

CNN-Based Eucalyptus Disease Classification Using MobileNet

Levita Wahyuni¹, Dian Ramadhani^{2*}

^{1,2}Dept. of Informatics Engineering, Faculty of Engineering, Universitas Riau, Indonesia

¹wahyunilevita@gmail.com, ²dianramadhani@lecturer.unri.ac.id

*Corresponding author, dianramadhani@lecturer.unri.ac.id

Abstract — Eucalyptus pellita is a key species in Indonesia's pulp and paper industry. However, it remains vulnerable to various foliar diseases, including Xanthomonas infections and pest infestations, particularly those caused by leaf roller caterpillars, which significantly reduce nursery productivity. This study presents a leaf disease classification system utilizing a Convolutional Neural Network (CNN) based on the MobileNet architecture and a transfer learning approach. A dataset of 600 images was compiled and categorized into three classes: healthy leaves, Xanthomonas-infected leaves, and caterpillar-damaged leaves. The dataset was divided into training (80%), testing (10%), and validation (10%) subsets. Multiple hyperparameter configurations were tested, with the optimal performance achieved using a learning rate of 0.0001, 20 training epochs, a batch size of 32, and the Adam optimizer. The resulting model achieved 97.29% training accuracy and 100% accuracy on both the validation and testing sets, demonstrating strong reliability in detecting leaf diseases. These findings provide a solid foundation for the development of technology-assisted disease management tools to support agronomic decision-making and agricultural extension services.

Keywords: CNN, Eucalyptus pellita, leaf disease, MobileNet, transfer learning.



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INTRODUCTION

Indonesia possesses extensive forest resources and plays a vital role in the global forestry sector, particularly in the pulp and paper industry. Among the primary species cultivated is Eucalyptus pellita, widely used by Industrial Plantation Forests (HTI) as a key raw material for pulp and paper production due to its rapid growth and high wood quality [1]. However, Eucalyptus pellita is susceptible to various diseases and pests during the nursery stage, including Xanthomonas leaf spot caused by Xanthomonas campestris which produces necrotic lesions that hinder photosynthesis [2], and leaf-rolling caterpillars that damage leaf structure and weaken plant resistance. According to data from PT. Perawang Sukses Perkasa Industri (PSPI), these issues caused a 3–5% reduction in seedling production between September 2023 and February 2024.

Currently, disease and pest identification is conducted manually through visual inspection by nursery personnel. This traditional method is time-consuming and error-prone, often delaying treatment and accelerating disease spread. Xanthomonas, for instance, can quickly propagate

through water droplets or leaf contact, while leaf-rolling caterpillars can rapidly infest nearby plants. To address these limitations, there is an urgent need for automated and accurate disease detection systems to support early intervention and improve nursery management. Convolutional Neural Networks (CNNs) have been widely applied in image classification tasks, including for plant disease detection in agriculture and forestry. [3] also demonstrated their effectiveness in classifying plant leaf diseases, highlighting their potential in practical applications. CNNs have shown strong performance in such tasks by learning patterns in leaf imagery [4], [5]. However, training CNNs from scratch typically requires large amounts of labeled data. Transfer learning provides a practical alternative by utilizing pre-trained models such as MobileNet, VGG-16, and NasNet Mobile, which reduce computational costs while maintaining high classification accuracy [6]. MobileNet is especially favored due to its lightweight architecture and suitability for mobile deployment, making it ideal for field applications. Several studies support its effectiveness across various plant types and dataset sizes. [7] achieved 98% accuracy on Eucalyptus leaves, while [8] reported 95% accuracy for tea leaf classification using MobileNet and surpassing NasNet Mobile's 88% [9]. In another study [10] found MobileNet outperformed DenseNet121 in classifying potato leaf diseases (98% vs. 95.99%). Conversely, [11] used VGG16 on 9,430 cassava leaf images, only achieved 75% validation accuracy. Large-scale implementations also confirm MobileNet's scalability and robustness. [12] achieved 95% accuracy on 76,000 plant images. [13] improved MobileNet further through dilated convolutions and GELU activation, achieving 97.17% accuracy and outperforming VGG16, DenseNet, and Xception on tomato leaves. Despite these advancements, no prior study has focused on classifying *Eucalyptus pellita* leaves affected by both *Xanthomonas* and caterpillar damage in the context of a commercial nursery such as PT. PSPI. This study proposes a CNN-based classification system using MobileNet and transfer learning to address that gap, aiming to enhance early disease detection and improve nursery decision making.

