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# HERBAL LEAF CLASSIFICATION USING DEEP LEARNING MODEL EFFICIENTNETV2B0

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***Abstract****—Science regarding plants has experienced significant progress, especially in the study of medicinal plants. Medicinal plants have been used in medicine and are still an important component in the world of health today. Among the various parts of the plant, the leaves are also one that can be used as medicine. However, not many people can recognize these herbal leaves directly. This is because the herbal leaves at first glance look almost the same, so it is difficult to differentiate them. The aim of this research is to classify herbal leaf images by identifying the structural features of the leaf images. The dataset in this study uses 10 classes of leaf images, namely, starfruit, guava, lime, basil, aloe vera, jackfruit, pandan, papaya, celery, and betel, where each class uses 350 images with a total of 3500 images of data. The EfficientNetV2B0 model was chosen because it has a minimalist architecture but has high effectiveness. Based on the results of research using the EffiecientNetV2B0 model, the accuracy was 99.14% and the loss value was 1.95% using test data.*

***Keywords****: classification, CNN EfficientNetV2B0, deep learning, herbal leaves.*

**Intisari**—*Ilmu pengetahuan mengenai tanaman telah mengalami kemajuan signifikan, terutama dalam kajian tentang tanaman obat. Tanaman obat telah dimanfaatkan dalam pengobatan dan masih tetap menjadi komponen penting dalam dunia kesehatan saat ini. Di antara berbagai bagian tanaman, daunnya juga merupakan salah satu yang dapat digunakan sebagai obat. Namun, tidak banyak orang yang dapat mengenali daun herbal tersebut secara langsung. Hal ini dikarenakan daun herbal sekilas terlihat hampir sama, sehingga sulit untuk membedakannya. Tujuan dari penelitian ini adalah mengklasifikasikan citra daun herbal dengan mengidentifikasi ciri bentuk struktural dari citra daun tersebut. Dataset pada penelitian ini menggunakan10 kelas citra daun yaitu, blimbing wuluh, jambu biji, jeruk nipis, kemangi, lidah buaya, nangka, pandan, pepaya, seledri, dan sirih, dimana setiap kelas menggunakan 350 citra dengan total data yaitu 3500 citra. Model EfficientNetV2B0 dipilih karena memiliki arsitektur minimalis namun memiliki efektivitas yang tinggi. Berdasarkan hasil penelitian menggunakan model EffiecientNetV2B0 mendapatkan accuracy sebesar 99.14% dan nilai loss sebesar 1.95% menggunakan data test.*

***Kata Kunci****: klasifikasi, CNN EfficientNetV2B0, deep learning, daun herbal.*

## INTRODUCTION

Herbal plants have long been known as health plants that have many benefits, from ancient times to the present. Apart from being used as medicine, herbal plants can also be used for body care [1]. How to recognize herbal plants is done by identifying the structural characteristics of the leaves such as leaf shape and texture [2]. Data from the World Health Organization (WHO) states that the use of herbal plants in developed countries reaches 65% to 80%, while in developing countries the average reaches 80% [3].

All elements of the plant can be used as medicinal ingredients, including the leaves. Leaves are plant components that grow on branches, generally green in color and function to capture energy from sunlight for the photosynthesis process. Clinical research has proven that the vitamins, minerals, and antioxidants included in leaves help people keep their health in check [4]. The government through the Ministry of Health has issued "Decree of the Minister of Health of the Republic of Indonesia Number HK.01.07/Menkes/187/2017" concerning "Indonesian Traditional Medicine Formulary". According to the Ministerial Decree, there are several types of leaves identified as components in traditional or herbal medicines. However, some people in society still do not properly recognize the types of leaves that fall into the herbal or traditional medicine category. The difficulty lies in the visual similarity of the leaves which makes distinguishing them difficult [5].

The topic of digital image processing covers the study of how pictures are made, handled, and

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evaluated to yield valuable information [6]. Classification is one use for image processing. Image classification involves steps to group pixels or image elements of an image into certain classes so that they can be identified [7].

In a similar study, leaf image identification on citrus plants was carried out using the Local Binary Pattern Histogram (LBPH) method with 6 amounts of test data. The leaf image identification process was carried out by analyzing the structural characteristics of orange leaves using shape and texture extraction [8].

