CNN Algorithm for Herbal Leaf Classification Using MobileNetV2 and ResNet50V2

Harry T. Pagiu[*1], Anita Ahmad Kasim[2], Nouval Trezandy Lapatta[3], Septiano Anggun Pratama[4], Rahma Laila[5]
[1,2,3,4,5] Information Engineering, Enginering Faculty, Tadulako University, Indonesia
E-mail: [*1]**harryypagiu@gmail.com**, [2]nita.kasim@gmail.com, [3]nouval@untad.ac.id, [4]rahma.laila@untad.ac.id, [5]septiano93@gmail.com

Abstract

Indonesia is home to over 30,000 types of herbal plants, with approximately 1,200 species utilized as raw materials for alternative and traditional medicine. Leaves play a crucial role in herbal medicine preparation. However, many people struggle to identify different herbal leaves due to their similar appearances, making classification difficult. Each leaf possesses unique characteristics such as shape, size, midrib, stalk, blade, and type, which can be used for differentiation. To assist in identifying herbal leaves, a classification system based on image recognition is essential. Convolutional Neural Networks (CNN) are deep learning algorithms designed for processing two-dimensional image data. Model performance can be enhanced through transfer learning, with MobileNetV2 and ResNet50V2 being widely used architectures. These pretrained models have been trained to recognize images with high accuracy. This study focuses on classifying herbal plants based on leaf shape using CNN architectures from MobileNetV2 and ResNet50V2. The evaluation results show that the MobileNetV2 architecture, with a 90%:10% data split, achieved an accuracy of 98.51%, precision of 98.92%, recall of 98.51%, and an F1-score of 98.56%. These findings indicate that CNN with transfer learning can effectively classify herbal leaves with high accuracy.

Keywords *— Leaf, Classification, MobileNetV2, ResNet50V2*

1. INTRODUCTION

Herbal plants are one of the plants that are useful in preventing and treating diseases[1]. As seen from the practice of the elderly who actively use plants from their gardens or nearby forests as components, people in Indonesia have long practiced traditional medicine using herbal plants[2]. In addition, Indonesia is known as a country that has the second largest number of herbal plants in the world, after Brazil[3]. There are more than 30,000 types of medicinal plants in Indonesia, and Indonesians have used about 1,200 of them as raw materials for traditional or alternative medicine[4].

Herbal plant leaves are used in traditional medicine[1], leaves are part of herbal plants as raw materials for making traditional medicines[1]. Each leaf has different qualities, including color, texture, and shape[1]. The different characteristics of the leaves cause people to not be familiar with the herbal leaves or medicinal leaves. This is because the leaves look like each other, making it difficult to distinguish them[5]. If you look closely, each leaf has

characteristics that distinguish it from one another [5]. Errors in identifying the type of herbal plants can have serious impacts on consumers, even risking fatalities. The determination of unrecognized medicinal plants depends on the knowledge of botanists[6]. A simple method in identifying plants is using manual methods based on morphological characteristics. Leaf characteristics that distinguish one from another such as shape, size, leaf structure such as midrib, stalk, and leaf blade, and leaf type. However, this manual method still has limitations because it involves several processes that depend on human knowledge and skills [6]. Therefore, a system is needed that can classify leaves based on their image, making it easier to recognize these herbal plants.

Deep learning methods are now widely used for automatic recognition of herbal plants[7]. Deep learning is a part of machine learning that involves algorithms that work by mimicking the structure and function of the brain, known as artificial neural networks [7]. One of the algorithms in deep learning is Convolutional Neural Network (CNN), which is designed to process two- dimensional data in the form of images [7][8]. However, to improve the performance of the model, transfer learning, which is the development of CNNs using pre-trained models, is an interesting research topic in various image processing tasks [9]. Transfer learning allows machines to learn a limited amount of data [10].

A popular transfer learning architecture is MobileNetV2 [11], which was developed by Google with a lightweight architecture. This allows MobileNetV2 to run on devices with low performance [10]. In addition to its lightweight design, MobileNetV2 can also recognize objects in images with a high degree of accuracy [10]. Another architecture is ResNet50, which is one of the pre-trained models, i.e. a model that is pre-trained and does not require further customization of the layers used. ResNet50 consists of 50 layers used in its convolution process. This model carries the concept of skip connections which serve to prevent loss of features during the convolution process [12]. Research conducted by Rio Juan Hendri Butar-Butar and Noveri Lysbetti Marpaung (2023) [10] applied transfer learning to identify medicinal plants using MobileNetV2. The results of this study showed an accuracy of 97% in the training stage, 96% in validation, and 93% in testing.

