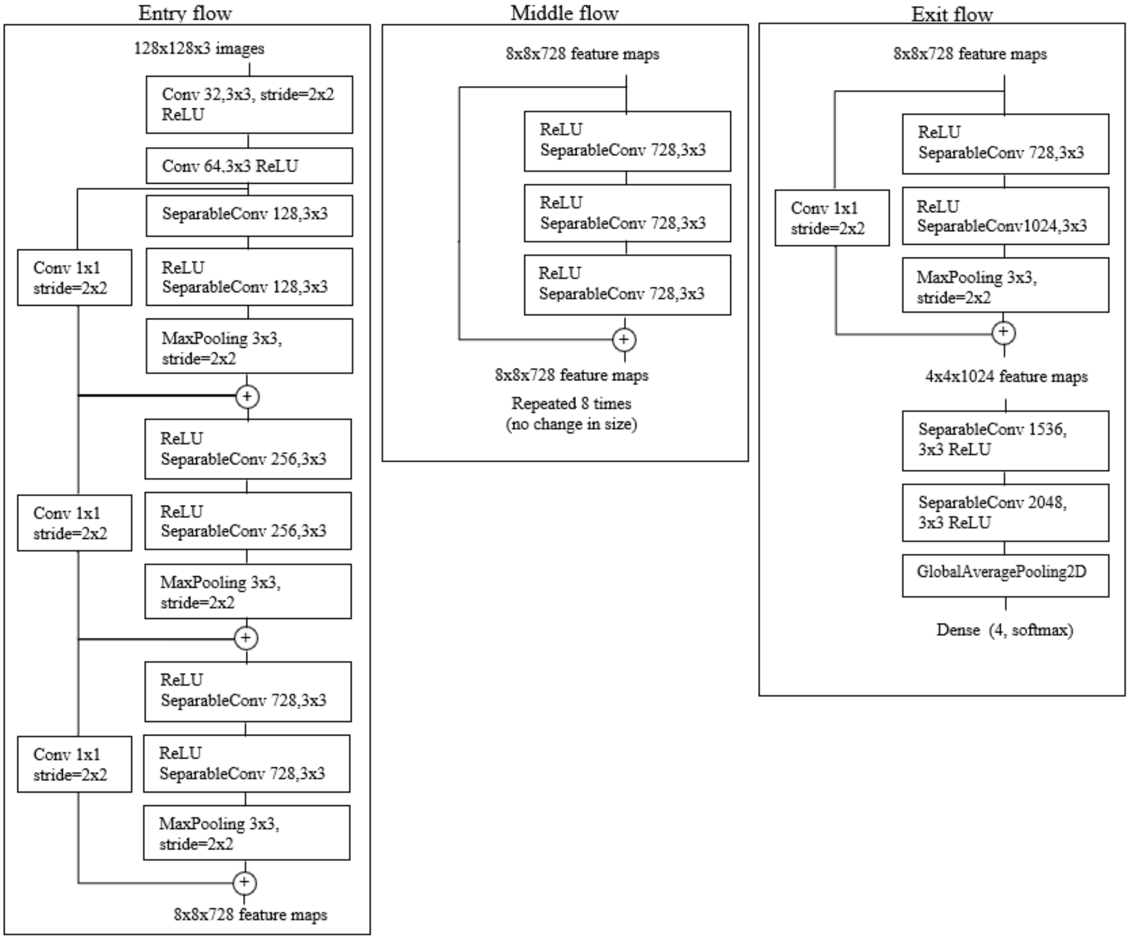

Fig. 4. Structure of the Xception model.

