Development of EfficientNet Model on Broad and Needles Leaved Species Tree Crowns with Forest Health Monitoring Method

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ABSTRACT
Forest Health Monitoring (FHM) is a method for monitoring forest health conditions using various ecological indicators, such as tree canopy density and transparency. This research aims to evaluate the performance of the EfficientNet model in classifying the density and transparency values of broadleaf and coniferous tree canopies. The dataset consists of 3,956 tree canopy images collected from Tahura Wan Abdul Rachman (WAR), a conservation forest in Lampung, and is divided into 10 classes based on magic cards. Magic cards are a learning medium in the form of picture cards containing values of density and transparency. This research uses the EfficientNet-B0 architecture with certain training parameters. The results show that the EfficientNet-B0 model provides the best performance with an accuracy of 90.00%, a precision of 97.00%, a recall of 97.00%, and an F1-score of 97.00%. This research shows that EfficientNet can be used effectively to assist decision making related to automatic visual monitoring of forest health.

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1. INTRODUCTION

This research aims to measure the EfficientNet performance in identifying canopy density and transparency values for broad leaved and needle leaved species using the Forest Health Monitoring (FHM) method. This research is useful for facilitating monitoring work that was previously only measured using a magic card tool. This magic card is a model design containing a range of density and transparency values. Density and transparency values are among the parameters used in this FHM method. Forests are very important ecosystems for life on earth. As a repository of biodiversity, forests provide habitat for various types of plants and animals. Some types of plants are broad leaved and needle leaved trees. One way to store information and data in the forest can be obtained through the FHM method [1]. FHM is a method for monitoring, assessing, and reporting on current status, changes, and long-term trends using ecological indicators [2]. There are five parameters for assessing the condition of the canopy, including crown density and foliage transparency [3]. Measurement of canopy density and transparency currently uses a magic card. This method less effective because it relies on direct vision and then compared with the value on the magic card [4]. Classification of canopy density and transparency values can utilize digital image processing technology to simplify and increase work effectiveness. The way to facilitate this identification requires deep learning technology.

Deep Learning is a part of computer vision that is often used to recognize and classify an image object. The way deep learning works is neatly arranged to form an algorithm that can continue to develop along with the needs and utilization of technology [5]. Convolutional Neural Network (CNN) in the process is divided into feature extraction layer and fully-connected layer [6]. Feature extraction layer is used to extract features from the image and then store them for use in the next stage, namely the fully connected layer. The fully-connected layer stage is a stage in the process of classifying objects in the image. One of the Convolutional Neural Network architectures is EfficientNet. EfficientNet is a development carried out by CNN to obtain the best accuracy, as well as increase model efficiency by reducing trainable parameters [7].

EfficientNet is one of the CNN architectures that was created to make it easier for CNN to enlarge its training scale without having to scale it manually. CNN initially required manual model scaling and manual tuning, to be able to read large input image resolutions and expand or deepen the CNN scale [8]. EfficientNet is the result of further learning to increase the scale and efficiency of CNN. This architecture is more efficient especially in terms of small size and processing speed [9]. EfficientNet is basically adapted from MobileNetV2 and MnasNet by using Mobile Inverted Bottleneck Convolution (MBConv) as its layer [10]. EfficientNet was chosen for this research because EfficientNet has a depth, width, and resolution scaling of the model so that it can perform very well in classification. In this research, EfficientNet will be used to identify one of the parameters, namely the density and transparency values of broad leaved and needle leaved tree crowns using the FHM method for forest health.

2. RESEARCH RELEVANT

Previous research by Sofiyana [11] identified the density and transparency scales of broad leaved tree canopies using the MobileNet architecture for classification. Accuracy results in the testing process for cocoa trees (94.20%), durian trees (87.50%), rubber trees (97.90%), and candlenut trees (98.70%) were obtained. Previous research conducted by Octarina [12] identified the canopy density and transparency scales of broad leaved trees. This research used the VGG-16 architecture for classification. Accuracy testing results were 92.00% for cocoa trees, 86.60% for durian trees, 96.60% for rubber trees, and 98.40% for candlenut trees.