Based on the explanation above, this research classifies herbal plants based on the shape of their leaves using the convolutional neural network (CNN) method. The innovation in this research lies in the application of transfer learning using MobileNetV2 and ResNet50V2 as a comparison to evaluate the performance of the model in herbal plant leaf image classification. ResNet50V2 is an improved version of ResNet50, which performs better than ResNet50 and ResNet101 on ImageNet datasets [13]. ResNet50V2 shows excellent results on ImageNet datasets, making it suitable for complex classification tasks [13]. Although ResNet50V2 has the advantage of better accuracy due to the larger number of layers compared to ResNet architecture, there is still relatively little use of ResNet50V2 for classification. This is due to the complexity of its architecture, which consists of convolutional layers, pooling layers, and fully connected layers, as well as the addition of skip connections in some convolution layers [14]. ResNet50V2's strong ability to overcome the vanishing gradient problem lies in the use of skip connections in every few layers, which allows for more effective gradient flow during the training process [15] and improves image classification

accuracy [14]. The dataset used in this study is a leaf image of a herbal plant. Although Indonesia has about 30. 000 types of herbal plants, but in this study only used 2006 herbal plant data such as holy fig, tamarind, spinach, malabar spinach, belimbing wuluh, cayenne pepper, sandalwood, cloves, pomegranate, ficus, jamblang, guava, rose guava, jatropha, cumin, kelabat, moringa, basil, hibiscus, kersen, cat's whisker, turmeric, lemon, galangal, crown of god, malapari, mango, jasmine, noni, neem, mint, miyana, mondokaki, jackfruit, pandanus, salam koja, sambiloto, mustard greens, lemongrass, betel nut, and srigading. The reason for using 41 (forty-one) classes with a total of 2006 herbal plant data is because these types are often used in everyday life. One of them is turmeric which contains curcumin which is an antioxidant and anti-inflammatory substance, to regulate cholesterol and blood sugar, and reduce the potential for cancer. In addition, this study has also explained that some herbal plant leaves look almost the same briefly. This can be seen in the leaves of galangal, turmeric, and lemongrass which have similar leaf patterns. So that people can have difficulty in distinguishing plants based on leaves with similar shapes. The research objective is to implement convolutional neural network (CNN) method with MobileNetV2 and ResNet50V2 architecture to classify herbal plants based on their leaves. The results showed the performance of the CNN model in classifying herbal plants.

2. RESEARCH METHOD

The research method explains the research steps in classifying herbal plants based on the shape of their leaves using the CNN method. The stages and flowchart of the research consist of literature study, dataset collection, classification model formation, application design, application development, implementation and application testing.

2.1. Literature Review

At the literature study stage, supporting data related to the research is collected as a reference, which includes previous research and relevant theories.

2.2. Dataset collections

Data collection is the process of collecting research datasets for the classification of herbal plants based on the shape of their leaves through the Central Sulawesi Agricultural Technology Research Agency (BPTP Sulteng). The dataset used in the classification of herbal plant leaves amounted to 580 data consisting of classes of jatropha, miyana, ficus, lemon, holy fig, mint, malabar spinach and spinach. The class distribution can be seen in Figure 1.

class	Total						
Pandan	19	Mengkudu	27	Kemangi	52		
Mahkota Dewa	19	Cengkeh	30	Jambu Mawar	56		
Kunyit	19	Sawi	34	Nangka	56		
Kumis Kucing	20	Kelabat	36	Mondokaki	56		
Asam Jawa	20	Belimbing Wuluh	39	Kersen	57		
Cabe Rawit	20	Jamblang	39	Lemon	57	Jambu	65
Sambiloto	20	Srigading	40	Cendana	58	Melati	71
Miyana	22	Kembang Sepatu	43	Salam Koja	60	Kelor	77
Jarak Pagar	22	Sirih	48	Malapari	61	Delima	80
Sereh	23	Jintan	48	Mangga	62	Mint	98
		Lengkuas	50	Ara Suci	63	Bayam Malabar	103
		Ficus	50	Mimba	63	Bayam	123

Figure 1. Class Distribution

2.3. Classification Model Building

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At the classification model formation stage using MobileNetV2 and ResNet50V2 architecture. At this stage the model is implemented into the Python programming language with Google Collab tools to classify herbal plants based on the shape of their leaves.

