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GreenEye: Plant Classification Using MobileNet V2

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ABSTRACT

Biodiversity in Indonesia includes more than 30,000 species of plantsand mushrooms, but public knowledge about these plants is still limited. The research aims to develop a mobile application called GreenEye that uses machine learning to detect and classify plants based on images. The model used is based on the MobileNet V2 architecture, a type of Convolutional Neural Network (CNN) designed for high-efficiency image classification tasks. Research data collected from PlantNet and Google Images, consisting of 2800 images covering seven plant species: Ananas comosus, Artocarpus heterophyllus, Carica papaya, Cocos nucifera, Musa spp, Nephelium lappaceum, and Salacca zalacca. Each species is categorized into four plant parts: fruit, flower, leaf, and habit. (habitus). This data is then processed through various preprocessing stages such as data cleaning, format conversion, resizing, cropping, and image augmentation. The results showed that the MobileNet V2 model was able to classify parts of plants with high accuracy, especially on fruits and leaves with accurations above 90%. However, the accuration was slightly lower for flowers and habits, which is about 70%. Classification errors occurred mainly in species with high visual similarities. To improve the performance of the model, it is recommended that further research increase the quantity and diversity of datasets.

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1. INTRODUCTION

The World Plants website notes that by 30 June 2024, the number of plant species scattered around the world is about 350,000 species. Of that number, it is highly likely that there are still other species of plants that have not been recorded and not yet discovered by humans. Each of these recorded plants has a scientific name that is usually taken from Latin, such as Carica Papaya, which is the Latin name of the papaya.

In Indonesia itself, the variety of these plants must be enormous. Source records [1]state that there are about 30,000 species of plants and mushrooms in Indonesia. But the absence of a checklist of these plants led to the presence of a website called Digital Flora of Indonesia where the plants were made their checklist.

With so many kinds of plants out there, not everyone knows about the plants. Whether it's beneficial, useful, or just the name of the plant, people don't know. Whether it's a plant that's hard to find or that grows around. Knowledge about this plant is important enough to know. As a simple example, plants that are ingredients such as ginger, turmeric and others have benefits to boost the body's immunity [2].

To help people get to know the plants better, this research will develop an app called GreenEye. It is mobile-based and uses machine learning. In this application, users can detect plants using images, then the model will classify the plants and provide the information available. It is hoped that people will be easier and more familiar with the plants that are around them and know the benefits or dangers. The machine learning model to be created is based on the MobileNet V2 architecture that includes the type of Convolutional Neural Network architecture (CNN) [3], [4].

Before this research was carried out, there must have been some previous research. There is research focused on the detection of plant diseases on leaves using the Deep Learning technique CNN [5]. The model in the study is used to classify and detect plant disease present in leaves. The accuracy achieved is quite high, up to 90% for each training and test dataset.

In other studies, CNN's algorithm was combined with two algorithms, the Support Vector Machine (SVM) and the k-Nearest Neighbours (KNN) [6]. The data set on the research to classify these plants focuses only on the leaf part alone. The accuracy results were 99.5%, 97.4%, and 80.04% for the three types of datasets.

Other research on plant detection has also been carried out with the creation of models based on the combination of Select Kernel Network and MobileNet V2 [7]. This study is the same as the previous one [5], aimed at detecting diseases in plants with leaf images as their datasets. The accuracy achieved is very high at 99.28%.

2. METHOD

The research was conducted in a phase-by-phase manner so that the expected implementation of machine learning could be realized. The phase begins with data collection until defining the final model for plant image classification.

2.1 Data

The data used in this study is collected from PlantNet and Google Images. The total data collected is 2800 images, consisting of different plant species.

Table 1. Fruit, Flower, Leaf, and Habit Class

Plant Class
Ananas comosus (Nanas)
Artocarpus heterophyllus (Nangka)
Carica papaya (Pepaya)
Cocos nucifera (Kelapa)
Musa spp (Pisang)
Nephelium lappaceum (Rambutan)
Salacca zalacca (Salak)

The image data that has been collected is divided into 7 classes based on plant species as shown in Table 1. Each species is then further categorized into 4 plant parts: fruit, flower, leaf, and habit, so each section has 7 different classes.

Table 2. Organs Class

Plant Organs Class
Fruit
Flower
Leaf
Habit

Of all seven species, parts of fruit, flower, leaf, and habit were taken to do the classification of plant parts. This data is then categorized into 4 main classes as shown in Table 2. Each class contains a picture of each part of the plant in each species for classification purposes.

