A Web-Based Convolutional Neural Network System for Indonesian Herbal Plant Identification Supporting Biodiversity Conservation

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Abstract.
Indonesia is one of the world's megabiodiversity countries, possessing a rich diversity of herbal plants that play an important role in traditional medicine and biodiversity conservation. However, the identification of herbal plant species remains challenging for the public due to similarities in leaf morphology, increasing the risk of misidentification and inappropriate utilization. This study aims to develop a web-based identification system for Indonesian herbal plants using a Convolutional Neural Network (CNN) to facilitate accurate and accessible species recognition. The system employs the MobileNetV2 architecture to classify herbal plants based on leaf images and provides an interactive web interface for users. Experimental results showed that the proposed model achieved a training accuracy of 96.30% and a validation accuracy of 95.75%. Performance evaluation using 50 independent leaf images yielded an identification accuracy of 89.24%, with 47 images correctly classified. These findings indicate that the proposed system is capable of supporting reliable herbal plant identification and can serve as a can serve as a practical digital tool for supporting biodiversity monitoring, medicinal plant documentation, public education, and the sustainable utilization of Indonesia's medicinal plant resources.
Keywords: *Identification, Indonesian herbal plant, CNN, biodiversity conservation and web-based.*

I. INTRODUCTION

The use of herbal plants as part of traditional medicine has been practiced for centuries in Indonesia and remains an important component of community healthcare and cultural heritage[1]. This practice is supported by Indonesia's exceptional biological richness, with approximately 30,000 plant species, of which around 6,000–7,000 have the potential to be utilized as medicinal plants [1-2]. As one of the world's recognized megabiodiversity countries, Indonesia has a global responsibility to conserve and sustainably utilize its rich medicinal plant resources. Beyond their contribution to traditional healthcare, medicinal plants play an important role in biodiversity conservation, ecological sustainability, and the sustainable use of biological resources. Consequently, accurate identification of medicinal plant species has become increasingly important for supporting conservation programs, preserving genetic diversity, and promoting the responsible utilization of Indonesia's medicinal plant resources [3], [4], [5].

Despite their importance, accurate identification of herbal plant species remains a major challenge for many users. Individuals without sufficient botanical knowledge often experience difficulty distinguishing between morphologically similar species, increasing the risk of selecting inappropriate plants for medicinal purposes[6]. Such misidentification may reduce therapeutic effectiveness and, in some cases, cause adverse health effects. Furthermore, inaccurate species identification also affects biodiversity conservation by reducing the reliability of biodiversity inventories, complicating species monitoring, and limiting effective conservation planning. Therefore, reliable plant identification is essential not only for public health but also for preserving plant diversity and supporting the sustainable utilization of medicinal plant resources [4], [7].

Traditional identification methods mainly rely on visual observation of leaf morphology, including shape, color, and texture. These approaches are often subjective, time-consuming, and highly dependent on the experience of the observer [8], [9], [10]. Morphological similarities among different species further increase the likelihood of misclassification, resulting in inconsistent identification outcomes. Such limitations demonstrate the need for automated identification systems that provide faster, more accurate, and more consistent results for both researchers and the general public [9], [11], [12].

Recent advances in image processing and artificial intelligence, particularly Convolutional Neural

Networks (CNNs), have provided promising approaches for automatic plant species identification. CNN models are capable of extracting complex visual features from leaf images and have demonstrated high classification performance in numerous plant recognition applications [11], [13], [14], [15], [16]. These capabilities make CNN-based image recognition an effective tool for supporting medicinal plant identification and biodiversity documentation.

Previous studies have successfully applied CNN models for herbal plant identification in several countries, including Thailand[11], the Philippines [17], [18], India [19], Malaysia [9], and Indonesia [2], [6], [10], [16], [20]. Although numerous CNN-based studies have reported high classification accuracy for herbal plants, most of them remain limited to offline implementations or experimental environments, with limited deployment as publicly accessible web-based identification systems specifically designed for Indonesian medicinal plants. Integrating deep learning with a web platform is essential to enable practical utilization by researchers, students, healthcare practitioners, and the general public. Therefore, this study develops a web-based Indonesian herbal plant identification system using a Convolutional Neural Network (CNN) to automatically recognize medicinal plant species from leaf images. The proposed system is intended not only to improve the accessibility of plant identification but also to support biodiversity conservation, digital documentation of medicinal plant resources, and the sustainable utilization of Indonesia's rich herbal plant diversity.

II. METHODS

The development of the herbal plant identification system for herbal medicine users based on leaf image patterns uses the prototyping method. The prototyping method is a software development approach that allows the creation of an initial version of the system, referred to as a prototype.