The proposed model starts with input dataset of herbal plant leaf images, then split data with proportions of 50:50, 80:20, 70:30, 90:10 and 60:40, divided into training data and testing data. Training data for model training and testing data for model testing. In the next stage, resizing is done by changing the image size to 224 x 224 pixels. In this research, resizing is done to the images so that they have a consistent size[16]. Next, data augmentation is performed with horizontal_flit which functions to flip the image horizontally randomly, vertical_flip which functions to flip the image vertically randomly, rotation_range which functions to rotate the image up to 40 degrees randomly, width_shift_range and height_shift_range which functions to shift the image horizontally and vertically up to 20%. Next, rescale is done by changing the image pixel value from 0-255 to 0-1 by dividing the pixel value by 255 which aims to lighten the computational load in the training stage [17]. Next, model training is carried out from the MobileNeV2 and ResNet50V2 architectures, followed by model testing using testing data. The last stage is model evaluation using confusion matrix, which produces accuracy, precision, recall, and f1-score values from MobileNeV2 and ResNet50V2 architectures, so that the performance of the two architectures can be known in the classification of herbal plants based on the shape of their leaves. The modeling flowchart can be seen in Figure 2.

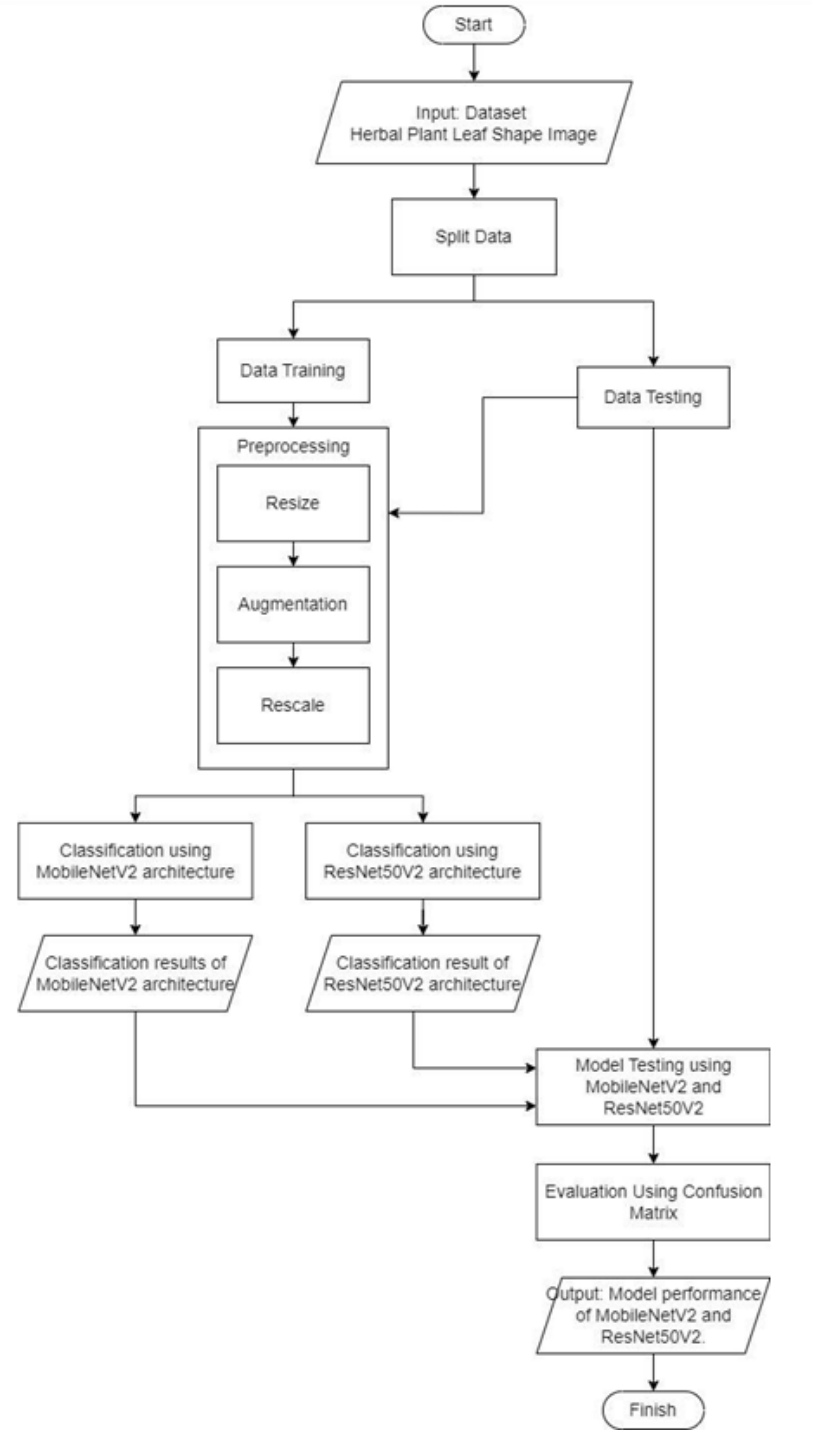


Figure 2. Flowchart Modelling

2.4. Model Analysis