2.2 Preprocessing

The preprocessing phase is carried out to ensure optimal image data quality before using it in model training [8], [9]. Out of the 2800 image data collected, some of the main steps of preprocecing are as follows:

a. Data Cleaning, removing irrelevant, low quality, or duplicate images to ensure only appropriate and high quality images are used.

b. Conversion format, images converted to JPG format to ensure consistency of file formats to be further processed.
c. Resizing and Cropping, images resized and croped with a 1:1 ratio aspect to ensure the consistencies of size and proportions to be used in model training.
d. Image Augmentation, in addition to the above steps, also performed data augmentation using the ImageDataGenerator function of Hard with the following parameters:

```
train_datagen =
       ImageDataGenerator(
       rescale=1.0/255,
       rotation_range=40,
       width_shift_range=0.2,
       height_shift_range=0.2,
       shear_range=0.2,
       zoom_range=0.2,
       horizontal_flip=True,
       fill_mode='nearest'
)
```

2.3 Classification Process

In this study, it used Convolutional Neural Network (CNN) with the MobileNet V2 architecture. MobileNET V2 was specially designed for image classification and generic characterization tasks using residual bottleneck [10]. The architecture divides the convolution into two main parts: Depthwise Convolution and Pointwise Convention. Then, added Linear Bottleneck and Shortcut Connection features [11], as shown in Figure 1.

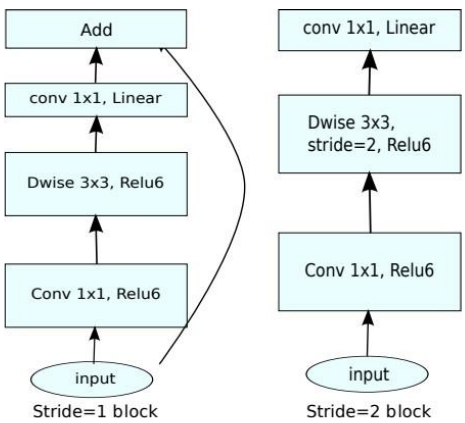

Figure 1. MobileNet V2 Architecture

The MobileNet V2 architecture consists of two main blocks: Stride=1 Block and Stride=2 Block. On Stride =1 Block, there are several convolution layers that start with Conv 1x1, Relu6, followed by Depthwise 3x3, Relu 6, then Conv1x1, Linear, and finally the Add layer that adds the result of the previous layer. Meanwhile, on Strid=2 Block there are 1x1 Conv layers, Relu6 layers which follow by 3x3 Deepwise, stride=2, Relu6.

These features make the training process more efficient and improve the model accuracy [12]. With a Shortcut Connection, MobileNet V2 is able to maintain important information throughout the network and reduce the problem of vanishing gradients. Meanwhile, Linear Bottleneck helps in reducing the dimension of features without losing important information.

2.4 Evaluation

After the model is trained with MobileNet V2, the next step is to evaluate the model through the Confusion Matrix and the Classification Report. In the confusion matrix, the performance of the machine learning method is measured to determine how many models can correctly predict according to the specified class [13].

Evaluations on this model were also performed using the Classification Report that can be seen in

Table 3. Classifications report looked at the great accuracy values of the correct prediction of all the images on the dataset. A good performance has accurations close to the number 1, and vice versa [14]. In addition to accuracy values, there are also precision, recall, and f1-score. Precision is a positive true prediction with an overall predicted positive outcome, while recall is a positive true prediction ratio compared to the total true data and f1-score is the average comparison of precision and recall weighed [15].

3. RESULTS AND DISCUSSION

The research was carried out using about 2800 photographs of 7 plant species and 4 plant parts in the machine learning model. This is done so that the model is not confused with the variety of data that needs to be identified with minimal datasets.

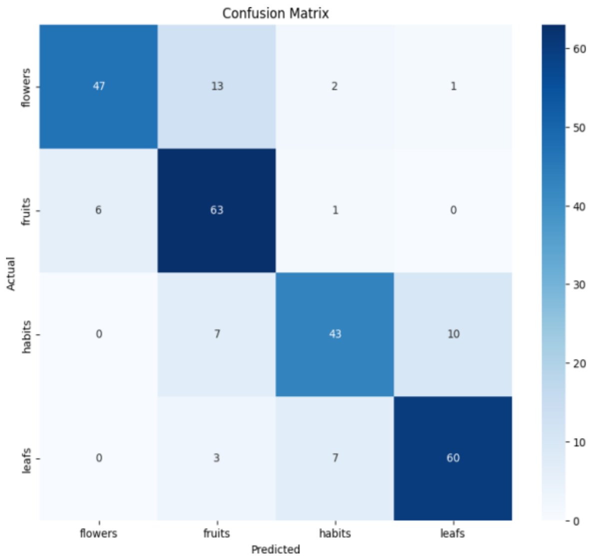

Figure 2. Organs Model Confusion Matrix

The organs model demonstrates its ability to recognize parts of plants well, especially fruit and leafs, with accuracy above 90%. However, for flowers and habits parts, the model accurateness is slightly lower, i.e. is around above 70%.