Previous research on canopy density and transparency in coniferous trees was conducted by Tarigan [13]. The CNN architecture used in this study was VGG-16. Accuracy results reached 90.00% for pinus merkusii, 92.00% for araucaria heterophylla, 96.00% for cupressus retusa, and 99.00% for shorea javanica. This research by Safe'I [2] as an application of deep learning related to forest health. Two CNN architectures were used in this study: LeNet and MobileNet. The model with the LeNet architecture achieved 88.99% accuracy, while the model with the MobileNet architecture achieved 99.06% accuracy. Research related to the use of the EfficientNet B0-B7 architecture has been conducted Himel[9] for the automatic identification and classification of sheep breeds in the context of smart farming. This study used 1680 images (420 images for each breed). The dimensions of each image were 156 × 181. During the training phase, all images were resized to 224 × 224. This study achieved an accuracy value of 97.62%.

3. RESEARCH METHOD

This research uses the EfficientNet B0 architecture evaluation model with fixed hyperparameters such as Learning Rate, batch size, epoch, optimizer.The evaluation will produce accuracy, precision, recall, F1-score, confusion matrix. This research was conducted at the Computer Science Department, Faculty of Mathematics and Natural Sciences (FMIPA), and Tahura WAR Sumber Agung, Kemiling [14], Bandar Lampung. In Figure 1 there is a research flow in this study.

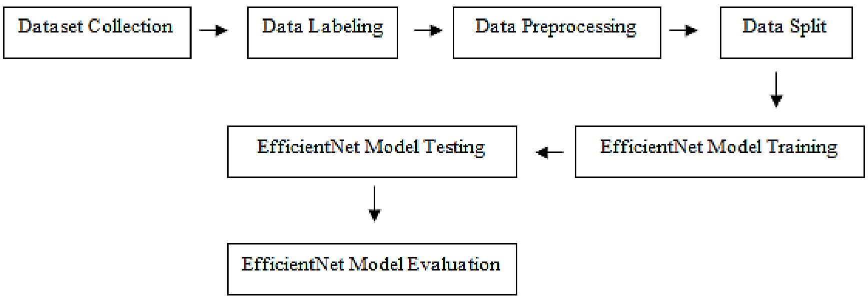

Figure 1. Research Design

2.1 Data Collection

The dataset collected is the image of broadleaf and needleleaf tree crowns. The top of a tree consists of a number of branches, leaves, twigs, and fruit. The distance between tree plants affects the shape and location of the crown. Trees that have a limited spread have small, upward-growing crowns, while trees that have a wide spread have wide or laterally inclined crowns [15]. The obtained broadleaf and needle species consisted of 8 tree species using 2,956 images of four broadleaf tree species, namely Theobroma cacao which is characterized by an average height between 4 to 8 meters, and rarely grows up to 20 m. This tree has dark gray bark. Theobroma cacao has leaves that range from 20 to 35 cm long and 6 to 10 cm wide [16], Durio zibethinus which has a height of 20-50 meters with a brown trunk. Durian has leaves with varying lengths and widths. The length of durian leaves ranges from 6-12 cm and the width of the leaves ranges from 2-4 cm [17], Hevea brasiliensis which has an average height of 25-30 meters, but in some cases the height of the tree can exceed 30 meters. Havea brasiliensis mostly has a tall canopy, a distinctive cone-shaped crown, a cylindrical trunk, and a generally enlarged base [18],

Aleurites moluccana is characterized by a height ranging from 10 to 40 meters and a trunk diameter of up to 110 cm [19]. Candlenut has a white, grayish white or slightly dull white dry wood color with a slightly rough texture and has straight fibers usda 2024 and used 1,000 images of four types of needle leaf type trees, namely araucaria heterophyllia which has the characteristics of Trees are described by branches that grow evenly, look like rough needles, forming three-sided vertical lines, pinus merkusii which has the characteristics of tree height reaching 20-40 meters and trunk diameter can reach 100 cm.