In the model analysis stage, it is carried out to analyze the classification results of herbal plants based on the shape of their leaves on the MobileNetV2 and ResNet50V2 architectures, so that the best model performance can be known.

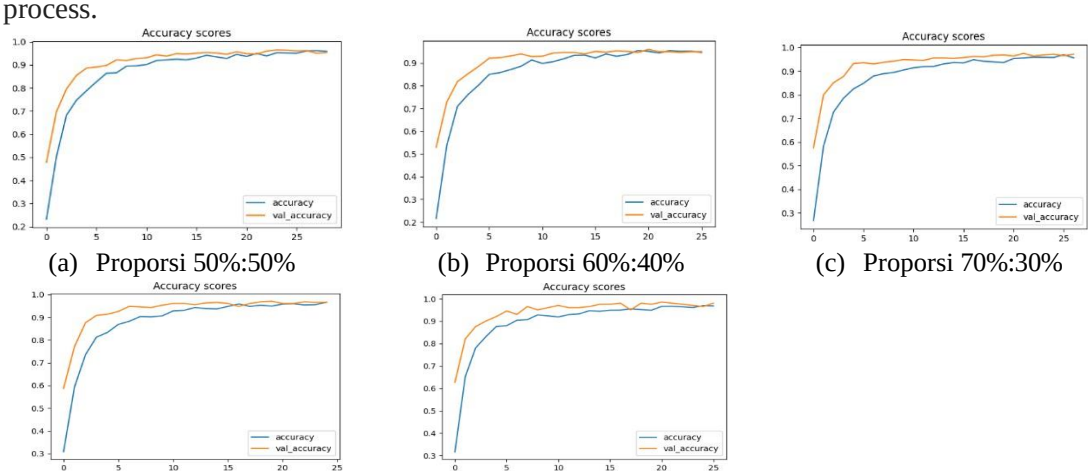
3. RESEARCH RESULTS AND DISCUSSION

The research results discuss the modeling results of the MobileNetV2 and ResNet50V2 architectures in the classification of herbal plants based on the shape of their leaves. In the formation of classification models using the Python programming language with Google Collab tools.

3.1. MobileNetV2 Model Evaluation Results

In the MobileNetV2 method, the base model is formed using a pre-trained model with weights derived from ImageNet. Then, there is a GlobalAveragePooling2D layer to reduce the output dimension of the base model by calculating the average of each feature (channel). Next, the Dense Layer (64 units, ReLU activation) is fully connected which takes the output of the previous layer. A Dropout Layer (0.2) is applied to reduce overfitting by randomly deactivating 20% of the neurons during the training process. The Output Layer (Dense layer with softmax activation) has the number of neurons corresponding to the number of classes in the dataset and a softmax activation function to convert the output into probabilities for each class. The model is compiled using Adam's optimizer, loss function and accuracy matrix. Next, the model is trained using training data, validation data part of the test data to monitor the performance of the model during training and batch size.