The research flow shown in Figure 1 begins with a literature review and image data collection of 10 types of herbal plant leaves in Indonesia. The collected data then undergo a preprocessing stage to enhance image quality before being used for modeling. Next, the prepared data are implemented in a CNN model, followed by training and testing processes to obtain the most optimal model. After the model is evaluated to measure its performance, it is integrated into a website platform, enabling the identification of herbal leaf types quickly and accurately.

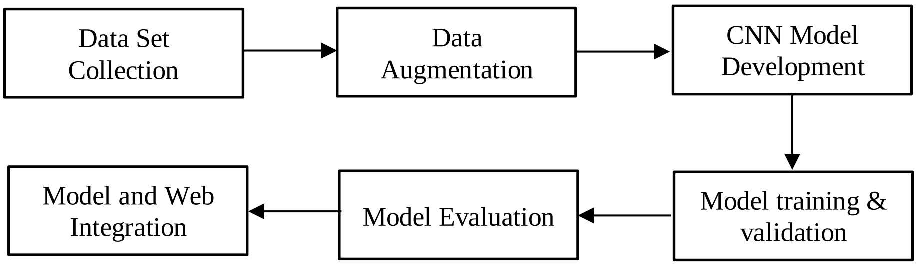


Fig. 1. Research Flowchart

Data Set Collection

At this stage, a dataset of herbal plant leaf images is collected from the Mendeley website. These herbal plant images are used in the training of a Convolutional Neural Network (CNN) model. The data collection was carried out using a public dataset, namely the Indonesia Herb Leaf Dataset from Mendeley data, which contains 3,200 images.

Data Augmentation

In this augmentation stage, the process was carried out using Image Data Generator to perform data augmentation and preprocessing on herbal leaf images.

CNN Model Development

In this stage, the Convolutional Neural Network (CNN) method was applied to build an image classification model using the MobileNetV2 architecture. MobileNetV2 is a CNN architecture that has been pre-trained on the ImageNet dataset, making it suitable as a base model for herbal leaf image classification.

The MobileNetV2 architecture is specifically designed for mobile devices, prioritizing efficiency and computational speed through the use of separable convolution techniques, thereby offering faster and more efficient performance with fewer resource requirements [21], [22], [23].

Training and Validation Model

After data augmentation, the model was trained using the Adam optimizer, categorical crossentropy as the loss function, and accuracy as the evaluation metric for 10 epochs, utilizing 2,500 training images and 400 validation images. The training process is carried out to train the model to recognize patterns in the data and make accurate predictions. The model is trained to ensure sufficient learning in capturing the important features of the data.

Evaluation Model

The model evaluation was carried out using several metrics, namely accuracy, precision, recall, and F1-score. The purpose of this evaluation was to determine how well the model had learned the data patterns and to ensure that it could be effectively applied to new data [24]. The calculation of the model's performance evaluation is carried out using the confusion matrix [25].

The confusion matrix is a matrix consisting of positive integer elements that indicate the number of instances corresponding to each possible combination of predicted and actual class labels [26]. Accuracy measures the number of correct predictions out of all predictions made by the model. The accuracy is calculated using Equation 1[27]. Precision indicates how accurate the model's positive predictions are and is calculated using Equation 2[27]. Recall, or sensitivity, represents the ratio of correctly predicted positive instances to all actual positive instances, and its value is determined using Equation 3[24]. The F1-score is the harmonic mean of precision and recall, and it can be calculated using Equation 4[24].

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$f-1\, score = \frac{2\ x\ Recall\ x\ Precission}{Recall+Precission} \tag{4}$$

where TP (True Positive) represents the number of positive cases correctly predicted, TN (True Negative) is the number of negative cases correctly predicted, FP (False Positive) refers to the number of negative cases incorrectly predicted as positive, and FN (False Negative) indicates the number of positive cases incorrectly predicted as negative.

Integration Model with Web

A website is a platform consisting of several pages interconnected through hyperlinks. The trained CNN model was then implemented into a web-based system using the Python programming language. The website was built using HTML, CSS, and JavaScript, allowing users to upload images of herbal plant leaves through a web interface.

The interaction between the user and the features available on the herbal plant identification website is illustrated in Figure 2. There are four main menus: "Identifikasi jenis tanaman herbal" (Herbal Plant Identification), "melihat tentang kami" (About Us), "mengirimkan masukan" (Submit Feedback), and "melihat detail tanaman herbal" (View Herbal Plant Details).