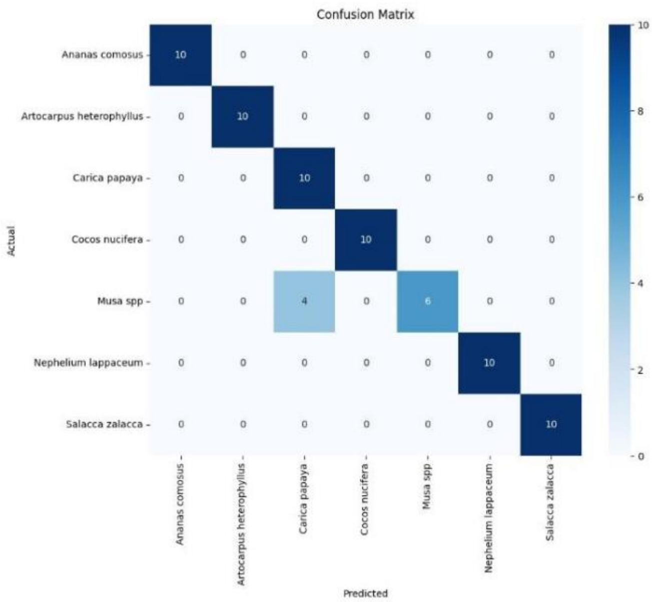

Figure 3. Fruit Model Confusion Matrix

The fruit model is able to classify plants by fruit very well, except for the Musa Spp type, sometimes known as the Carica Papaya.

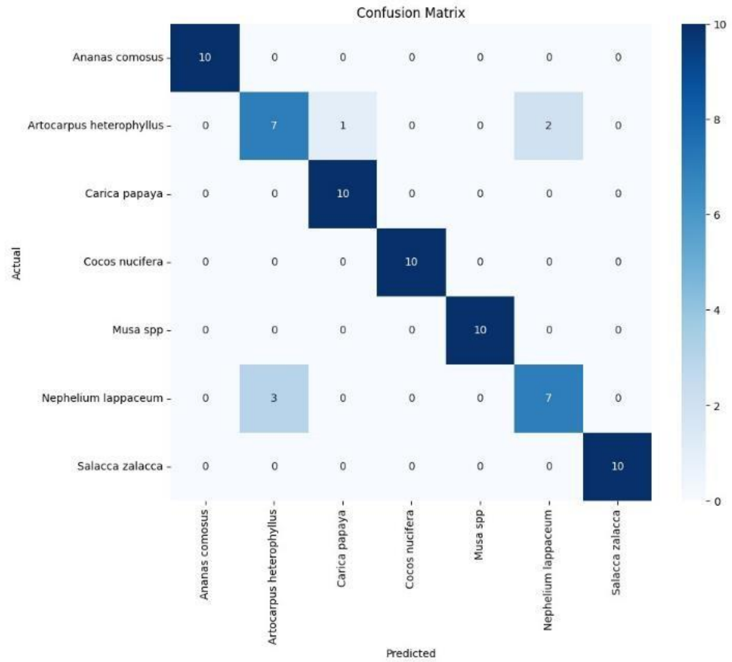

Figure 4. Leaf Model Confusion Matrix

The leaf model is able to classify plants based on leaves well with accuracy above 90%, except for the species Artocarpus heterophyllus and Nephelium lappaceum that have accurations just above 70%.

