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Herbal Plant Classification Using EfficientNetV2B0 Model and CRISP-DM Approach

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Abstract

Herbal remedies have long been utilized by Indonesian communities as part of traditional medicine. However, identification of these natural resources is often challenging due to the morphological similarities among various species, which demand expert knowledge to differentiate. This study aims to implement the EfficientNetV2B0 model architecture for classifying medicinal leaves through an Android-based application designed to support recognition tasks. The dataset was composed of augmented images of plant foliage. The model was trained using the TensorFlow framework and evaluated to measure classification performance. Results demonstrate that EfficientNetV2B0 achieves excellent accuracy, with validation scores exceeding 97%, outperforming several other deep learning models. The resulting application allows the general public to identify local medicinal species more easily. This study contributes to the field of computer vision by providing an accurate and efficient classification framework, particularly beneficial for health-related informatics in biodiversity-rich regions.

Keywords : *Classification, EfficientNetV2B0, Herbal Plants.*

1. INTRODUCTION

Indonesia is a country that has extraordinary biodiversity. As an archipelagic country with thousands of islands, Indonesia is blessed with a variety of ecosystems ranging from tropical rainforests, coral reefs, to mountains. This diversity not only includes flora and fauna, but also diverse cultures and traditions, making Indonesia one of the countries with the most complete natural and cultural wealth in the world. The country has around 30,000 types of plants, accounting for around 75% of the world's plants. Therefore, Indonesia is often referred to as the mega-center of global biodiversity [1] . According to National Geographic Indonesia (2019), Indonesia is ranked second after Brazil in terrestrial biodiversity, and is the highest in the world if marine biodiversity is added. With around 31,750 types of plants, including 25,000 flowering plants and 15,000 with medicinal potential, Indonesia has a significant wealth of herbal plants. However, only about 7,000 species have been used as medicinal raw materials[2] and of the 20,000 types of herbal plants that exist, only 300 types are used for traditional medicine [3].

Herbal plants are types of plants that have medicinal functions and properties and are used for healing or preventing various diseases. According to the 2018 Basic Health Research (Riskesdas), as many as 48.0% of people used ready-made concoctions, 31.8% used home-made concoctions, and 24.6% admitted that they had used the Family Medicine Garden (TOGA) [4]. Herbal plants are plants that have been identified and known, based on human observation, to contain compounds that are

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beneficial for preventing, curing, or performing specific biological functions [5]. Herbal medicines can be used by drinking, applying, applying, inhaling, and so on, and can also be developed into commercially available or marketable health products [6]. Medicine itself means that it contains active substances that can treat certain diseases or if it does not contain certain active substances but contains the resultant effect or synergy of various substances [5]. On the other hand, widely used modern synthetic drugs are often associated with undesirable side effects that can lead to other pathological complications. As a result, herbal medicines seem to have an important role because they have minimal or unknown side effects compared to modern medicines [7].

As public awareness of health increases, the use of herbal plants is also increasing. However, the challenge in identifying herbal plants lies in the visual similarity of their leaves, which makes manual identification difficult. Lack of knowledge about objects around us is a problem that can be overcome by leveraging technology to make it more efficient. Technological advances, particularly in Machine Learning and Deep Learning, provide opportunities to automate this process. Many previous studies have examined the use of Convolutional Neural Network (CNN) in herbal plant identification. For example, research by Rakha Pradana Susilo Putra, Christian Sri Kusuma Aditya, and Galih Wasis Wicaksono [8] used the Herbal Leaf dataset from Mendeley Data as many as 10 classes with 350 images each, so there were a total of 3,500 images. The model used is EfficientNetV2B0, a CNN architecture with compound scaling techniques to improve model performance. The results of this study showed an accuracy of 99.89% on training data and 99.14% on validation data. Similar research was conducted by Bella Dwi Mardiana, Wahyu Budi Utomo, Ulfah Nur Oktaviana, Galih Wasis Wicaksono, and Agus Eko Minarno [9] with the same dataset. The data is divided into 70% for training, 20% for validation, and 10% for testing. The model used is VGG16, with an augmentation method using Image Data Generator and the addition of Fully Connected Layer in the form of Dense Layer. As a result, the accuracy reached 96.73% on training data and 97% on testing data after 100 epochs. Another research by Jiangchuan Liu, Mantao Wang, Lie Bao, and Xiaofan Li [10] applied augmentation in the form of scaling, translation, and rotation to overcome the limited number of datasets. As a result, the EfficientNet model with transfer learning achieved 98.52% accuracy with a loss of 1.48%. Meanwhile, research by Qinghe Zheng, Mingqiang Yang, Xinyu Tian, Nan Jiang, and Deqiang Wang [11] used augmentation such as translation, horizontal flip, rotation, transformation, and noise to improve model performance.