Another approach that can be utilized in completing image classification is using the deep learning method, which is a computational model that adopts the working pattern of human neural networks, employing numerous layers of non-linear processing units for feature extraction and manipulation [9]. Similar to other studies, which used the Convolutional Neural Network (CNN) deep learning model with the EfficientNetB3 architecture to classify rice plant illnesses, the results showed an accuracy of 99% on testing data and a training loss value of 0.012 [10]. The highest accuracy value was obtained at the 30th epoch.

In other research, the use of the Visual Geometry Group (VGG)16 method which was integrated with the Image Data Generator augmentation technique obtained accuracy results of 96.73%, and training loss of 0.097 at the 100th epoch [11], and if the augmentation process was not used then reducing the accuracy value to 96%.

Apart from EfficientnetB3 and VGG16, there is another architecture for the CNN deep learning model, namely EfficientNetV2B0, which is part of the EfficientNetV2 family and was designed by the Google Brain team [12]. The EfficientNetV2 model was created to have faster training times and more efficient parameters than previous models [13]. The CNN EfficientNetV2B0 architecture model has been implemented in research with a case study of early detection of queuing pressure at the entrance to an event, where this research uses moving image or video data in real time [14]. The experimental results in this research were able to identify visitor queue pushing behavior with an accuracy rate of 87%, and when compared to the EfficientNetV1B0 model, it got an accuracy of 83% [15]. EfficientNetV2B0 itself has the advantage of forming a much smaller model and faster convergence speed with minimal computing costs.

Based on previous research, VGG16 architecture has the advantage of high image classification accuracy, but has the disadvantage of being computationally heavy and slow due to the large number of parameters [16]. Therefore, in this study we implemented the EfficientNetV2B0 architecture which is specifically designed to cover the shortcomings of VGG16. EfficientNetV2B0 is able to maintain computational efficiency by using far fewer parameters, as well as providing more optimal results on the same large dataset [17]. In this research, digital image classification of herbal leaves will be carried out using the EfficientNetV2B0 architecture, making it easier for someone to recognize and obtain information about the type of herbal leaf, with the use of modern technological advancements, particularly for individuals without specialized botany knowledge. The author uses the Adaptive Moment Estimation optimizer or known as Adam, which is an adaptive learning rate method for optimizing the values of each layer to produce accurate predictions [18].

## MATERIALS AND METHODS

In this research, there were 4 stages carried out, namely dataset collection, pre-processing, deep learning modeling and evaluation. The following is the research flow as presented in Figure 1.

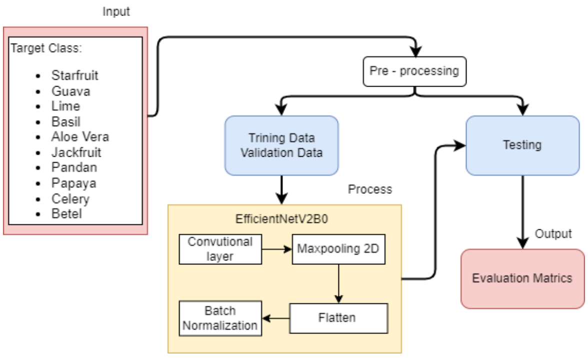


Figure 1. Design Research Flow Diagram

A. Dataset

The dataset used is images of herbal leaves in Indonesia [19]. This dataset consists of 10 categories or classes, namely starfruit, guava, lime, basil, aloe vera, jackfruit, pandan, papaya, celery, and betel, as can be seen in Figure 2. Each class or category has a total of 350 images, so the entire dataset has 3500 images of herbal leaves. The image format is in ".jpg" form and the initial dimensions of each image are 1600x1200 pixels.


Figure 2. Dataset for Each Leaf Category


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B. Pre-processing

At this stage, the data which has dimensions of 1600x1200 pixels is subjected to an image resizing process to reduce the dimensions of the data to a size of 224x224 pixels without eliminating various features in the image. Another goal of image resizing is to speed up computing time during training. The size of 224x224 pixels was chosen because it matches the input shape of the EfficientNet architecture [20]. Following pre-processing, the data is separated into test, validation, and training sets. This dataset is separated into three categories: 80% of the data are training data, 10% are validation data, and 10% are test data. The total amount of data in this dataset is 3500 data. Validation data is used to confirm through testing based on the dataset that has been studied in the training stage.

C. EfficientNetV2B0

CNN is a network that has a 3-dimensional MxNxC neuron arrangement (M width, N height, C channel) which was designed to overcome the problem of overfitting. Overfitting occurs when the system loses the ability to recognize general patterns and is only able to recognize training data. This is often caused by a network architecture that is too complex or by too many iterations in the system.