The outer bark of the trunk has a rough texture with a brownish gray to dark brown color, cupressus retussa scaly leaves, about 2-6 mm long, arranged crosswise, and can last for three to five years, and sorea javanica overlapping fruit petals and thicker in the middle, has a number of chromosomes x = 7, skin that varies from gray to blackish, with a smooth surface, striated, scaly, to peeling[13]. The image was taken by standing under the tree at a distance of 10-20 cm from the trunk. The initial image dimensions were 1600×1600 pixels.

2.2 Data Labeling

The data used amounted to 3,956 canopy images from 8 tree species (4 broad leaves, 4 needle leaves), each classified into 10 classes. To balance the data when processing the dataset, down sampling and up weighting were carried out on the majority class to 4,000 datasets. Balancing the dataset makes model training easier because it helps prevent the model from being biased towards a class. Density and transparency classes are named from the 1-100% range. For example, if density is 15% and transparency is 95%, each class is named CD15TF95. Tables 1 and 2 are tables containing the number of images per tree type in each density and transparency class.

Table 1. Number of Canopy Density and Transparency Images For Each Type Of Broad Leaf Tree In The Canopy Density and Transparency Classes

Density and Transparency Classes	Number of Images of Density and Transparency of the Crown of Each Type of Broad-leaf Tree			
	Theobroma cacao	Durio zibethinus	Hevea brasiliensis	Aleurites moluccana
CD5FT95	50	50	50	50
CD15FT85	50	50	50	50
CD25FT75	50	50	50	50
CD35FT65	50	50	50	50
CD45FT55	50	50	50	50
CD55FT45	50	50	50	50
CD65FT35	50	50	50	50
CD75FT25	50	50	50	50
CD85FT15	50	50	50	50
CD95FT5	50	50	50	50
Total Per Tree Type	500	500	500	500
Total	2.000			

Table 2. Number of Crown Density and Transparency Images of Each Type of Coniferous Tree In The Crown Density and Transparency Class

Density and Transparency Classes	Number of Images of Density and Transparency of the Canopy of Each Type of Coniferous Tree			
	Araucaria Heterophyllia	Pinus Merkusii	Cupressus Retussa	Sorea Javanica
CD5FT95	50	50	50	50
CD15FT85	50	50	50	50
CD25FT75	50	50	50	50
CD35FT65	50	50	50	50
CD45FT55	50	50	50	50
CD55FT45	50	50	50	50
CD65FT35	50	50	50	50
CD75FT25	50	50	50	50

Density and Transparency Classes	Number of Images of Density and Transparency of the Canopy of Each Type of Coniferous Tree			
	Araucaria Heterophyllia	Pinus Merkusii	Cupressus Retussa	Sorea Javanica
CD85FT15	50	50	50	50
CD95FT5	50	50	50	50
Total Per Tree Type	500	500	500	500
Total	2.000			

2.3 Data Preprocessing

The first step in preprocessing is changing the image dimensions (resize) and increasing the number of images with data augmentation. Resizing is done by changing the image dimensions from 1600 × 1600 pixels to 224 × 224 pixels. Resizing is done to reduce the computational load.

2.4 Data Split

The labeled dataset is then divided into three parts, namely training data, validation data, and test data. This division of the dataset is a validation set method. Training data for broadleaf and needle tree crowns is 70% of each tree type. Validation data for broadleaf and needle tree crowns is 15% of each tree type. Test data for broadleaf tree crowns is 15% of each tree type. Data division uses assistance from the sklearn library. Table 3 explains the results of training, validation, and test data.

Table 3. Number of broadleaf and needle-leaf tree canopy data for each tree type.

Subsets	Number of Tree Head Data of Broad Leaf Type			
	Theobroma Cacao	Durio Zibethinus	Hevea Brasiliensis	Aleurites Moluccana
Training Data	350	350	350	350
Validation Data	75	75	75	75
Test Data	75	75	75	75

Subsets	Number of Tree Head Data of Needle Leaf Type			
	Araucaria Heterophyllia	Pinus Merkusii	Cupressus Retussa	Sorea Javanica
Training Data	350	350	350	350
Validation Data	75	75	75	75
Test Data	75	75	75	75

2.5 EfficientNet Model

This study applies the EfficientNet architecture to image classification tasks. Classification of header images using T4 GPU (Graphics Processing Unit) available on Google Colab online. EfficientNet architecture is used to train each type of tree with several configurations. The determination of the value of each hyperparameter does not have a definite number or type. The number and type of hyperparameters to obtain the appropriate combination can be done through experiments on the training dataset. Table 4 shows the results of the Efficientnet model training.