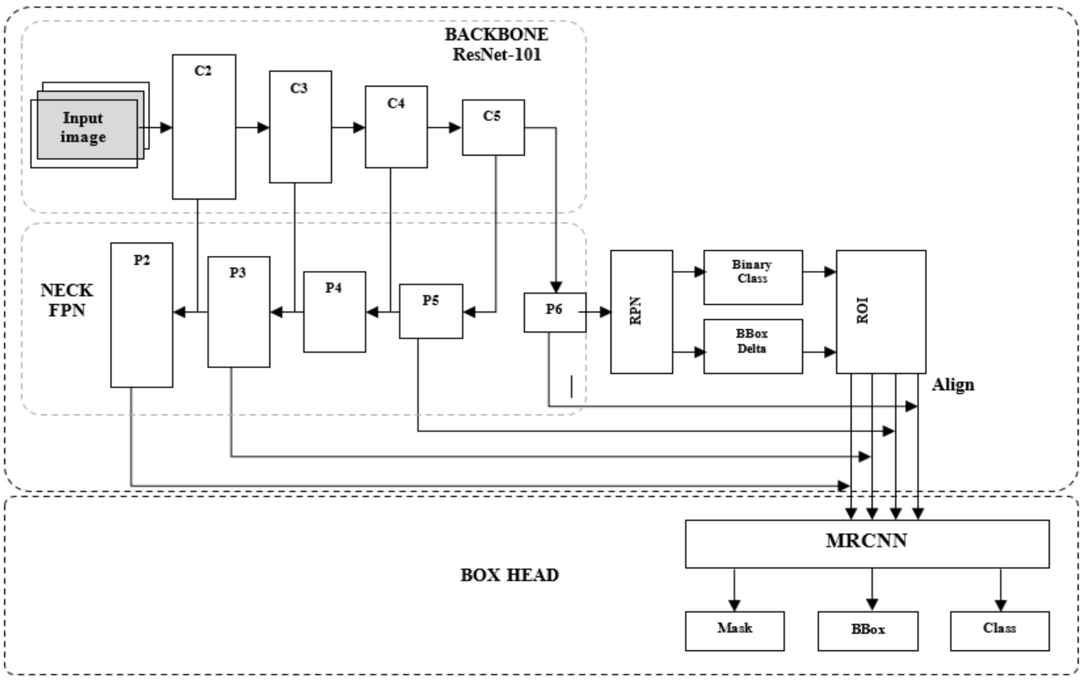

Fig. 5. Structure of the Mask R-CNN model.

F. Classification by the Mask R-CNN model

The same CPU, GPU, and RAM were used with PyTorch version 0.15.2+cu118 and Detectron version 0.6. Figure 5 shows the structural diagram of the selected Mask R-CNN model. First, the model starts with the ResNet-101 convolutional backbone, which is one of the most accurate CNN-based models in the ResNet family. ResNet 101 was used to extract features, represented by a feature map of the input images (C2, C3, C4, and C5). These were then forwarded to the NECK FPN layer (P2, P3, P4, P5, and P6). The purpose of the NECK was to extract features from lesions on different scales, which were integrated with a Region Proposal Network (RPN) module that generated the output values for classification (binary class) and bounding box regression (BBox Delta). The initial layers of the architecture were pre-trained using the weights from the COCO dataset [13]. A Region of Interest (RoI) Align layer was used to perform the segmentation task more efficiently, preserving the spatial location of objects.

The architecture consists of the Box Head module, which receives regions selected by RoI for classification, generating bounding boxes (BBox) and segmentation masks (Masks). The model classifies durian leaves based on these regions [8]. The hyperparameters include a batch size of 128, and the rest Mask R-CNN model's training details are shown in Table III.

TABLE III. TRAINING DETAILS FOR MASK R-CNN

Hyperparameter	Detail
Backbone	ResNet101 FPN 3×
Adjusted anchor size	(32, 64, 128, 256, 512)
Image per Batch	2
Max Iterations (It)	5,055(60 epochs), 5,898(70 epochs), 6,740(80 epochs)
Optimizer	Adam, SGD
Momentum	0.9 for SGD
Learning rate (LR)	0.01, 0.005, 0.001
ROI Batch size per image	128
RPN Batch size per image	128
Test Eval period	200

G. Model Evaluation

The classification metrics used to evaluate performance were accuracy, precision, recall, and F1-score, as shown in the following equations [17].

$$\text{Accuracy(Ac)} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad (1)$$

$$\text{Precision(Pr)} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Recall(Re)} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \quad (4)$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives.

III. RESULTS AND DISCUSSION

In [10], a ResNet-9 model was proposed for the classification of durian leaf diseases. To show the effectiveness of the proposed models, the ResNet-9 model was used as a baseline for comparison, with its performance shown in Table IV. Results at 20, 30, and 40 epochs showed progressive gains in accuracy (51.56%, 64.50%, and 69.44%, respectively), indicating that extended training substantially improves performance. The peak at 80 epochs suggests an optimal trade-off between minimizing loss and maximizing accuracy.