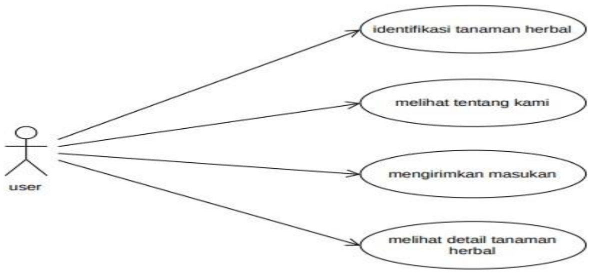


Fig. 2. Use Case User

III. RESULT AND DISCUSSION

The first stage involves collecting image data of herbal plant leaves consisting of 10 plant types: starfruit leaf, guava leaf, lime leaf, basil leaf, aloe vera leaf, jackfruit leaf, pandan leaf, papaya leaf, celery leaf, and betel leaf. The data collection was carried out using a public dataset, namely the Indonesia Herb Leaf Dataset, which contains 3,200 images. The collected data are RGB images divided into three groups: 2,500 images for training data, 400 images for validation data, and 300 images for testing data, as shown in Table 1.

Table 1. Data Set

Leaf data set	Training	Validation	Testing
Belimbing Wuluh (Starfruit)	250	40	30
Jambu Biji (Guava)	250	40	30
Jeruk Nipis (Lime)	250	40	30
Kemangi (Basil)	250	40	30
Lidah Buaya (Aloe vera)	250	40	30
Nangka (Jackfruit)	250	40	30
Pandan	250	40	30
Pepaya	250	40	30
Seledri (Celery)	250	40	30
Sirih (Betel)	250	40	30
Total	**2500**	**400**	**300**

Data Augmentation

The training data were augmented with rotation, shifting, shearing, zooming, and horizontal flipping to increase variation, while the validation and test data were only normalized by scaling the pixel values to a range of 0–1. Subsequently, the data were loaded at a size of 224×224 pixels to ensure compatibility with the MobileNetV2 model, using a batch size of 32.

Figure 3 shows the data augmentation process.

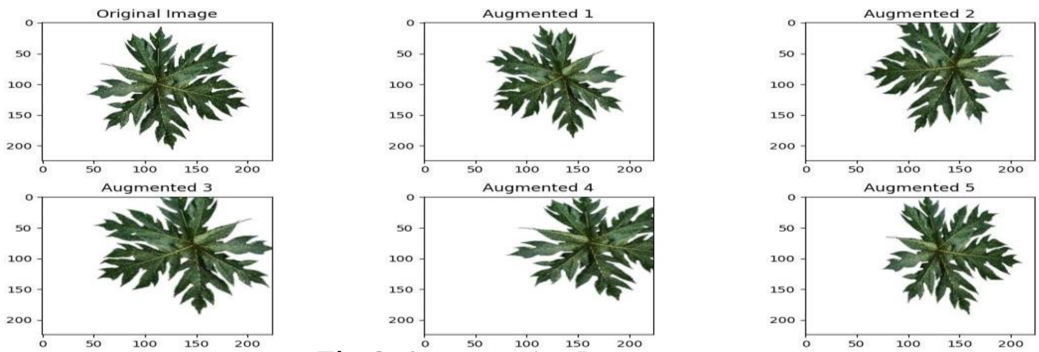


Fig. 3. Augmentation Process

Model Development

The MobileNetV2 model was loaded with the parameter weights='imagenet' and include_top=False to utilize the pre-trained weights without the final classification layer, and the input was adjusted to the image size of (224, 224, 3).

Next, custom layers were added to produce classification outputs according to the desired number of classes. The first layer was a GlobalAveragePooling2D layer, used to convert the output of MobileNetV2 into a one-dimensional vector. After that, a Dense layer with 256 units and a ReLU activation function was added to perform further feature processing. To prevent overfitting, a Dropout layer with a dropout rate of 0.5 was included. In the output layer, a Dense layer with a softmax activation function was used to generate the probability of each class, allowing the model to perform multi-class classification.

Training and Validation

In the first epoch, the training accuracy reached 61.34%, while the validation accuracy was 89.25%. The accuracy increased significantly with each epoch, reaching 94.16% for training and 95.50% for validation at the fifth epoch.

As shown in Figure 4, at the end of training in the tenth epoch, the model achieved a training accuracy of 96.30% and a validation accuracy of 95.75%, with a decrease in loss indicating that the model is increasingly able to recognize leaf image patterns effectively.