In Figure 3, the accuracy graph of the MobileNetV2 method shows the accuracy graph of the training and validation training results that the epoch used is 100 epochs. The results of the train and validation process show that the accuracy value increases from the initial step to the last step with an accuracy value in the last step at a proportion of 50%: 50% of 0.9651. Meanwhile, in validation get an accuracy of 0.9531. At the proportion of 60%: 40% of 0.9510. Meanwhile, in validation get an accuracy of 0.9502. At a proportion of 70%: 30% of 0.9574. Meanwhile, in validation get an accuracy of 0.9718. At a proportion of 80%: 20% of 0.9658. Meanwhile, in validation get an accuracy of 0.9652. At a proportion of 90%: 10% of 0.9730. Meanwhile, in validation get an accuracy of 0.9801. These results get good accuracy for the train because at each epoch the value increases until the last step in the train and validation process.

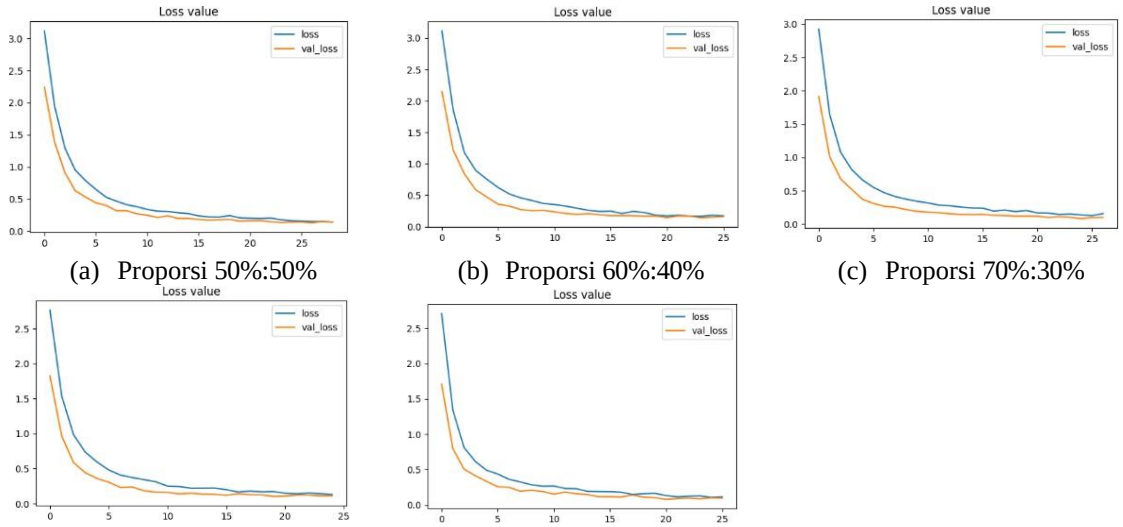


(a) Proporsi 50%:50% (b) Proporsi 60%:40% (c) Proporsi 70%:30%

(d) Proporsi 80%:20% (e) Proporsi 90%:10%

Figure 3. Accuracy Graph Result of MobileNetV2 Method

In Figure 4 the results of the MobileNetV2 method loss graph. From the graph there is loss and validation loss (val_loss). In the loss and val_loss graphs show that there is a decrease in the loss value from the initial step to the end with the final value at the proportion of 50%: 50%, which is 0.282. Meanwhile, in validation, the loss value is 0.1419. Meanwhile, the proportion of 60%: 40% is 0.1568. Meanwhile, the validation obtained loss value is 0.1587. Meanwhile, the proportion of 70%: 30% is 0.1587. Meanwhile, the validation obtained loss value is 0.1000. In the proportion of 80%: 20% which is 0.1364. Meanwhile, the validation obtained loss value is 0.1123. At the proportion of 90%: 10% which is 0.1185. Meanwhile, the validation obtained a loss value of 0.0970. Figure 4 shows the occurrence of good fit conditions, namely training loss and validation loss of the same low value [18].



(a) Proporsi 50%:50% (b) Proporsi 60%:40% (c) Proporsi 70%:30%

(d) Proporsi 80%:20% (e) Proporsi 90%:10%

Figure 4. Loss Graph Results of MobileNetV2 Method

The evaluation results of the MobileNetV2 method show that at a proportion of 50%: 50%, the accuracy value is 96.41%, precision is 96.7%, recall is 96.41% and f1-score is 96.36%. At the proportion of 60%: 40%, the accuracy value is 96.01%, precision is 96.52%, recall is 96.01% and f1-score is 95.91%. In the proportion of 70%: 30%, the accuracy value is 97.51%, precision is 97.71%, recall is 97.51% and f1-score is 97.48%. In the proportion of 80%: 20%, the accuracy value is 97.01%, precision is 97.22%, recall is 97.01% and f1-score is 96.99%. In the proportion of 90%: 10%, the accuracy value is 98.51%, precision is 98.92%, recall is 98.51% and f1-score is 98.56%.