METHOD

This study adopts an experimental methodology to develop a CNN-based classification model for detecting *Eucalyptus pellita* leaf diseases, targeting a classification accuracy above 90%. The model was built using the MobileNet architecture due to its efficiency and suitability for mobile deployment. Key hyperparameters including learning rate, batch size, and number of training epochs were systematically varied to identify the optimal configuration. The research began with problem identification through field observations, staff interviews, and a literature review to assess disease detection challenges. Data collection involved capturing leaf images in collaboration with trained nursery personnel using an iPhone 11 camera under natural lighting. Each leaf was photographed from four different angles to increase dataset variability and generalization. The images, stored in JPG format, were categorized into three classes: healthy, *Xanthomonas*-infected, and caterpillar-damaged leaves. Prior to training, images were resized to 224×224 pixels and underwent normalization and augmentation techniques such as rotation, zooming, shifting, and horizontal flipping. A MobileNet-based CNN was trained on the preprocessed dataset using a combination of hyperparameter configurations to evaluate their impact on accuracy and loss. Model evaluation was performed using a confusion matrix and standard metrics such as precision and recall. If the model achieved accuracy above 90%, it was deemed suitable for deployment in a mobile application; otherwise, further retraining and tuning were conducted. The final outcome of this study is a lightweight, mobile-compatible CNN model designed for real-time detection of *Eucalyptus pellita* leaf diseases in nursery settings, as illustrated in Figure 1.