This study presents a significant update compared to previous research by building an accurate herbal plant classification model using the EfficientNetV2B0 architecture and implementing it in a mobile-based recognition system. The dataset used is not only sourced from existing data but also manually developed by the authors to increase the diversity of data characteristics, and is equipped with more diverse augmentation techniques to improve the accuracy and adaptability of the model in recognizing various types of herbal plants in real environments.

2. METHOD

The method used in this research is CRISP-DM (Cross Industry Standard Process for Data Mining) a standardization of data mining processing that has been developed where existing data will go through each phase structured and clearly and efficiently defined [12].

In this research, the CRISP-DM methodology is used as a systematic approach to solve the problem of herbal plant identification. Some of the advantages of the CRISP-DM methodology include its de-facto and reliable nature, ease of use and structure, the right start, reduced costs and time, and the optional deployment phase [13]. The initial stage, Business Understanding, defines the problem and goal, which is to develop an accurate machine learning model for herbal plant classification. Next, in Data Understanding, the herbal leaf image dataset is explored to understand its characteristics and distribution. Data Preparation includes image cleaning, augmentation, and division of data into training,

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validation, and testing subsets. The Modeling stage focuses on developing the EfficientNetV2B0 model, which is then evaluated using performance metrics such as accuracy and F1-score. Finally, in the Application stage, the optimized model is integrated into the identification system, so that it can help people recognize herbal plants quickly and accurately.

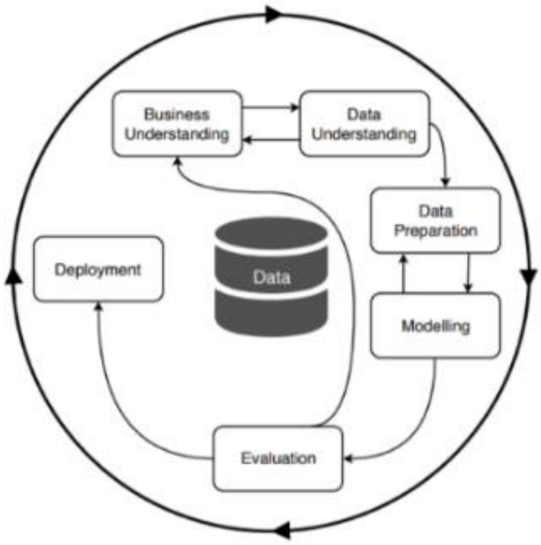

Figure 1. CRISP DM

2.1. Business Understanding

Errors in manual identification of herbal plants are a serious problem, as this process is often only mastered by botanists, making it difficult for the public to recognize plants independently. In fact, errors in the identification of herbal plants used as alternative medicine can have fatal consequences, even risking death for those who consume them. Morphology-based identification methods have proven to be effective and simple, but they rely heavily on human expertise, which requires time, effort, and in-depth knowledge [8]. Therefore, specialized technology is needed to overcome this problem. Machine learning offers an innovative solution to simplify the identification of herbal plants accurately and efficiently, thereby reducing the risk of misidentification and providing wider benefits to society.

2.2. Data Understanding

Datasets are crucial in research, especially image processing. The herbal plant dataset was taken around Bengkulu City. Data collection is a step taken for research needs by obtaining the required information [14]. The data needed related to research is in the form of images / images measuring 960 x 1280 pixels, where this size is also used in research by Cholilul Rosyidin, Resty wulanningrum, Siti Rochana [9] in Image Improvement Using Gaussian and Median Filter Methods. The image collected from a herbal plant must represent the classification target and have a good level of clarity.

Figure 2 shows the entire plant, while Figure 3 focuses on a single leaf. Both types of images were taken to improve the machine learning model's ability to recognize plant characteristics from multiple perspectives. With these data, the model can learn the morphological characteristics of the plant more comprehensively, both from the leaf structure and the overall shape of the plant. This study produced a total of 10,000 images from 10 types of plants, where each type has 1,000 images consisting of both perspectives.