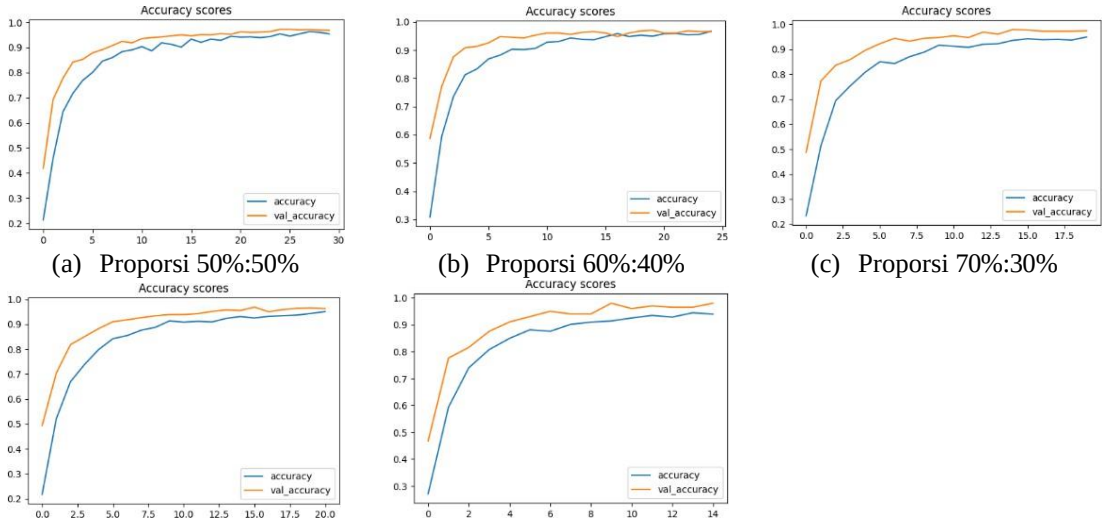
3.2. ResNet50V2 Model Evaluation Results

ResNet50V2 architecture, which is known for using shortcut connections to overcome the vanishing gradient problem in deep networks. Then set trainable to False which means the weights will not be updated during training. GlobalAveragePooling2D layer to reduce the output dimension of the base model by calculating the average of each feature (channel). Next, the Dense Layer (64 units, ReLU activation) is fully connected which takes the output of the

previous layer. The Drospout layer (0.2) is applied to reduce overfitting by randomly disabling 20% of the neurons during the training process ignoring 20% of the neurons during training. The Output Layer (Dense layer with softmax activation) has the number of neurons corresponding to the number of classes in the dataset and a softmax activation function to convert the output into probabilities for each class.

The model is compiled using Adam's optimizer, loss function and accuracy matrix. Next, the model is trained using training data, validation data part of the test data to monitor the performance of the model during training and batch size. From the results of model training, testing and evaluation are carried out which results in accuracy, loss and confusion matrix graphs.

In Figure 5, the results of the ResNet50V2 method accuracy graph show the accuracy graph of the training and validation training results that the epoch used is 100 epochs. The results of the train and validation process show that the accuracy value increases from the initial step to the last step with an accuracy value in the last step at a proportion of 50%: 50% of 0.9537. Meanwhile, in validation get an accuracy of 0.968. At the proportion of 60%: 40% of 0.9364. Meanwhile, in validation get an accuracy of 0.9626. At a proportion of 70%: 30% of 0.9565. Meanwhile, in validation get an accuracy of 0.9734. At a proportion of 80%: 20% of 0.9300. Meanwhile, in validation get an accuracy of 0.9502. At a proportion of 90%: 10% of 0.9433. Meanwhile, in validation get an accuracy of 0.9801. These results get good accuracy for the train because at each epoch the value increases until the last step in the train and validation process.