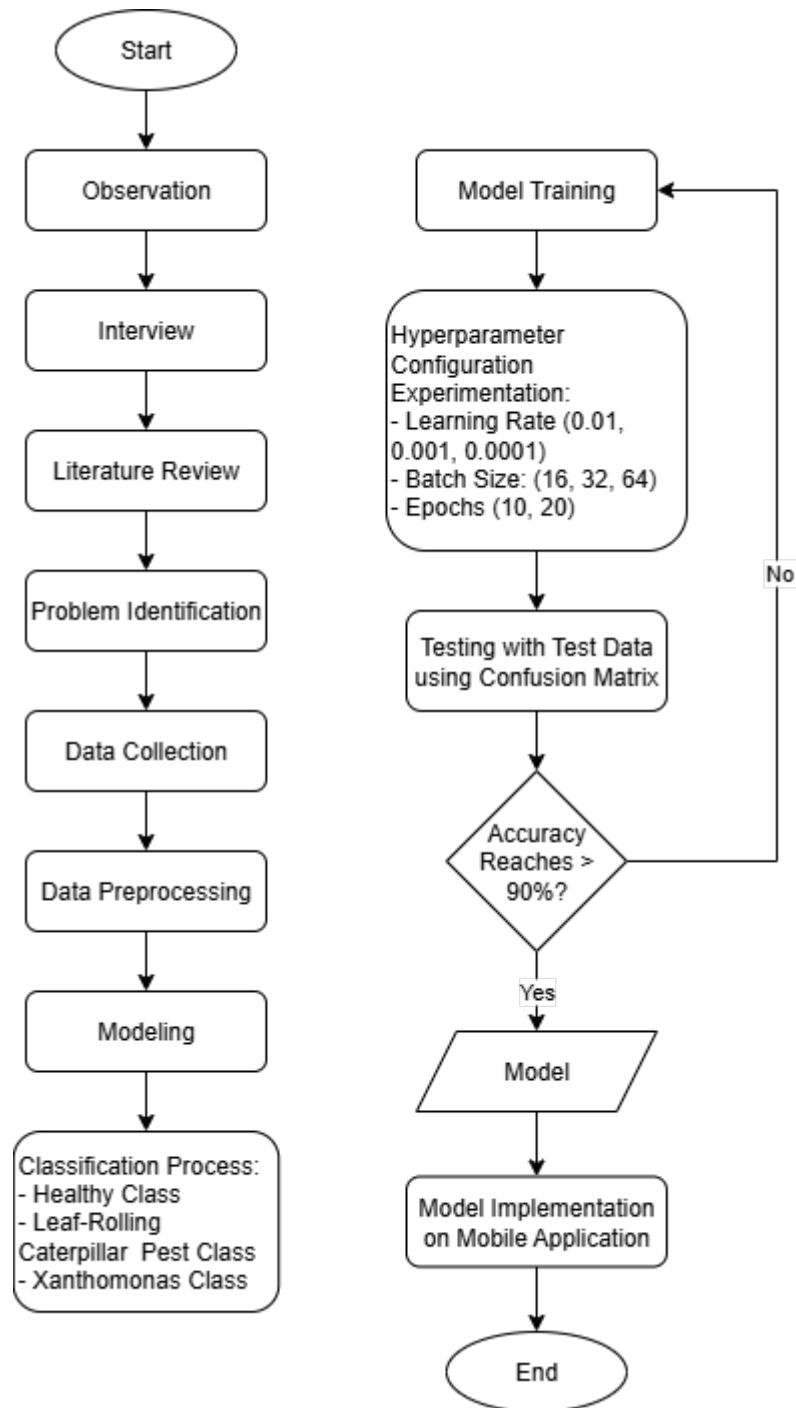


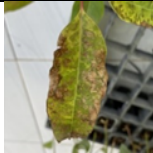
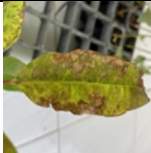
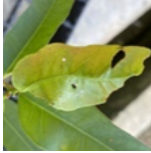
Figure 1. Research Methodology

RESULT AND DISCUSSION

The dataset utilized in this study consisted of images of *Eucalyptus pellita* leaves categorized into three classes: healthy leaves, leaves infected by *Xanthomonas* disease, and leaves damaged by leaf-rolling caterpillar pests. Image acquisition was conducted in collaboration with experienced nursery personnel, whose expertise in identifying disease and pest symptoms ensured the accuracy and reliability of the collected data. All images were captured using an iPhone 11 smartphone camera under natural sunlight conditions. For each leaf

sample, four images were taken from different angles to increase dataset variability and enhance the model's generalization capability. The image capture process involved rotating the camera 90° clockwise after each shot, beginning from a perpendicular angle to the leaf surface. All images were stored in JPG format. A total of 600 images were collected, comprising 200 images for each of the three classes: *Xanthomonas*-infected, caterpillar-damaged, and healthy leaves. The dataset was subsequently divided into three subsets: 80% (480 images) for training, 10% (60 images) for testing, and 10% (60 images) for validation. Representative examples of each leaf class are shown in Table 1.

Table 1. Eucalyptus Plant Leaf Image Dataset

Label	Leaf Image			
<i>Xanthomonas</i>				
Healthy				
Leaf Roller Caterpillar				

Following the identification and visualization of representative samples, the dataset underwent a preprocessing stage to enhance its quality and suitability for model training. Several data augmentation techniques were applied to increase dataset variability, including rotation, width and height shifts, shearing, zooming, horizontal flipping, and the use of nearest fill mode. Additionally, all images were resized to 224 × 224 pixels to meet the input dimension requirements of the MobileNet architecture. Data augmentation is a widely used method to reduce overfitting by introducing variation in the training set, allowing the model to learn more generalized patterns. Nevertheless, due to the relatively limited size of the dataset, the risk of overfitting could not be entirely avoided. To further improve model robustness and stability on unseen data, future work should consider expanding the dataset and implementing additional regularization techniques such as dropout and early stopping [14]. In addition, validating the model using external datasets would help assess its generalization capability and ensure consistent performance across different real-world scenarios.