Table. 4. EfficientNet Model Training Results for Classification of Tree Crown Density and Transparency Values of Broad and Needle Leaves

EfficientNet Model Training Results for Tree Crown Density and Transparency Value Classification	Accuracy	Loss
Training Data	97,68%	61,00%
Validation Data	88,33%	79,92%

2.6 Epoch

Epoch is the result that determines the value of the training process. Epoch is successfully read when the entire training data has been learned by the model in each batch [20]. In Figure 2 there is a visualization of the accuracy and loss of the epochs used.

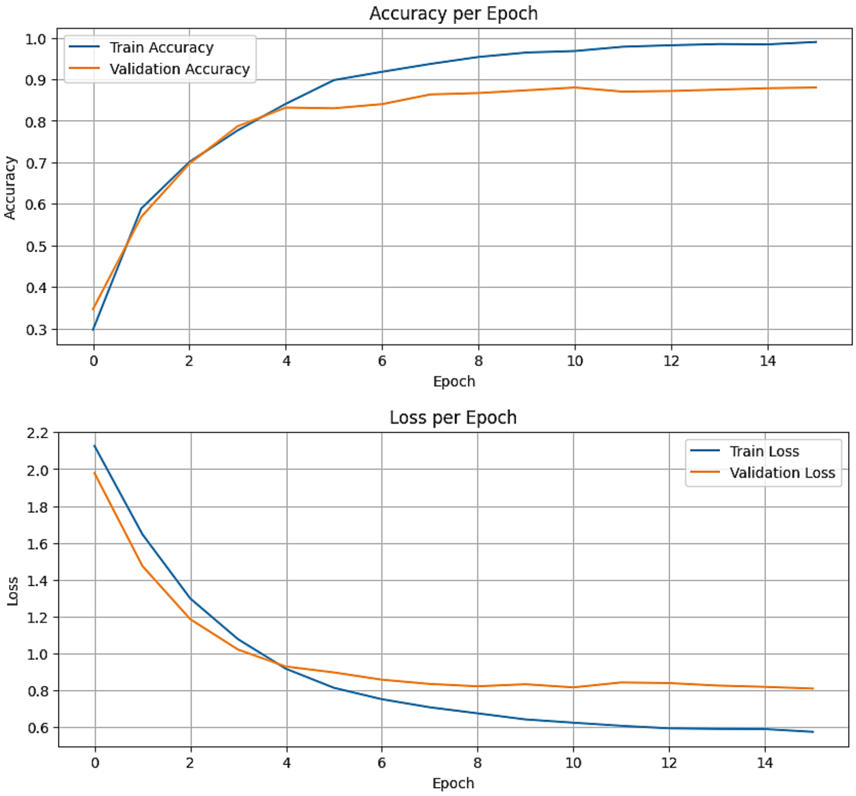

Figure 2. Accuracy and Loss Epoch

4. RESULTS AND ANALYSIS

This research proves that the results of the confusion matrix (see Figure 3) in testing the EfficientNet model for classifying the density and transparency values of broadleaf and needle-leaf tree crowns produce a diagonal shape and successfully read more than 50% of images.