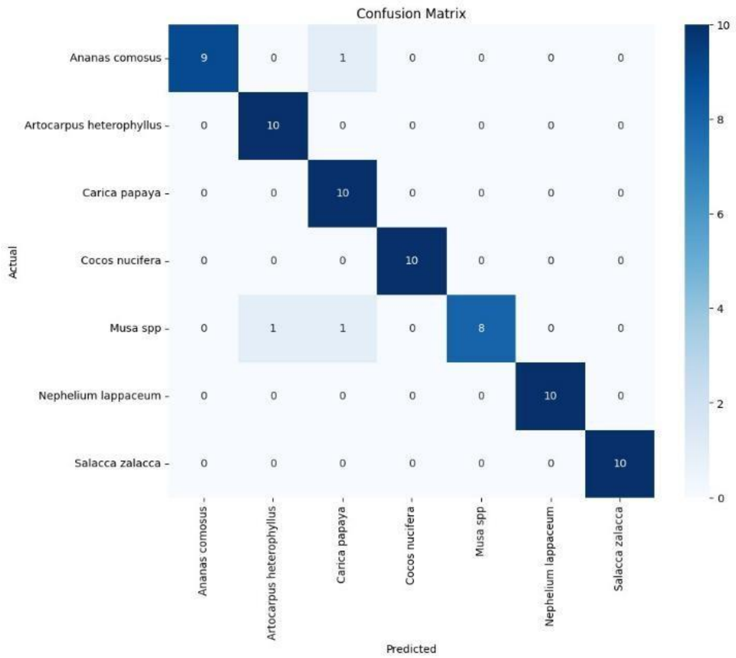

Figure 5. Flower Model Confusion Matrix

The flower classification model demonstrates strong performance across all plant species, achieving an average accuracy exceeding 90%. As shown in Figure 5, the confusion matrix reveals that most flower samples are correctly classified into their respective species, with only a small number of misclassifications. This indicates that flower-related visual features, such as shape, color patterns, and structural characteristics, are effectively learned by the model, resulting in high classification reliability.

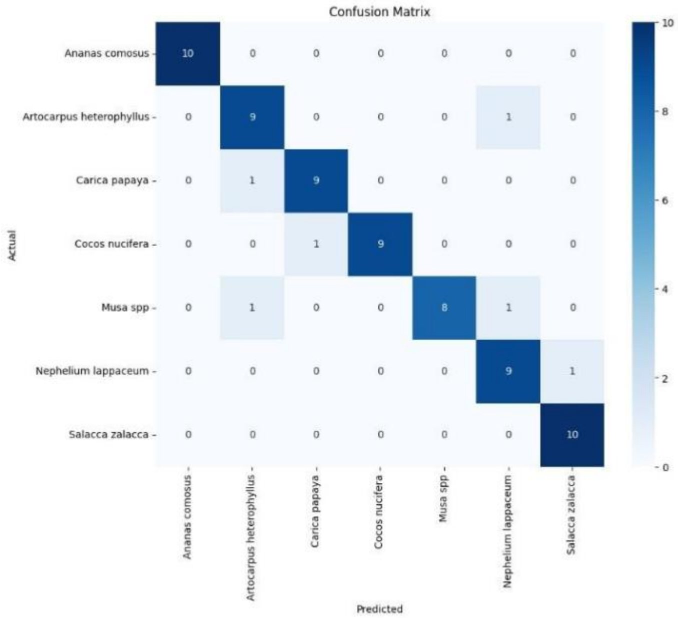

Figure 6. Habit Model Confusion Matrix

The habit model was able to classify plants by habitat (the entire plant part) very well. The most optimal model is one for recognizing flower models with an accuracy of up to 96%. The results obtained had an average accuracy of over 90% in all species. It shows in the table 3.

Table 3. Machine Learning Model Performance

Model	Accuracy	Precision	Recall	F1-Score
Organs	0,81	0,82	0,8	0,81
Fruit	0,94	0,96	0,94	0,94
Leaf	0,91	0,91	0,91	0,91
Flower	0,96	0,96	0,96	0,96
Habit	0,91	0,92	0,91	0,91

In other performance parameters, such as precision, recall, and F1-Score, high results are seen for each plant species. This is due to the unique shape and color of each species, which makes it a distinctive sign that makes it easy for the model to recognize each existing species.

Based on the model performance data as well as the confusion matrix image given, MobileNetV2 demonstrates its superiority in the classification of plant image tasks. All models have accuracy levels above 90%. The results show that there are some species that have been misclassified, such as Musa Spp (Pisang) which is thought to be Carica Papaya (Pepaya) on the fruit model or Nephelium Lappaceum (Rambutan) that is believed to be Artocarpus Heterophyllus (Number) in the leaf model.

4. CONCLUSION

This research successfully showed that MobileNetV2 can be used to recognize different parts of plants with a high degree of accuracy. Organs, fruit, leaf, flower and habit models show good performance in classifying plant images with an average accuracy above 90%. Organs models show best performance on fruit and leaf identification, but slightly lower on flowers and habits identification. Fruits and flower models show excellent performance with high precision, recall, and F1-Score values, due to the visual characteristics of fruit and flowers in each species.