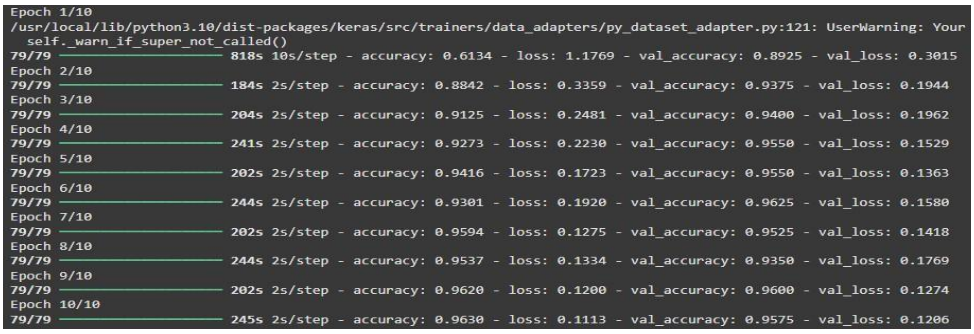


Fig. 4. Epoch result

Prototype Model Evaluation

After the model was trained, a system evaluation was conducted using the developed prototype model to identify herbal plants based on leaf image patterns. This evaluation aimed to measure the system's performance and user satisfaction with the developed application. The model evaluation was carried out using Python with the help of the scikit-learn library.

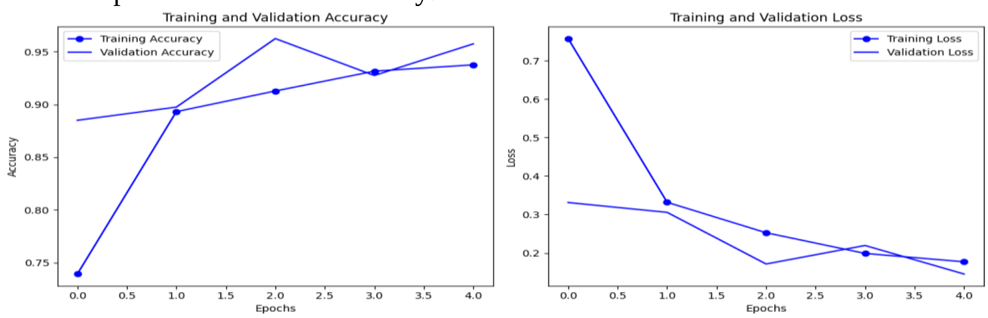


Fig. 5. Accuracy and Loss Graphs

In the accuracy graph as shown in Figure 5, both training and validation accuracies exhibited a stable increase. The training accuracy started at around 75% in the first epoch and continued to rise to over 96% in the final epoch. The validation accuracy also increased from approximately 89% in the first epoch and remained stable above 93%, reaching 96% in the last epoch, although with slight fluctuations. Meanwhile, in the loss graph, the training loss decreased significantly from around 0.7 to nearly 0.1, indicating that the model consistently minimized errors. The validation loss also decreased steadily from about 0.3 in the early epochs to around 0.12 in the final epoch, showing that the model did not experience significant overfitting. Overall, Figure 6 demonstrates that the model performed well, achieving high accuracy and consistent loss reduction, indicating that it was able to classify herbal leaf images accurately with minimal errors on the validation data.

The overall values of precision, recall, and f1-score for each class based on the model testing results can be seen in Table 2.