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Figure 2. Sample Whole Plant Dataset Requirements

Figure 3. Sample Dataset Requirements for a Leaf

2.3. Data Preparation

This data preparation includes resizing, augmentation and split data. The augmentation process will change and modify the image in such a way that the computer will detect that the changed image is a different image. [15]. Resize is changing the size of the image into pixels, to ensure the image size is consistent and makes it easier for the model to understand the pattern [16]. This data preparation includes augmentation and split data. Augmentation is the process of processing image data by modifying the image through techniques such as rotation, horizontal and vertical flip, noise addition, and Gaussian blur [17]s. Augmentation is a useful technique to provide more information from less data [18] In this system, the raw data which initially amounted to 50 was augmented to 1000. This augmentation process aims to create variation in a small dataset, expand the dataset meaningfully, and increase the generalization ability of the model, so that the model can recognize herbs under various conditions and variations that may be encountered in the real world

Table 1. Data

No	Nama	Jumlah Data Mentah		Jumlah Data Hasil Augmentasi
		Keseluruhan Tanaman	Sehelai Daun	
1	Ashoka	50	0	1000
2	Butterfly Pea Flower	50	0	1000
3	Guava Leaves	25	25	1000
4	Castor Leaves	25	25	1000
5	Lime Leaves	25	25	1000
6	Eucalyptus Leaves	25	25	1000
7	Papaya Leaves	25	25	1000
8	Aloe Vera	25	25	1000
9	Clover	25	25	1000
10	Betel Leaf	25	25	1000
	Total	300	200	10000

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The augmentation techniques used in this study include horizontal flip, crop, contrast adjustment, brightness adjustment, transformation (which includes scale, translation, rotation, and shear), Gaussian noise, and salt and pepper noise. Augmentation is needed to adapt data to varying environmental conditions and increase data variation, so that models can learn patterns more effectively. Data augmentation will be carried out to overcome the problem of insufficient datasets [19].

Table 2. Augmentation Phase

Augmentation Technic	Number of Augmented Images	Unaugmented Image Count
i. *Flip horizontal :* 50% (Probabilitas 50%)	500	500
ii. *Crop :* 0% - 10% (Probabilitas 100%)	1000	0
iii. *Contast :* 0.75 – 1.5 (Probabilitas 100%)	1000	0
iv. *Brightness :* 0.8 – 1.2 (Probabilitas 100%)	1000	0
v. *Transformation :* (Probabilitas 100%) - *Scala : 0.8 – 1.2* - *Translasi : -20%-20%* - *Rotate : -25 derajat – 25 derajat* - *Shear : -8 derajat – 8 derajat*	1000	0
vi. *Gaussian :* 10% - 60% (Probabilitas 10%)	100	900
Salt and pepper : 5% (Probabilitas 100%)	100	900

Table Explanation:
Raw Data = 50 Images/class
Augmentation Data = 1 Raw Data Image → 20 Augmentation Images
= 50 Raw Data Images × 20 = 1000 Images
The result of augmentation is strongly influenced by the probability level of each augmentation.
A probability of 50% means that only 10 out of 20 images are augmented.
100% probability means 20 out of 20 images will be augmented.
A 10% probability means only 2 out of 20 images will be augmented.

This variation makes the dataset more diverse, which in turn can help machine learning models become more resilient to changes or disturbances in the input images. This approach can also reduce the risk of overfitting as the model will be more accustomed to a wider variety of images, not just specific patterns from the original dataset. Each technique is applied with a certain probability, resulting in the number of augmented and unaugmented images according to the probability setting. From the augmentation used, 1000 new images of each class were generated. Split data is dividing the data into several parts. The divided data is the augmentation result data which amounts to 10,000. Split data is done by dividing the data into three parts, namely train by 80% of the total data or 8000, validation by 10% of the total data or 1000 and 10% for test data from the total data or 1000.