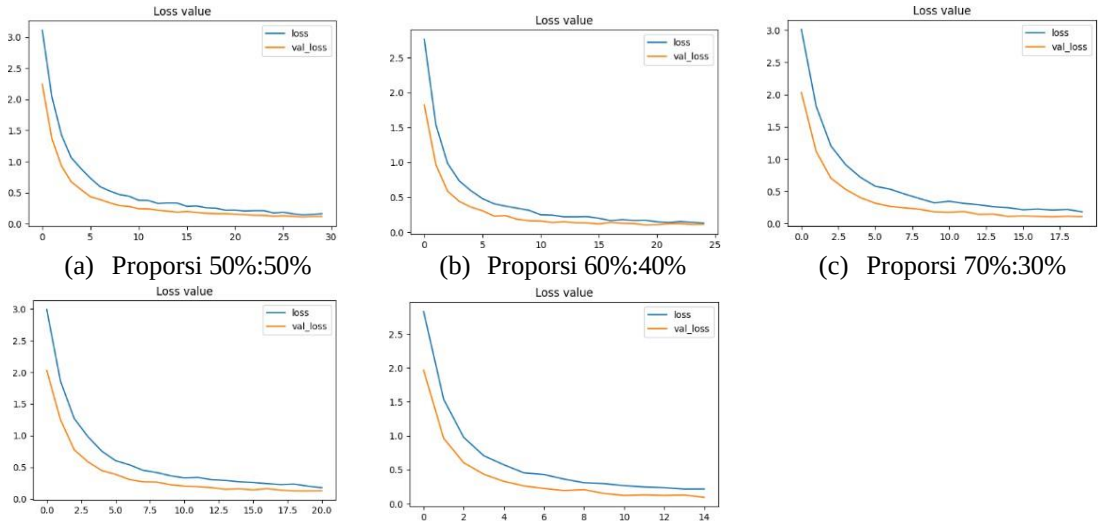
(a) Proporsi 50%:50% (b) Proporsi 60%:40% (c) Proporsi 70%:30%

(d) Proporsi 80%:20% (e) Proporsi 90%:10%

Figure 5. Accuracy Graph Result of ResNet50V2 Method

In Figure 6, the results of the ResNet50V2 method loss graph. From the graph there are loss and validation loss (val_loss). In the loss and val_loss graphs show that there is a decrease in the loss value from the initial step to the end with the final value at the 50%: 50% proportion of 0.1533. Meanwhile, in validation, the loss value is 0.1147. Meanwhile, the proportion of 60%: 40% is 0.2133. Meanwhile, the validation obtained loss value is 0.1282.

Meanwhile, the proportion of 70%: 30% is 0.1663. Meanwhile, the validation obtained loss value is 0.1069. At the proportion of 80%: 20% which is 0.2563. Meanwhile, the validation obtained loss value is 0.1511. At the proportion of 90%: 10% which is 0.2205. Meanwhile, the validation obtained a loss value of 0.0965. Figure 6 shows the occurrence of good fit conditions, namely training loss and validation loss of the same low value [18].



(a) Proporsi 50%:50% (b) Proporsi 60%:40% (c) Proporsi 70%:30%

(d) Proporsi 80%:20% (e) Proporsi 90%:10%

Figure 6. Loss Graph Results of ResNet50V2 Method

The evaluation results of the ResNet50V2 method show that at a proportion of 50%: 50%, the accuracy value is 97.21%, precision is 97.35%, recall is 97.21% and f1-score is 97.2%. At the proportion of 60%: 40%, the accuracy value is 96.89%, precision is 97.09%, recall is 96.89% and f1-score is 96.85%. In the proportion of 70%: 30%, the accuracy value is 97.84%, precision is 97.92%, recall is 97.84% and f1-score is 97.82%. In the proportion of 80%: 20%, the accuracy value is 96.02%, precision is 96.44%, recall is 96.02% and f1-score is 95.96%. In the proportion of 90%: 10%, the accuracy value is 98.01%, precision is 98.33%, recall is 98.01% and f1-score is 97.98%.

3.3. Discussion

Classification of herbal plants based on their leaf shapes using the CNN method with transfer learning from the MobileNetV2 and ResNet50V2 architectures was successfully implemented, and the evaluation results of the architecture comparison can be seen in Table 1.