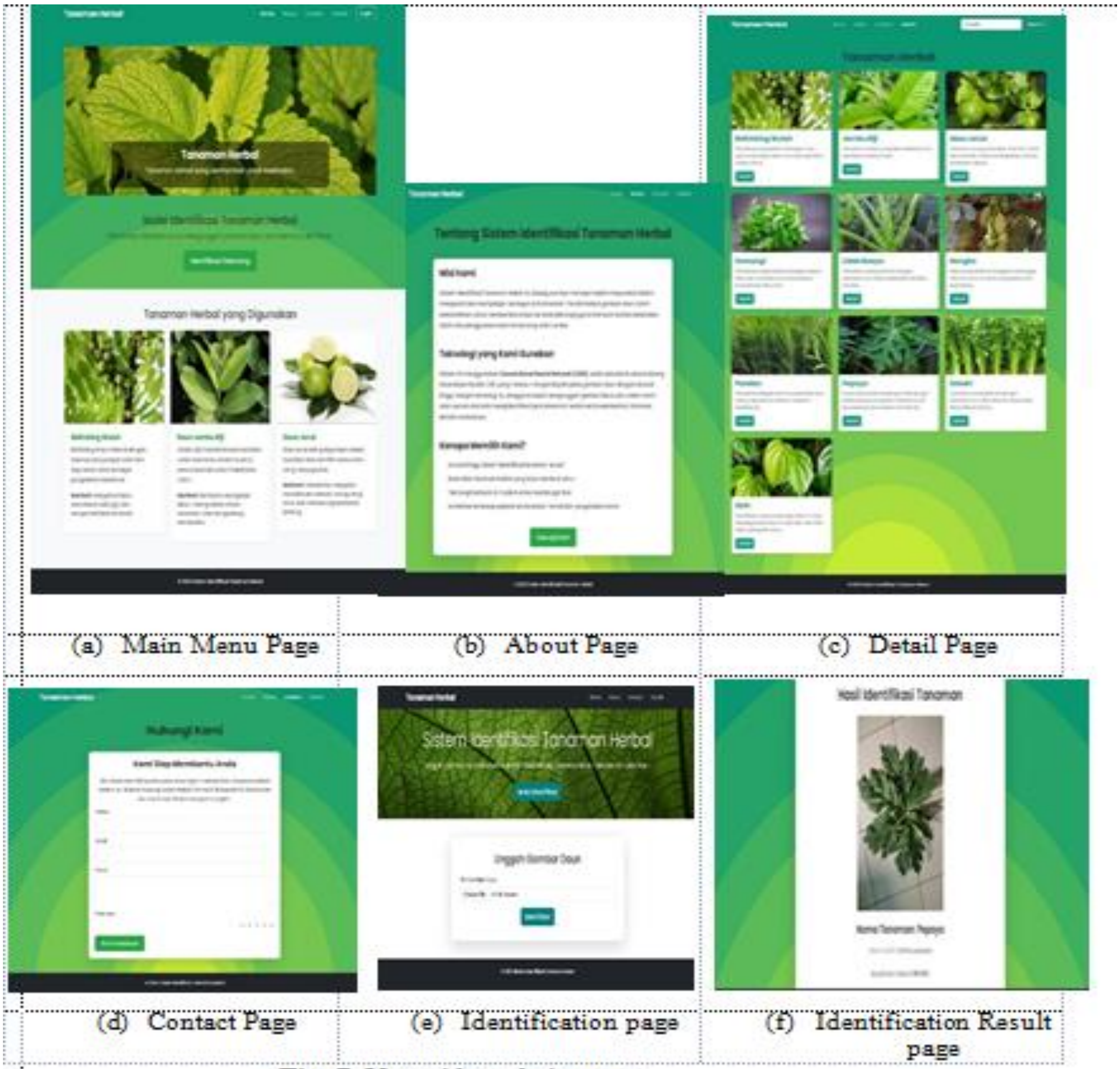
Table 2. Model Testing Results

Leaf data set	Precision	Recall	F1-score
Belimbing Wuluh (Starfruit)	1.00	0.93	0.97
Jambu Biji (Guava)	0.97	1.00	0.98
Jeruk Nipis (Lime)	1.00	1.00	1.00
Kemangi (Basil)	0.97	1.00	0.98
Lidah Buaya (Aloe vera)	1.00	1.00	1.00
Nangka (Jackfruit)	0.94	1.00	0.97

Pandan	1.00	1.00	1.00
Pepaya	0.91	1.00	0.95
Seledri (Celery)	1.00	0.90	0.95
Sirih (Betel)	1.00	0.93	0.97
Accuracy			0.98
Macro avg	0.98	0.98	0.98
Weight avg	0.98	0.98	0.98

Integration Model with Web

Figure 6 shows the pages available on the developed website from the user side. Figure 6a displays the Home page, which provides the main functionality related to herbal plants. Figures 6b, 6c, and 6d respectively present the About page, Detail page, and Contact page. Users can upload images of plant leaves for analysis and subsequently receive identification results. The identification flow is illustrated in Figure 6e, and the identification result is shown in Figure 6f.



(a) Main Menu Page (b) About Page (c) Detail Page

(d) Contact Page (e) Identification page (f) Identification Result page

Fig. 7. User side website page

IV. CONCLUSION

Based on the results obtained, this study successfully developed an herbal plant identification system for traditional medicine users by leveraging leaf image patterns using a Convolutional Neural Network (CNN) integrated into a web platform. The CNN model was designed using the MobileNetV2 architecture. The training process achieved an accuracy of 96.30%, with a validation accuracy of 95.75%. Furthermore, when tested on 50 leaf images, the system achieved an accuracy of 89.24%, correctly classifying 47 images and misclassifying only 3. The model was subsequently implemented into a web-based interface, enabling users to upload leaf images and obtain identification results directly, quickly, and conveniently. The proposed web-based system demonstrates that deep learning can facilitate practical herbal plant identification while contributing to biodiversity documentation and promoting the sustainable utilization of Indonesia's medicinal plant resources. Future work will focus on expanding the number of plant species, improving model robustness under field conditions, and developing a mobile-based implementation.

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