TABLE IV. RESULTS OF RESNET-9 WITH ADAM OPTIMIZER

LR	Ep	TL	Ac	Pr	Re	F1	T(s)
0.001	60	0.0896	0.7139	0.7162	0.7122	0.7141	1044
0.001	70	0.0500	0.7889	0.7913	0.7878	0.7895	1681
0.001	**80**	**0.0652**	**0.8350**	**0.8298**	**0.8295**	**0.8296**	**2096**
0.005	60	0.1694	0.7210	0.7975	0.7025	0.7469	1056
0.005	70	0.8010	0.7994	0.8003	0.7972	0.7987	1247
0.005	80	0.0769	0.8172	0.8192	0.8156	0.8173	1647
0.01	60	0.1845	0.7061	0.7121	0.7050	0.7085	1234
0.01	70	0.1771	0.7222	0.7263	0.7150	0.7206	1490
0.01	80	0.0936	0.7983	0.8078	0.7894	0.7984	1740

A. Xception Model Training and Testing Results

Table V presents the results of the Xception model using the Adam optimizer, which achieved an accuracy of 67.40-89.42%, a precision of 70.50-84.75%, and a recall of 60.75-82.50%. Using the SGD optimizer, as shown in Table VI, led to an accuracy range of 51.26-82.45%, a precision of 52.00-84.25%, and a recall of 50.75-82.25%. Although both Adam and SGD optimizers enable the model to perform well, Adam led to better accuracy, peaking at 89.42%. Thus, for the Xception model, the optimal performance was obtained with the Adam optimizer at a learning rate of 0.001 and 80 epochs. The Xception model performs better than the ResNet-9 model.

TABLE V. RESULTS OF XCEPTION WITH ADAM OPTIMIZER

LR	Ep	TL	Ac	Pr	Re	F1	T(s)
0.001	60	0.1090	0.8400	0.8550	0.8375	0.8401	1608
0.001	70	0.0814	0.8623	0.8225	0.8375	0.8299	1758
0.001	**80**	**0.0743**	**0.8942**	**0.8475**	**0.8250**	**0.8250**	**2012**
0.005	60	0.1694	0.7210	0.7975	0.7025	0.6850	1074
0.005	70	0.0997	0.7610	0.8125	0.7600	0.7475	1382
0.005	80	0.0237	0.8845	0.8800	0.8750	0.8750	1596
0.01	60	0.1599	0.6740	0.7875	0.7075	0.6750	1222
0.01	70	0.1548	0.6821	0.7050	0.6850	0.6825	1270
0.01	80	0.1543	0.7017	0.8000	0.6075	0.5600	1585

TABLE VI. RESULTS OF XCEPTION WITH AN SGD OPTIMIZER, MOMENTUM 0.9

LR	Ep	TL	Ac	Pr	Re	F1	T(s)
0.001	60	0.1693	0.6829	0.7400	0.5100	0.6351	1076
0.001	70	0.1526	0.7723	0.7925	0.7675	0.7650	1800
0.001	**80**	**0.1175**	**0.8245**	**0.8425**	**0.8225**	**0.8200**	**2040**
0.005	60	0.1556	0.5126	0.6212	0.5075	0.5350	1098
0.005	70	0.1356	0.5689	0.5200	0.5600	0.4775	1372
0.005	80	0.1352	0.6357	0.7125	0.6300	0.5721	2054
0.01	60	0.1955	0.6900	0.7675	0.6925	0.6825	1100
0.01	70	0.1851	0.6854	0.7275	0.6775	0.6700	1358
0.01	80	0.1184	0.6915	0.7750	0.6925	0.7314	2036

B. Xception Model Training and Testing Results

Tables VII and VIII show the results of the Mask R-CNN model with Adam and SGD optimizers. Mask R-CNN showed outstanding performance with Adam, with an accuracy range of 93.75-99.61%, a precision of 76.90-97.80%, and a recall of 92.91-98.81%. The experimental results show that the Mask R-CNN model was superior to the Xception model, as shown in Table VII. However, the loss function of the Xception model was slightly lower than that of the Mask R-CNN model. The hyperparameter tuning of both models was in the same manner, as discussed in Tables II and III. These experiments highlight the potential of Mask R-CNN in detecting durian leaf diseases, emphasizing the significance of choosing the appropriate optimizer to enhance the model's performance.

