

**DEEP LEARNING MODEL FOR THE DETECTION AND
CLASSIFICATION OF BANANA DISEASES
BASED ON LEAF IMAGES**

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BOGOR
2024**

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Bogor, June, Year 2024
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SUMMARY

SHABAN NASSOR SHABAN. Deep Learning Model for The Detection and Classification of Banana Disease Based on Leaf Images, supervised by KARLISA PRIANDANA and MUSHTHOFA.

Fungal diseases are among the main reasons for low productivity in banana farming. Black Sigatoka and fusarium wilt race 1 are the major fungal diseases that threaten banana production. black Sigatoka is a fungal disease caused by a wind-borne fungus, *Mycosphaerella fijiensis* Morelet. On the other hand, fusarium wilt is another fungal disease originating from soil caused by a fungus named *Fusarium oxysporum* f. sp. *cubense* (Foc). The spread of these diseases is accelerating in many countries and threatens the production of bananas globally. Early detection of fungal diseases is essential and one of the possible approaches is using machine vision. Due to its high accuracy, deep learning is the most widely used algorithm in machine vision for many solutions. Its ability to model the data into multiple levels of abstraction makes it suitable for many agricultural solutions. Furthermore, deep learning can be trained with a vast amount of data. However, deep learning requires a high computational resource, challenging many agricultural solutions implemented on low-computing devices such as edge, mobile, and IoT devices. Therefore, this research proposes deep-learning models for detecting and classifying banana diseases based on leaf images. The study proposes the use of lightweight deep learning algorithms instead of off-shelf algorithms. Lightweight deep learning algorithms have a small architecture which make them suitable for low computing resources devices.

The research is conducted in two stages: the first stage focuses on identifying the diseases using deep learning where default algorithms are trained. In this stage, four lightweight deep learning utilized namely mobileNetv2, mobileNetv3-small, ShuffleNetv2, and SqueezeNet. The choice of algorithms is based on the popularity of the algorithm in the research community. The second stage focuses on modification of the algorithms to increase the performance of the models. Modifications introduced include the addition of a convolutional block attention module (CBAM). CBAM is a lightweight attention module that enhances both channel and attention features. In both stages, sequential model-based optimization (SMBO) is used for automatic hyperparameter tuning (HPO). SMBO is a variant of Bayesian optimization that selects the parameters sequentially. This makes SMBO to be faster than other optimization algorithms.

The study used a dataset of images representing three classes: healthy, black Sigatoka, and fusarium wilt race 1. The dataset was collected in Northern Tanzania for a period of six months by the Mandela African Institution of Science and Technology (NM-AIST) and the International Institute of Tropical Agriculture (IITA). The preprocessing conducted after acquiring the dataset includes resizing, removing the stem images, splitting, and augmentation. The model's performance is measured by calculating accuracy, precision, recall, and f1-score as well as measuring model complexity.

The results indicated that for stage one, mobileNetv2 outperforms all other models with 97,73% accuracy, 97,74% precision, 97,73% recall, and 97,73% f1-score, while shuffleNetv2 had poor performance with an accuracy of 84,21%,

precision of 84,76%, recall of 84,21%, and f1-score of 84,03%. SqueezeNet is a light model with a size of 2,78 MB, while mobileNetv3-small is the heaviest model with a size of 8.74 MB. However, all models had trouble distinguishing between black sigatoka and fusarium wilt race 1. This indicates generalization ability of the models is poor. For lightweight deep learning with CBAM (stage two), shuffleNetv2 outperforms all other models with 99,07% accuracy, 99,07% precision, 99,07% recall, and 99,07% f1-score. SqueezeNet is a light model with a size of 2,09 MB, while mobileNetv2 is the heaviest model with 14,40 MB. SqueezeNet took a short time, with an estimated 558.0961, equal to 9.301 minutes. Generally, the classification capability of all models increased significantly compared to stage one. Also, the CBAM module helps to increase the generalization capability of the models by reducing the number of misclassified images as well as increasing the performance of the models. However, the classification is still not 100% for all classes.

Overall, the lightweight deep learning proposed by this research showed a good performance and can be used to overcome computational challenges. Also, classification and detection of banana diseases can be done based on image leaf, which can be a solution for early detection of the diseases and destruction method. Furthermore, the improvement of light-weight deep learning can be achieved by enhancing feature extraction ability. The approach proposed by this study can also be applied to other banana diseases and other plant species.

Keywords: banana, CBAM, deep learning, HPO, SMBO.

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Thesis
as one of the requirements for obtaining a Master degree in
Computer Science Study Program

**COMPUTER SCIENCE STUDY PROGRAM
FACULTY OF MATHEMATICS AND NATURAL SCIENCES
IPB UNIVERSITY
BOGOR
2024**

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Thesis Exam Date: 22 May 2024

Finishing Date:

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