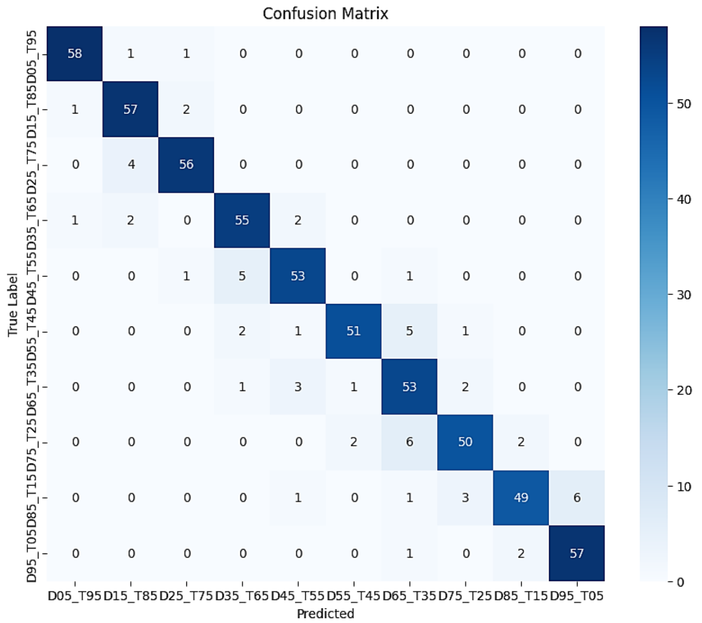

Figure 3. Confusion matrix results in testing the EfficienNet model for classifying the density and transparency values of wide and needle-like tree crowns

Precision, Recall, and F1-Score Results of EfficientNet Model for Tree Crown Density and Transparency Classification can see table 5.

Table 5. Manual calculation results of Precision, Recall, and F1-Score of EfficientNet Model Classification of Tree Crown Density and Transparency Values

Class	TP	FN	FP	TN	Precision	Recall	F1_Score	Accuracy
D05_T95	58	2	3	537	0.9508	0.9666	0.9586	0.9916
D15_T85	57	3	5	535	0.9193	0.9500	0.9344	0.9866
D25_T75	56	3	8	532	0.8769	0.9500	0.9120	0.9816
D35_T65	55	6	6	534	0.9000	0.9000	0.9000	0.9800
D45_T55	53	9	2	538	0.9622	0.8500	0.9026	0.9816
D55_T45	51	9	11	529	0.8225	0.8500	0.8360	0.9666
D65_T35	53	8	6	534	0.8965	0.8666	0.8813	0.9766
D75_T25	50	9	4	536	0.9272	0.8500	0.8869	0.9783
D85_T15	49	8	7	533	0.8813	0.8666	0.8739	0.9750
D95_T05	57	3	5	535	0.9193	0.9500	0.9344	0.9866
Average					0.9056	0.9000	0.9020	0.8983

The confusion matrix calculation is the result of object classification and error generated by the model. The number of correct and incorrect predictions will be calculated in the confusion matrix and then produce an overall prediction for each class. Confusion matrix consists of accuracy, precision, recall, and f1-score. Confusion matrix has an assessment measure through four main matrices, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [21]. Can be seen in Table 5 and compare the results of the EfficientNet model with previous research on tree crown density classification and transparency values in Table 6.

Table 6. Results of the EfficientNet Model with previous research on Tree Crown Density and Transparency Value Classification

No.	Result	Research	Sofiyana[11]	Tarigan[13]
1.	Dataset	3.965	2.965	1.000
2.	Class	10 classes	10 classes	10 classes
3.	Tree Types	8 Tree Types	4 Tree Types	4 Tree Types
4.	Architecture	EfficientNet	MobileNet	VGG-16
5.	Accuracy average	98.05%	74.785%	94.25%

5. CONCLUSION

The development of the EfficienNet model for classifying broadleaf and coniferous tree canopy density and transparency values yielded a training data accuracy of 97.68%, a validation data accuracy of 88.33%, and a test data accuracy of 90.00%. The classification model for broad and needles leaved and coniferous tree canopy density and transparency values yielded a training data loss of 61.00% and a validation data loss of 79.92%. This demonstrates EfficienNet's ability to be used for classification. Other factors influencing the model's performance in classifying density and transparency values are the hyperparameters and model structure used. These hyperparameters and model structure were obtained through a fine-tuning process. Experiments conducted using the most optimal hyperparameter configuration and model structure, although the resulting model failed to overcome overfitting.

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