In this study, we found classification errors in species that have a high degree of similarity. Among them are Moses Spp and Carica Papaya on the fruit model, as well as Nephelium Lappaceum and Artocarpus Heterophyllus on the leaf model. This error suggests the need for larger and more diverse datasets to improve model accuracy in classifying plants with high visual similarities.

The recommendation for further research is to increase the number of datasets and use a more diverse dataset, then add classifiable plant classes and improve the accuracy of the organs model. This step is expected to improve the performance of the model, especially in classifying species with high levels of visual similarity.

REFERENCES

[1] Retnowati, Rugayah, J. S. Rahajoe, and D. Arifiani, *Status Keanekaragaman Hayati Indonesia: Kekayaan Jenis Tumbuhan dan Jamur Indonesia*. Jakarta, Indonesia: LIPI Press, 2019. [Online]. Available: https://penerbit.brin.go.id/press/catalog/view/206/193/403

[2] R. Pertiwi, D. Notriawan, and R. H. Wibowo, "Pemanfaatan Tanaman Obat Keluarga (TOGA) Meningkatkan Imunitas Tubuh sebagai Pencegahan COVID-19," *DR*, vol. 18, no. 2, pp. 110–118, Dec. 2020.

[3] Q. Xiang, G. Zhang, X. Wang, J. Lai, R. Li, and Q. Hu, "Fruit image classification based on Mobilenetv2 with transfer learning technique," *ACM International Conference Proceeding Series*, Oct. 2019, doi: 10.1145/3331453.3361658.

[4] Y. Gulzar, "Fruit Image Classification Model Based on MobileNetV2 with Deep Transfer Learning Technique," *Sustainability 2023, Vol. 15, Page 1906*, vol. 15, no. 3, p. 1906, Jan. 2023, doi: 10.3390/su15031906.

[5] M. A. Jasim and J. M. AL-Tuwaijari, "Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques," in *2020 International Conference on Computer Science and Software Engineering (CSASE)*, 2020, pp. 259–265. doi: 10.1109/CSASE48920.2020.9142097.

[6] S. Ghosh, A. Singh, Kavita, N. Z. Jhanjhi, M. Masud, and S. Aljahdali, "SVM and KNN Based CNN Architectures for Plant Classification," *Computers, Materials and Continua*, vol. 71, no. 2, pp. 4257–4274, 2022, doi: 10.32604/cmc.2022.023414.

[7] G. Liu, J. Peng, and A. A. A. El-Latif, "SK-MobileNet: A Lightweight Adaptive Network Based on Complex Deep Transfer Learning for Plant Disease Recognition," *Arab. J. Sci. Eng.*, vol. 48, no. 2, pp. 1661–1675, 2023, doi: 10.1007/s13369-022-06987-z.

[8] D. Tribuana, Hazriani, and A. L. Arda, "Image Preprocessing Approaches Toward Better Learning Performance with CNN," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 8, no. 1, pp. 1–9, Jan. 2024, doi: 10.29207/resti.v8i1.5417.

[9] G. I. Ivan, A. I. Elizarov, and S. V. Artyom, "Image processing methods to increase the distinguishability of objects," *https://doi.org/10.1117/12.2688653*, vol. 12780, pp. 68–71, Oct. 2023, doi: 10.1117/12.2688653.

[10] C. H. Karadal, M. C. Kaya, T. Tuncer, S. Dogan, and U. R. Acharya, "Automated classification of remote sensing images using multileveled MobileNetV2 and DWT techniques," *Expert Syst. Appl.*, vol. 185, p. 115659, 2021, doi: 10.1016/j.eswa.2021.115659.

[11] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 4510–4520. doi: 10.1109/CVPR.2018.00474.

[12] P. Nagrath, R. Jain, A. Madan, R. Arora, P. Kataria, and J. Hemanth, "SSDMNV2: A real-time DNN-based face mask detection system using single shot multibox detector and MobileNetV2," *Sustain. Cities Soc.*, vol. 66, p. 102692, 2021, doi: 10.1016/j.scs.2020.102692.

[13] M. Koklu, I. Cinar, and Y. S. Taspinar, "Classification of rice varieties with deep learning methods," *Comput. Electron. Agric.*, vol. 187, p. 106285, 2021, doi: 10.1016/j.compag.2021.106285.

[14] S. Ramesh and D. Vydeki, "Application of machine learning in detection of blast disease in south indian rice crops," *Journal of Phytology*, vol. 11, pp. 31–37, 2019, doi: 10.25081/jp.2019.v11.5476.

[15] A. Sagar and J. Dheeba, "On Using Transfer Learning For Plant Disease Detection," *bioRxiv*, 2020, doi: 10.13140/RG.2.2.12224.15360/1.