Other CNN architectures often require the use of a large number of parameters and are also accompanied by a fairly large dataset. This requires quite large computing resources and long training times [21]. Further experiments are needed using the latest CNN models as carried out in research [22] using EfficientNetV2B0, which updates the previous architecture, EfficientNet. A novel convolutional neural network (CNN) model, EfficientNetV2 outperforms its predecessors in terms of parameter efficiency and training speed [23]. This study builds on earlier work by [24] and aims to use EfficientNetV2B0 to categorize the stages of Ambarella fruit development.

EfficientNetV2B0 is a type of CNN architecture that uses compound scaling techniques to enable better performance. Through a reduction in the number of parameters and Floating point Operations Per Second (FLOPs), EfficientNetV2B0 seeks to increase computational efficiency while improving performance [25]. Table 1 illustrates how contemporary research, although claiming significant gains in training or inference performance, frequently outperform EfficientNet in terms of FLOPs parameters and efficiency [26].

Table 1. Performance Comparison of CNN Architectures

| | Accuracy(%) | Parameter (M) | FLOPs (B) |
|---|---|---|---|
| EfficientNetV2B0 [16] | 84.6 | 43 | 19 |
| ResNet-RS-420 [27] | 84.4 | 192 | 64 |
| NFNet-F1[28] | 84.7 | 193 | 36 |

The EfficientNetV2B0 model is proven to be able to outperform other models only by using fewer parameters [29], A modest number of parameters will expedite the classification process and shorten the model's overall training time. The EfficientNetV2B0 model's design can be seen in Figure 3.

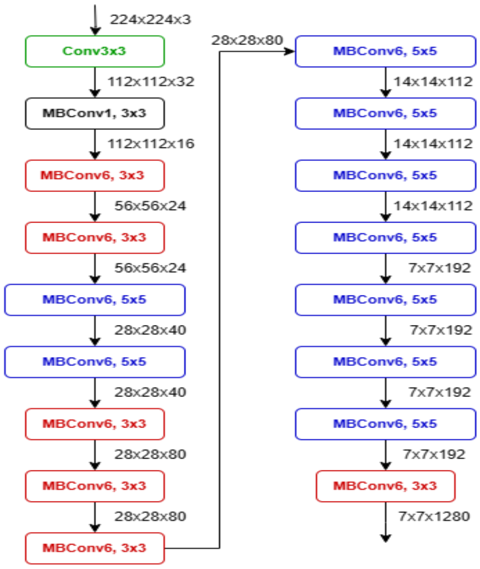

Figure 3. EfficientNetV2B0 Model Architecture

In the EfficientNetV2B0 model, an output layer will be added to adjust the number of target classes in the dataset used. Before the output layer, 2 layers are also added to reduce overfitting so that we can get better results. As well as adding MaxPooling2D, Flatten, and Batch Normalization as additional layers to the model created. The function of MaxPooling2D is to reduce the spatial dimensions of the feature representation produced by the previous layer [30]. Then Flatten functions to change the multidimensional feature representation into a one-dimensional vector so that the layers become fully-connected [31]. Batch Normalization helps in speeding up training and has a function similar to L2 Regularization in dealing with overfitting [32]. The entire model can be seen in Figure 4.

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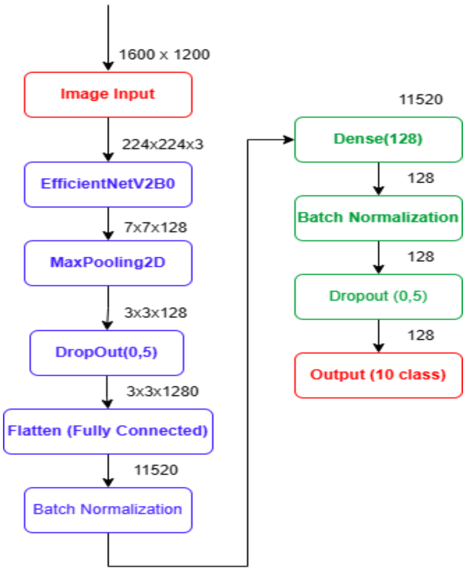