Table 1 Comparison Results of Mobilenetv2 and Resnet50v2 Architectures

Proportions	Evaluatio	MobileNetV2	ResNet50V2
50% data training, 50% data testing	***Accuracy***	96.41%	**97.21%**
	Precision	96.7%	97.35%
	Recall	96.41%	97.21%
	F1-Score	96.36%	97.2%

Proportions	Evaluatio	MobileNetV2	ResNet50V2
60% data training, 40% data testing	***Accuracy***	96.01%	96.89%
	Precision	96.52%	97.09%
	Recall	96.01%	96.89%
	F1-Score	95.91%	96.85%
70% data training, 30% data testing	***Accuracy***	97,51%	97,84%
	Precision	97,71%	97,92%
	Recall	97,51%	97,84%
	F1-Score	97,48%	97,82%
80% data training, 20% data testing	***Accuracy***	97.01%	96.02%
	Precision	97.22%	96.44%
	Recall	97.01%	96.02%
	F1-Score	96.99%	95.96%
90% data training, 10% data testing	***Accuracy***	98,51%	98,01%
	Precision	98,92%	98,33%
	Recall	98,51%	98,01%
	F1-Score	98,56%	97,98%

From Table 1 comparison of evaluation results in the classification of herbal plants based on the shape of the leaves, it is found that the ResNet50V2 and MobileNetV2 architectures produce good accuracy. In this study using the Adam optimizer, the optimizer combines the advantages of the RMSprop and Momentum methods. By adaptively adjusting the learning rate for each parameter, Adam offers more stable and faster training [19]. This is evident from the high accuracy based on experimental results using both ResNet50V2 and MobileNetV2 architecture algorithms. In addition, the low loss value also indicates that the model is able to identify very well and minimize prediction errors during training. In addition to using Adam as an optimizer, this research also applies a learning rate. The selection of the learning rate is a challenge in itself because if the value is too small, the training will take a long time, on the other hand, if it is too large, the learning will be less optimal because it is too fast and the training process becomes unstable [20]. In this study using a learning rate of 0.001. This is proven by doing a combination of Adam's optimizer, and the learning rate value shows a match and can produce high accuracy in the model.

This research obtained the best model performance using MobileNetV2 architecture which resulted in accuracy of 98.51%, precision of 98.92%, recall of 98.51% and f1-score of 98.56% with a proportion of 90% training data and 10% testing data. Despite producing the best performance, MobileNetV2 also produces a computation time of 905.0803176471964 seconds. MobileNetV2 is superior to ResNet because the data used is better using MobileNetV2. In addition, MobileNetV2 is designed to be a lightweight and fast model, making it more computationally efficient than the more complex RestNet50. MobileNetV2 has fewer parameters compared to RestNet50 which makes it faster to train and implement [21]. However, the two architectures are not very different.

4. CONCLUSION

From the results of research that has been carried out related to the classification of herbal plants based on the shape of their leaves using the CNN method, the following conclusions are obtained:

1. In classifying herbal plants based on leaf shape using convolutional neural network (CNN) method with MobileNetV2 and ResNet50V2 architecture through several stages of research, namely input dataset of herbal plant leaf images, then split data dividing data into train data and test data with a ratio of 50%: 50%, 60%: 40%, 70%: 30%, 80%: 20%, 90%: 10%. Next, preprocessing is done consisting of resize, augmentation and rescale. The next stage performs classification using MobileNetV2 and ResNet50V2 architectures and produces MobileNetV2 and ResNet50V2 architectures. Followed by classification using test data and evaluation using confusion matrix to evaluate the best architecture in herbal plant classification based on leaf shape from MobileNetV2 and ResNet50V2 architectures.
2. The accuracy performance results of the MobileNetV2 and ResNet50V2 architectures in classifying herbal plants based on their leaf shape, namely the best results of the MobileNetV2 architecture obtained in the proportion of 90% training data and 10% testing data getting an accuracy value of 98.51%, precision of 98.92%, recall of 98.51% and f1- score of 98.56%. Meanwhile, the best results of the ResNet50V2 architecture were also generated at a proportion of 90%: 10%, getting an accuracy value of 98.01%, precision of 98.33%, recall of 98.01% and f1-score of 97.98%. The evaluation results show that the MobileNetV2 architecture has the best model performance compared to ResNet50V2

5. SUGGESTED

From the conclusions that have been made, in this study there are suggestions given for research development, namely

1. Further research can add data and other herbal plant classes in order to get varied results and provide a broad picture of herbal plant classes based on the shape of their leaves.
2. Further research can visualize the results of herbal plant classification in the form of an android-based application to help lay people about the types of herbal plants based on the shape of their leaves.

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