TABLE VII. RESULTS OF MASK R-CNN WITH ADAM OPTIMIZER

LR	It	TL	Ac	Pr	Re	F1	T(s)
0.001	5055	0.1543	0.9648	0.8947	0.976	0.9335	1582
0.001	5898	0.1322	0.9922	0.9713	0.9715	0.9713	1778
0.001	**6740**	**0.0987**	**0.9961**	**0.9780**	**0.9881**	**0.9830**	**2389**
0.005	5055	0.2081	0.9375	0.9269	0.955	0.9407	1574
0.005	5898	0.1829	0.9511	0.9708	0.971	0.9708	1763
0.005	6740	0.1279	0.9929	0.978	0.9636	0.9707	2365
0.01	5055	0.3057	0.9567	0.7863	0.9407	0.8565	1562
0.01	5898	0.2267	0.9746	0.7690	0.9291	0.8415	1760
0.01	6740	0.1713	0.9883	0.9107	0.9411	0.9256	2329

TABLE VIII. RESULTS OF MASK R-CNN WITH SGD OPTIMIZER, MOMENTUM 0.9

LR	It	TL	Ac	Pr	Re	F1	T(s)
0.001	5055	0.1681	0.9672	0.9446	0.9650	0.9546	1608
0.001	5898	0.1466	0.9821	0.9739	0.9860	0.9799	1710
0.001	**6740**	**0.1356**	**0.9867**	**0.9766**	**0.9851**	**0.9808**	**2340**
0.005	5055	0.1896	0.9666	0.9331	0.9542	0.9435	1942
0.005	5898	0.1811	0.9674	0.9555	0.9701	0.9627	1707
0.005	6740	0.1445	0.9852	0.9548	0.9712	0.9629	2174
0.01	5055	0.1548	0.9668	0.7555	0.9010	0.8218	1560
0.01	5898	0.1974	0.9743	0.9690	0.9587	0.9587	1140
0.01	6740	0.1815	0.9844	0.9098	0.9501	0.9295	2328

The results in Table IX show that the Mask R-CNN model is superior to ResNet-9 and the Xception models due to its two-stage process. First, the model identifies the region of the object in the input image using the backbone and RPN, enabling it to isolate the lesions on the durian leaves with high precision. In the second stage, the feature map value of the lesions is refined by RoI Align, which ensures that the feature map size is consistent, making the lesions more prominent and easier to classify.

TABLE IX. PERFORMANCE COMPARISON OF THREE MODELS FOR DURAIN LEAF DISEASE CLASSIFICATION

Evaluation	Resnet-9	Xception	Mask R-CNN
Accuracy	83.50%	89.42%	99.61%
Precision	82.98%	84.75%	97.80%
Recall	82.95%	82.50%	98.81%
F1	82.96%	82.50%	98.30%
Loss	0.0652	0.0743	0.0987
Time (s)	2096	2012	2389

IV. CONCLUSION

This study compared three deep learning models, ResNet-9, Xception, and Mask R-CNN, for the detection and classification of durian leaves in four classes: algal spot leaf, blight leaf, other diseased durian leaves, and healthy leaves. The dataset comprised 648 images, including 228 collected from farmers in Yala province, Thailand, and 420 from open-source resources on Roboflow. All images were preprocessed, including duplicate removal, expert label validation, and normalization, before augmentation for training, validation, and testing. ResNet-9 achieved its best performance at a learning rate of 0.001 and 80 epochs, with 83.50% accuracy, 82.98% precision, 82.95% recall, 82.96% F1-score, and the lowest loss of 0.0652, requiring 2,096 s of training. Although ResNet-9's accuracy was lower than that of Xception and Mask R-CNN, its lower computational cost and minimal loss make it suitable for resource-constrained scenarios. Xception reached 89.42% accuracy, 84.75% precision, 82.50% recall, and 82.50% F1-score, with a loss of 0.0743 and a training time of 2,012 s. Mask R-CNN, trained for 6,740 iterations, achieved the greatest performance, with 99.61% accuracy, 97.80% precision, 98.81% recall, and 98.30% F1-score, with a loss of 0.0987, albeit with a longer training time of 2,389 seconds. Overall, Mask R-CNN achieved the highest classification performance, benefiting from its segmentation stage, while Xception balances accuracy and speed. Model selection should consider the desired trade-off between accuracy, computational cost, and deployment feasibility in practical durian farming applications.

In the future, the developed models could be integrated into a mobile or IoT-based application to support real-time detection and provide accessible tools to farmers in remote areas. In addition, the framework could be adapted for other crops to further expand its impact in the field of precision agriculture.

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