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2.4. Modelling

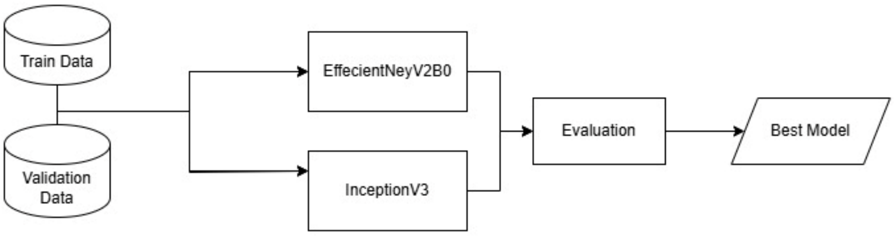

Figure 4. Modelling Chart

In the modeling process, two experiments were conducted with the transfer learning model architecture because it had to use the TensorFlow library. The purpose of this experiment is to find the best performing model in terms of accuracy, efficiency, and prediction speed. In this case, the authors compare between InceptionV3 and EfficientNetV2B0 model architectures. The system will be built through three stages: pre-processing, training, and testing. The pre-processed training data will be trained using the transfer learning model. After that, the results of training and testing will be evaluated to select the most appropriate model for classifying herbal plant types.

3. RESULT

The basic architecture of EfficientNet is based on a novel scalability method to increase model capacity by changing the width, depth, and resolution dimensions of the model using simple mixture coefficients [20]. In this study, a pre-trained model is used. The concept of pre-trained models in machine learning refers to the use of pre-trained models on large datasets such as ImageNet, which contains millions of images with thousands of classes. The model is then further customized through fine-tuning to make it more optimal in handling specific tasks. The application of transfer learning and image augmentation techniques has demonstrated its effectiveness in solving challenges in the image analysis process [21]

The EfficientNetV2B0 base model adds several layers such as MaxPooling2D, EfficientNetV2B0 is a type of CNN architecture that uses combined scaling techniques to enable better performance. Through reducing the number of parameters and floating point Operations Per Second (FLOP)[8], EfficientNetV2B0 seeks to improve computing efficiency while improving performance [22]. The function of MaxPooling2D is to reduce the spatial dimensions of the feature representation produced by the previous layer [23] Dropout, Flatten, BatchNormalization Batch Normalization speeds up the training process and has a function similar to L2 Regularization in dealing with overfitting [24]., and Dense to adapt the model output to a classification task that has 10 classes. With this combination of pre-trained model and fine-tuning, it is expected that the model can achieve optimal performance in detecting and classifying objects with high efficiency.

3.1. Evaluation

Model training was performed by compiling the model using Adam's optimizer and the Sparse Categorical Crossentropy loss function. Training was conducted for 10 epochs with a batch size of 128, using the training and validation data provided.

Training accuracy and validation accuracy show very stable results without significant bias. The validation accuracy line remains consistent after the first few epochs, indicating that the model performs very well and has sufficient data to learn patterns. The sharp decrease in the loss value indicates that the model quickly understands the data, and the very low loss value indicates minimal prediction errors. With a batch size of 128, 8,000 training samples, and 1,000 validation samples, the model achieved optimal performance in a relatively short time.

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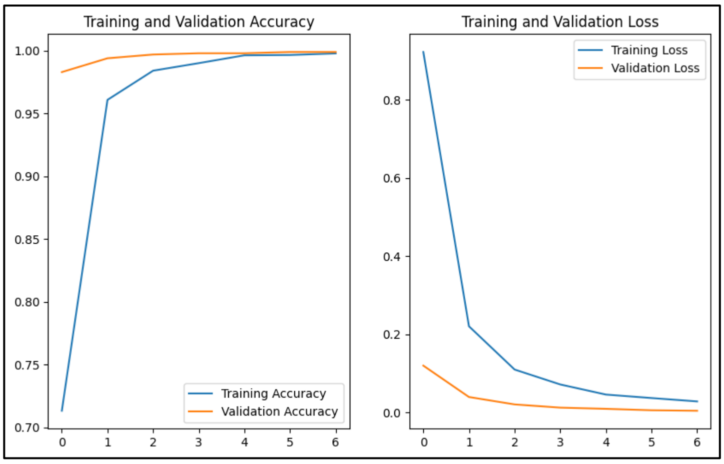