Figure 4. EfficientNetV2B0 Model Architecture After Adding Layers

D. Evaluation

Equation (1) describes precision values; equation (2) recall values; equation (3) accuracy values; and equation (4) the F1-Score value. The Confusion Matrix is a predictive analytical tool that shows and compares actual values with predicted model values. It can be used to produce evaluation metrics such as these. The confusion matrix table yields four values: False Positive (FP), True Positive (TP), False Negative (FN), and True Negative (TN).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \tag{3}$$

$$\text{F1} - \text{Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{4}$$

## RESULTS AND DISCUSSION

In this research, the Tensorflow library was chosen to create a Deep Learning model. Tensorflow has the advantage of being comprehensive in various APIs for creating models. Tensorflow also provides a basic model of EfficientNetV2B0. The training process uses 10 classes of herbal leaves including Starfruit, Guava, Lime, Basil, Aloe Vera, Jackfruit, Pandan, Papaya, Celery and Betel as classification tests. The model in this research was run using the M1 GPU with the 'adam' optimizer. learning rate = 0.001, batch size = 128 and epoch = 30.

A. Model Accuracy Evaluation

During training, validation data is used as a measurement at each epoch. The measurements are used as a reference to measure the accuracy of the model being developed. The following is a graph of accuracy results using the EfficientNetV2B0 model which can be seen in Figure 5.

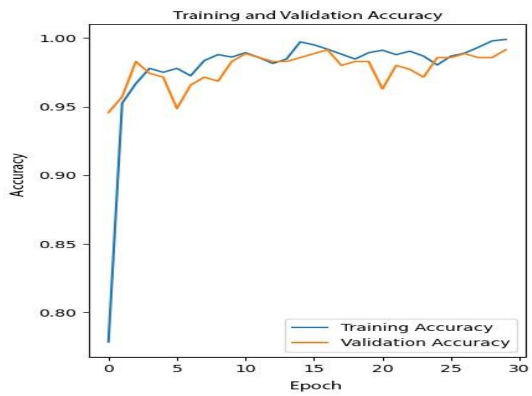


Figure 5. EfficientNetV2B0 Model Accuracy Graph

Based on the graph above, training accuracy and validation accuracy show less stable results or experience fluctuations, especially on the validation accuracy line. This is caused by several things, one of which is a lack of data so that the model lacks information to learn patterns. However, it can be seen that in the 30th epoch, both the accuracy values in training and validation have started to stabilize and are moving towards linear. The training results from the graph above obtained the highest accuracy of 99.89% using the training data and 99.14% using the validation data.

B. Model Loss Evaluation

The training accuracy value is inversely related to the loss value. The resulting loss value decreases with increasing precision. Thus, it is preferable if the loss value achieved is smaller.

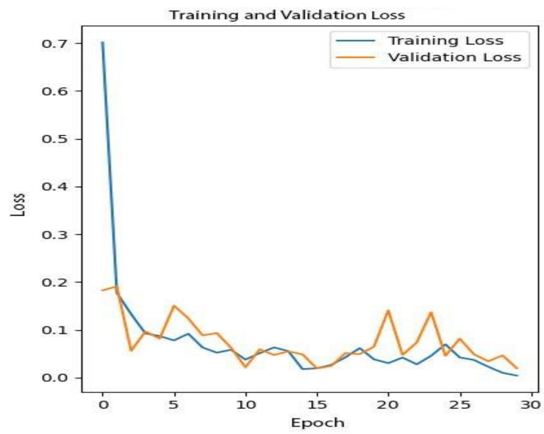


Figure 6. EfficientNetV2B0 Model Loss Graph



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In Figure 6, training loss and validation loss show quite good results, where the training and validation lines are not too far apart or can be said to be overfitting. Although the validation loss line experiences slight fluctuations, it is the same as the previous validation accuracy line. The training results of the EfficientNetV2B0 model obtained a loss value of 0.42% using the training data and 1.95% using the validation data.

The early stopping technique is used to stop the model training process before it reaches the overfitting point. In both evaluations, both accuracy and loss values were able to reach their optimal values up to the 30th epoch.

C. Confusion Matrix Evaluation

To evaluate the efficacy of this classification model, we created a confusion matrix from the validation data, as shown in Figure 7, which compares the expected and observed values, so that we can measure the developed model appropriately.