Table 2 presents a visual comparison of the image data before and after preprocessing, highlighting the transformations applied to enhance dataset quality and variability. To ensure the training data was of optimal quality, all images were resized to meet the model's input requirements and enhanced through augmentation techniques to increase data diversity [15]. All images were resized to 224 × 224 pixels to match the input size of the MobileNet architecture, enabling consistent processing throughout the model pipeline. Augmentation techniques were then applied to introduce controlled variability and improve generalization. These included:

- The Width Shift Range and Height Shift Range, both set to 0.2, shifted the images horizontally and vertically by up to 20% of their original size.
- Shear Range = 0.2 applied angular distortion of up to 20 degrees counterclockwise.

- Zoom Range = 0.2 introduced random zooming of up to 20%.
- Horizontal Flip = True mirrored the image along the horizontal axis.
- Rotation Range = 20 enabled random rotations of up to ± 20 degrees.

Table 2. Comparison of image data before and after preprocessing

Image Before preprocessing	After preprocessing			
	Resize 	Rotation Range 	Width shift range 	Flip horizontal 
	Height shift range 	Shear range 	Zoom range 	

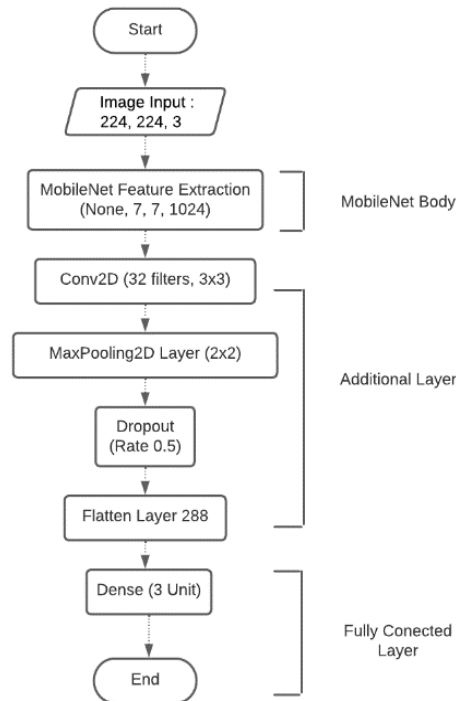


Figure 2. MobileNet Architecture

These augmentation parameters were carefully selected to introduce controlled variability into the dataset, with the aim of enhancing the model's generalization capability and mitigating the risk of overfitting. Nevertheless, the relatively small dataset size, limited to 600 images, remains a significant constraint. While augmentation simulated diversity, it cannot fully substitute for genuine image variation obtained from real-world samples. For deep learning architectures such as MobileNet, larger datasets are typically more effective in capturing complex patterns and reducing the risk of overfitting. Consequently, future research should prioritize expanding the dataset in both size and variability to ensure greater model robustness

and generalizability across diverse environmental contexts and leaf conditions. The experimental approach in this study, illustrated in Figure 2, involved evaluating various combinations of hyperparameters to determine the optimal configuration that achieved the highest classification accuracy and lowest loss. A total of 18 experimental trials were conducted, in which the learning rate (0.01, 0.001, and 0.0001), batch size (16, 32, and 64), and number of training epochs (10 and 20) were systematically varied. The Adam optimizer was selected based on prior studies reporting its superior performance in achieving higher accuracy and reduced loss compared to alternative optimization algorithms. The selected hyperparameter values were informed by previous research. Learning rates of 0.01, 0.001, and 0.0001 were chosen based on recommendations from [16], [8], and [7], recognizing the critical role of learning rate in maintaining training stability. An improperly configured learning rate can lead to erratic or divergent loss behavior, whereas an appropriately tuned rate facilitates smooth convergence during training [17]. Likewise, batch sizes of 16, 32, and 64 were adopted based on empirical findings in [7] and [8]. Epoch counts of 10 and 20 were selected based on guidelines from [9] and [7].