Figure 5. Graph Training

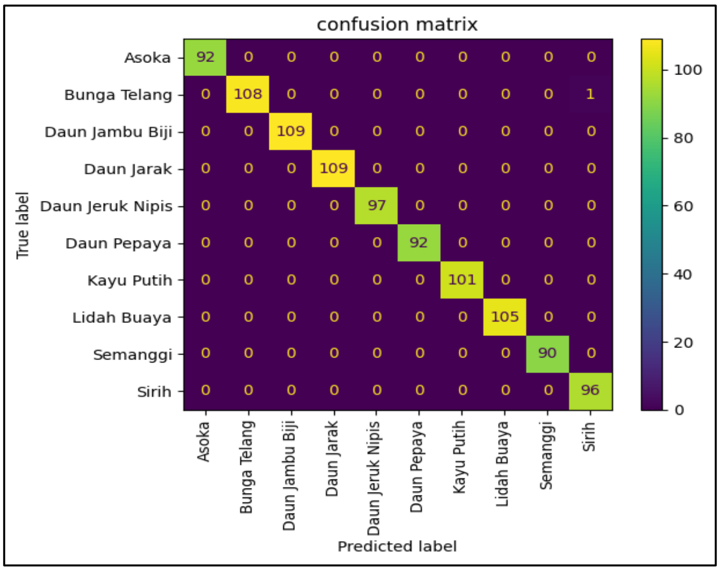

Figure 6. Confusion Matrix

Overall, from this confusion matrix it can be seen that the model has very good performance with most of the predictions being on the main diagonal, which shows that most of the samples are classified correctly. There were also very few prediction errors, such as the Telang Flower class which was incorrectly classified as Betel.

4. DISCUSSIONS

In this study, the application of the data augmentation process also helped this research. In the study of Classification of herbal plant leaves for traditional medicine using convolutional neural networks by Fauzi et al., where the accuracy increased when modeling augmented images from 91.43% to 98.74% [25] then the author conducted a comparison using a new dataset. Two new additional schemes were also carried out with datasets from the Indonesian Herb Leaf Dataset 3500 to see the performance of the model. The dataset used consists of herbal leaf images from Indonesia which include 10 categories or classes, namely starfruit, guava, lime, basil, aloe vera, jackfruit, pandan, papaya, celery, and betel. Each category contains 350 images so that the total dataset reaches 3500 herbal leaf images to see the performance of the EfficientNetV2B0 model. Testing the model and additional data from the Indonesian Herb Leaf Dataset 3500 to see the performance of the model.

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Testing the model from mixed data, namely the author's data as many as 5 classes and data from the Indonesian Herb Leaf Dataset 3500 as many as 5 classes.

Comparison of InceptionV3 and EfficientNetV2B0 Models using the newly constructed dataset:

Table 3. Comparison results using a newly constructed dataset

	InceptionV3	EfficientNetV2B0
Accuracy	0.98	0.99
Loss	0.04	0.02

Comparison of InceptionV3 and EfficientNetV2B0 Models using dataset from Indonesian Herb Leaf Dataset 3500:

Table 4. Comparison results using the Indonesian Herb Dataset 3500 dataset

	InceptionV3	EfficientNetV2B0
Accuracy	0.98	0.9942
Loss	0.0559	0.0718

* *For mixed datasets, this cannot be done due to the different image shapes*

5. CONCLUSION

This study successfully addressed the problem that dataset processing has a significant impact on model performance in classification tasks. The results demonstrated that the EfficientNetV2B0 model achieved excellent performance in classifying various types of herbal plants, including Ashoka, Butterfly Pea Flowers, Guava Leaves, Castor Leaves, Lime Leaves, Eucalyptus Leaves, Papaya Leaves, Aloe Vera, Clover, and Betel Leaves. The model also performed exceptionally well on the Indonesian Herb dataset, which contains 3,500 images and is widely used in various research studies focused on herbal plant classification.

By reaching a high classification accuracy of 99%, and with graphs indicating consistent and significant improvement, the application of EfficientNetV2B0 as a transfer learning model has proven to be very effective in the field of deep learning for plant identification. The results clearly highlight the strength of modern convolutional neural networks, especially when combined with transfer learning techniques.

In addition, this study found that data augmentation plays a vital role in boosting model performance. Through augmentation, the dataset becomes more diverse and robust, which helps reduce overfitting and improves the model's generalization ability on unseen data. The augmentation process allows the model to better learn key features from limited data, resulting in more accurate and reliable predictions.

Overall, the findings underline the importance of both choosing the right deep learning architecture and properly preparing the dataset, including applying augmentation strategies, to build a high-performance classification system for herbal plant recognition. This work contributes to the application of deep learning in ethnobotany, enabling scalable herbal recognition tools in low-resource settings. Future research could explore real-time deployment on edge devices and expansion to more diverse plant species.

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