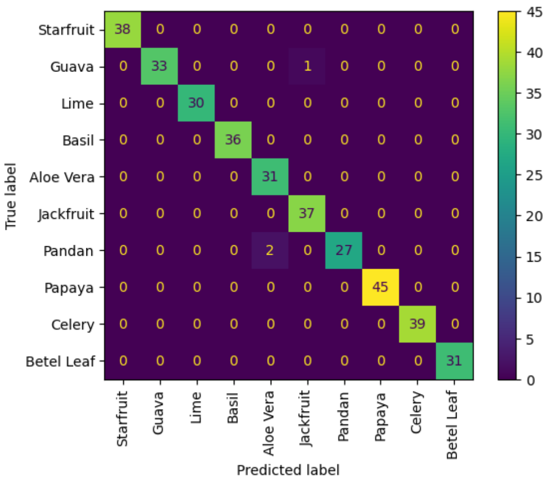


Figure 7. Confusion Matrix Table

Figure 7 shows It's very good results where the highest value of error or discrepancy between the true label and predicted label is only 2. This is directly proportional to the results of the confusion matrix which is said to be very good hen the error value is close to 0.

D. Comparative Evaluation of Previous Research

The evaluation results of this research on test data using the EfficientNetV2B0 architecture, obtained an accuracy value of 99.14% and a loss value of 1.95%, where these results were able to outperform the evaluation results obtained by previous research using the VGG16 + Data Augmentation architecture [11]. Apart from that, the loss comparison resulting from this research is quite low due to the addition of the MaxPooling2D, Batch Normalization, Flatten layers. More detailed comparisons can be seen in Table 2.

Table 2. Comparison of Accuracy Values

| | VGG16 + Augmentasi (%) | EfficientNetV2B0 (%) |
|---|---|---|
| Accuracy | 96.00 | 99.14 |
| Loss | 9.75 | 1.95 |

Apart from the difference in accuracy and loss values, another finding that was obtained was that the average epoch value that could produce the highest accuracy on the EfficientNetV2B0 architecture used in the research was 30, while the average epoch value in previous research was 100. Even though the accuracy value for both designs The architecture is not much different, but in terms of effectiveness in forming models from the training data used, EfficientNetV2B0 is far superior as proven by the lower epoch value obtained.

The assessment findings of the VGG16 architectural model were surpassed by the comparative results of recall, precision, and average F1-score of EfficientNetV2B0; Table 3 displays the full results.

Table 3. Comparison of recall, precision and F1-score values

| Herbal Leaves Category | Recall | | Precision | | F1-score | |
|---|---|---|---|---|---|---|
| | VGG 16 | Efficient NetV2 B0 | VGG16 | Efficient NetV2 B0 | VGG16 | Efficient NetV2 B0 |
| Starfruit | 1.00 | 1.00 | 0.80 | 1.00 | 0.89 | 1.00 |
| Guava | 0.97 | 0.97 | 0.97 | 1.00 | 0.97 | 0.99 |
| Lime | 1.00 | 1.00 | 0.97 | 1.00 | 0.93 | 1.00 |
| Basil | 0.92 | 1.00 | 1.00 | 1.00 | 0.96 | 1.00 |
| Aloe Vera | 0.97 | 1.00 | 1.00 | 0.94 | 1.00 | 0.97 |
| Jackfruit | 0.97 | 1.00 | 1.00 | 0.97 | 0.97 | 0.99 |
| Pandan | 1.00 | 0.93 | 1.00 | 1.00 | 1.00 | 0.96 |
| Papaya | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Celery | 0.97 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Betel | 1.00 | 1.00 | 0.97 | 1.00 | 0.99 | 1.00 |
| Macro Average | 0.97 | 0.99 | 0.97 | 0.99 | 0.97 | 0.99 |
| Weighted Average | 0.97 | 0.99 | 0.98 | 0.99 | 0.97 | 0.99 |

## CONCLUSION

The EfficientNetV2B0 model obtained very good results in classifying herbal leaves such as starfruit, guava, lime, basil, aloe vera, jackfruit, pandan, papaya, celery, and betel. The evaluation results using test data obtained an accuracy value of 99.14% and a loss value of 1.95%. The results obtained were able to outperform the model from previous research, namely VGG16. The EfficientNetV2B0 architectural model is able to reduce the total duration of training time and still produce effectiveness with high accuracy, this is proven by the epoch value to produce the highest accuracy of 30. Future research will focus on developing the architecture by adding the number of herbal leaf classes and increasing the amount of training data and One way to do good test data is by doing data augmentation. In addition, further exploration of the EfficientNetV2B0 deep learning model will be carried out by expanding the use of multi-class identification to other objects.

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