Table 3. Experimental Result

Training Set	Learning rate	Epoch	Batch Size	Accuracy		Difference (Valid – Train)	Loss	
				Train	Valid		Train	Valid
1	0.01	10	16	0.7563	0.8500	0.0937	0.7176	0.4516
2	0.01	10	32	0.8500	0.9500	0.1	0.5173	0.3610
3	0.01	10	64	0.8833	0.9000	0.0167	0.3355	0.2060
4	0.01	20	16	0.6979	0.8833	0.1854	0.9167	0.5011
5	0.01	20	32	0.8438	0.9167	0.0729	0.4802	0.3068
6	0.01	20	64	0.7563	0.8333	0.077	0.6075	0.4092
7	0.001	10	16	0.9625	0.9833	0.0145	0.0994	0.0595
8	0.001	10	32	0.9375	1.0000	0.0625	0.1760	0.0225
9	0.001	10	64	0.9583	1.0000	0.0417	0.1344	0.0113
10	0.001	20	16	0.9542	1.0000	0.0458	0.1640	0.0139
11	0.001	20	32	0.9729	1.0000	0.0271	0.0738	0.0110
12	0.001	20	64	0.9542	0.9667	0.0125	0.1165	0.0501
13	0.0001	10	16	0.9187	0.9667	0.048	0.2404	0.0753
14	0.0001	10	32	0.9125	0.9500	0.0375	0.2334	0.0857
15	0.0001	10	64	0.8687	0.9167	0.0480	0.3188	0.2206
16	0.0001	20	16	0.9396	0.9667	0.0271	0.1519	0.0726
17	0.0001	20	32	0.9563	0.9667	0.0104	0.1160	0.0868
18	0.0001	20	64	0.9167	0.9500	0.0333	0.2411	0.1287

Each experiment followed a standardized procedure, beginning with data preprocessing, followed by model training and evaluation using classification accuracy and loss as key performance metrics. The tuning of hyperparameters is crucial for constructing a well-generalized model, as it helps balance training efficiency and model complexity [18]. This experimental framework provided an objective basis for identifying the most effective model configuration based on empirical results. The experimental results, as shown in Table 3, revealed that the 11th configuration, which comprised a learning rate of 0.001, 20 training epochs, and a batch size of 32, yielded the best performance with a validation accuracy of 100% and a training accuracy of 97.29%. This configuration resulted in a low error rate, indicating the model's effectiveness in learning relevant patterns without exhibiting signs of overfitting. Overfitting occurs when a model fits the training data too closely, thereby failing to generalize well to unseen data [19]. Among the evaluated learning rates, 0.001 demonstrated superior training stability and convergence. In contrast, the higher learning rate of 0.01 tended to produce unstable training behavior, while the lower rate of 0.0001 converged more slowly and less effectively. Therefore, a learning rate of 0.001 was determined to be the most optimal for classifying disease symptoms in *Eucalyptus pellita* leaves. The training and validation

performance corresponding to this configuration is further illustrated through the graphical visualization presented in Figure 3.

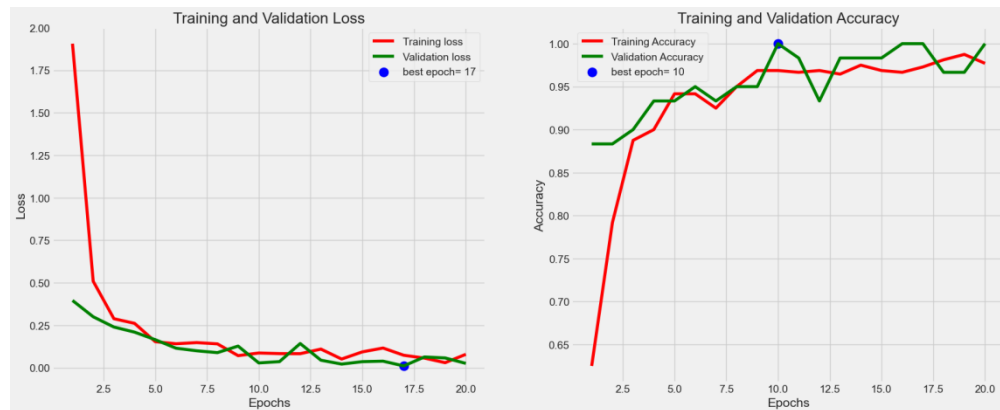


Figure 3. Training and Validation Graph

As illustrated in Figure 3, the training accuracy reached 97.29%, while the validation accuracy attained 100%, with a minimal discrepancy of only 0.0271%. The corresponding training and validation loss values were also low, recorded at 0.0738 and 0.0110, respectively. These results suggest that the model was effectively optimized using the selected hyperparameter configuration, achieving both high classification accuracy and strong generalization performance. Figure 4 presents the confusion matrix obtained during the experimental phase, providing a summary of the model's classification performance across the three target classes.

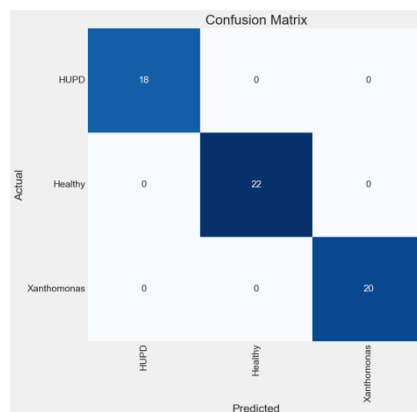


Figure 4. Confusion Matrix

Figure 5 provides a detailed breakdown of the confusion matrix, which serves as the foundation for calculating key evaluation metrics, including accuracy, precision, and recall.

	precision	recall	f1-score	support
HUPD	1.00	1.00	1.00	18
Healthy	1.00	1.00	1.00	22
Xanthomonas	1.00	1.00	1.00	20
accuracy			1.00	60
macro avg	1.00	1.00	1.00	60
weighted avg	1.00	1.00	1.00	60

Figure 5. Model Performance

The performance of the model was evaluated using four key metrics: accuracy, precision, recall, and F1-score. These metrics are defined as follows:

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

$$Precision = \frac{TP}{TP + FN} \quad (2)$$

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

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

In this equation, TP, FP, FN, and TN represent the values for True Positive, False Positive, False Negative, and True Negative, respectively.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{60}{60} = 1.00$$

Leaf Roller Caterpillar Class

$$Precision = \frac{TP}{TP + FN} = \frac{18}{18 + 0} = \frac{18}{18} = 1.00$$

$$Recall = \frac{TP}{TP + FN} = \frac{18}{18 + 0} = \frac{18}{18} = 1.00$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{1 \times 1}{1 + 1} = \frac{2}{2} = 1.00$$

Healthy Class

$$Precision = \frac{TP}{TP + FN} = \frac{22}{22 + 0} = \frac{22}{22} = 1.00$$

$$Recall = \frac{TP}{TP + FN} = \frac{22}{22 + 0} = \frac{22}{22} = 1.00$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{1 \times 1}{1 + 1} = \frac{2}{2} = 1.00$$

Xanthomonas Class

$$Precision = \frac{TP}{TP + FN} = \frac{20}{20 + 0} = \frac{20}{20} = 1.00$$

$$Recall = \frac{TP}{TP + FN} = \frac{20}{20 + 0} = \frac{20}{20} = 1.00$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{1 \times 1}{1 + 1} = \frac{2}{2} = 1.00$$

Following the evaluation of the confusion matrix, additional testing was performed using previously unseen input data to further assess the model's predictive capabilities. A representative example from this test set is shown in Figure 6. This evaluation involved 15 images selected from the test dataset, representing 25% of the total 60 test images, with five samples from each of the following classes: Caterpillar, Healthy, and Xanthomonas. The model successfully classified all 15 images, achieving a 100% accuracy. These results further confirm the model's strong generalization capability and its effectiveness in accurately detecting and classifying *Eucalyptus pellita* leaf diseases on previously unseen data.

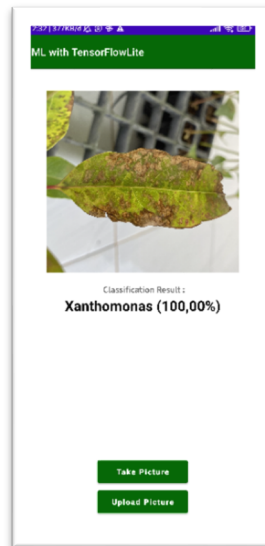


Figure 6. Sample image from the unseen test dataset

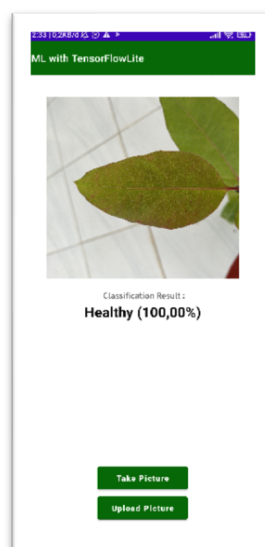


Figure 7. Model Implementation Images to Android

The final stage of this study involved deploying the trained model into a mobile application. The primary objective of this phase was to facilitate the practical detection of disease in *Eucalyptus pellita* through an accessible, Android-based interface. Figure 7 displays the interface of the Android application, which features a user-friendly and straightforward layout designed to support testing of the eucalyptus disease classification model. The main screen allows users to either upload an image from their device's gallery or capture a new photo using

the built-in camera. Upon image selection, the application processes the input through the trained model and displays the predicted class along with its associated confidence score. Two nursery staff members informally tested the Android application to assess its response time and usability. The average classification time, from image input to result display, was approximately 1.2 seconds. Both users were able to operate the application without prior training and reported that the interface was intuitive, with clearly labeled buttons and rapid, easy-to-understand output. Feedback indicated that the application could support practical, real-time use in a nursery setting and how the Android application was tested, including response times, usability evaluation, and any initial user feedback.

CONCLUSION

Based on the training and testing outcomes, the CNN model utilizing the MobileNet architecture successfully classified *Eucalyptus pellita* leaves into three categories: caterpillar-damaged, healthy, and *Xanthomonas*-infected with high accuracy. This performance was achieved through a combination of data preprocessing, augmentation, and systematic hyperparameter tuning. Among the tested configurations, the best results were obtained in the 11th experiment, which employed a learning rate of 0.001, 20 epochs, and a batch size of 32, yielding a training accuracy of 97.29% and perfect accuracy (100%) on both the validation and testing sets, using 60 test images deployed on an Android device. The model demonstrated strong generalization capability, as evidenced by minimal variation in accuracy and low validation loss values, indicating stable performance on unseen data. However, the relatively limited dataset of 600 images may constrain the model's ability to generalize across more diverse leaf conditions. Additionally, the current Android implementation requires manual image input and does not yet support real-time processing, limiting its applicability for continuous field monitoring. Future enhancements should focus on expanding the dataset in both size and variability, exploring additional hyperparameter tuning and regularization techniques, and integrating real-time classification capabilities into the mobile application to improve both performance and practical usability.

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BIOGRAPHIES OF AUTHORS



LEVITA WAHYUNI was born in Pematang Siantar, Sumatera Utara. She is a student at the Faculty of Engineering, majoring in Informatics Engineering at Riau University. Her studies focus on Intelligent Computing and Visualization (KCV), including artificial intelligence, computer vision, and data visualization. She graduated from the university in 2024.



DIAN RAMADHANI was born in Duri, Riau, Indonesia. She completed her bachelor's degree in Informatics Engineering in 2011 and a master's degree from the Bandung Institute of Technology (ITB) Bandung in 2017. Her research interests include data mining, data analysis, machine learning, natural language processing, business intelligence, and decision support systems.