
Deep Learning-Based Herbal Plant Classification Using Leaf Shape and Pattern: The UII Botanical Leaf Dataset

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Abstract — Herbal plants play a crucial role in healthcare and are widely used as traditional medicines. However, identifying herbal species remains a major challenge due to morphological similarities, particularly in leaf shape and texture. This study aims to develop an intelligent classification system for Indonesian herbal plants based on leaf image analysis using artificial intelligence (AI) and digital image processing techniques. A localized dataset of 47 herbal species collected from Botanical SmartPark SMA UII was used to train a deep learning model employing the MobileNetV2 architecture through transfer learning. The proposed model achieved an average accuracy of 96.6% on the testing dataset, demonstrating high reliability in recognizing species with complex visual variations. The trained model was then implemented into an Android-based application called HERBfull Botanical SmartPark, enabling real-time plant identification and interactive access to botanical information. The system successfully enhances efficiency, accessibility, and educational value in the identification of local herbal species. This research contributes to the advancement of AI applications in botanical education, promoting digital literacy, biodiversity conservation, and the integration of smart technology into sustainable environmental learning platforms.

Keywords –Herbal plant classification, deep learning, MobileNetV2, image recognition, artificial intelligence, biodiversity education.

I. INTRODUCTION

Herbal plants play an essential role in maintaining human health and have long been used as a source of traditional medicine. According to the World Health Organization (WHO), approximately 80% of the global population still relies on herbal plants for healthcare purposes [1]. These plants contain bioactive compounds that contribute to disease prevention and treatment [2]. Globally, about 40,000 herbal species have been identified, of which 30,000 are found in Indonesia, representing 90% of Asia's herbal diversity and 25% (7,500 species) with known medicinal benefits [3]. This remarkable biodiversity places Indonesia among the countries with the richest herbal plant resources in the world.

However, despite this potential, public knowledge of herbal plant identification remains limited, particularly among students and general users [4]. The main challenge arises from the morphological similarity between species, especially in leaf structures such as shape, color, and venation [5]. These similarities often make it difficult to distinguish species visually without expert assistance or analytical tools.

For instance, *Curcuma longa* (turmeric) and *Curcuma xanthorrhiza* have nearly identical leaves, differing only in subtle aspects of size and texture [6]. Such conditions highlight the need for efficient and accurate identification methods.

The rapid advancement of Artificial Intelligence (AI) and Digital Image Processing (DIP) provides new opportunities to automate herbal plant classification. Several studies have demonstrated the effectiveness of AI-based approaches. Research [7] applied the Gray Level Co-occurrence Matrix (GLCM) and K-Nearest Neighbor (KNN) algorithms for ten herbal species, achieving 83.33% accuracy, while another study [8] utilized deep learning for nine herbal species with 98.51% accuracy. Although these approaches show promising results, most rely on non-local or generalized datasets that may not represent the unique morphological characteristics of Indonesian herbal plants.

In this context, Botanical SmartPark SMA UII in Yogyakarta serves as an educational and research garden hosting 137 species of herbal and spice plants. The park currently uses barcode-based identification, which, while informative, is inefficient and lacks

interactivity. The absence of automated recognition tools limits visitor engagement and learning experiences, creating an urgent need for a smart, accessible, and educational plant identification system tailored to local biodiversity.

This study addresses that gap by focusing on the development of an AI-based herbal plant classification system designed specifically for Indonesian species. The novelty lies in employing deep learning techniques for leaf-based classification trained on a locally collected dataset from Botanical SmartPark SMA UII—an approach that directly adapts AI technology to Indonesia’s native herbal context. Furthermore, the research contributes to educational technology and biodiversity conservation by proposing an intelligent identification framework that can enhance digital learning, promote scientific literacy, and support environmental sustainability.

Early studies on automatic plant identification primarily relied on handcrafted feature extraction techniques combining shape, texture, and color descriptors. For example, *Automatic Plant Identification: Is Shape the Key Feature?* [9] used SIFT for shape, color moments for color, and fractal segmentation for texture, achieving 94% accuracy but suffering from distortion due to physical leaf damage. Similarly, *Plant Classification System based on Leaf Features* [10] applied Random Forest (RF) and Linear Discriminant Analysis (LDA) using leaf shape, texture, and vein features, achieving 92.65% and 88.82% accuracy, respectively. Classical machine learning models such as Artificial Neural Networks (ANN) and Multi-Layer Perceptrons (MLP) [11] also demonstrated improved accuracy through supervised learning, although they required longer training time and manual feature selection. These early approaches were limited by sensitivity to lighting variations, dataset size, and the need for extensive preprocessing.

With the rise of deep learning, particularly Convolutional Neural Networks (CNN), plant classification performance significantly improved. Several studies [12-17] demonstrated CNN’s capability to automatically extract hierarchical features directly from raw images, reducing the need for manual feature engineering. For example, *Deep Learning for Medicinal Plant Species Classification and Recognition* [12] and *How Deep Learning Extracts and Learns Leaf Features for Plant Classification* [13] achieved near-perfect accuracy through transfer learning and end-to-end feature learning. Disease detection studies such as *Using Deep Learning for Image-Based Plant Disease Detection* [14] and *Plant Disease Identification from Individual Lesions and Spots Using Deep Learning* [15] further extended CNN applications, surpassing 99% accuracy in large datasets like PlantVillage. Meanwhile, *CNN Algorithm for Plant Classification in Deep Learning* [16], *Plant Species Classification Using Deep Convolutional Neural Network* [17], and *Plant Classification using Convolutional Neural Networks* [18] confirmed CNN’s superiority over traditional methods such as SVM, achieving accuracies between 86–97%. Despite their success, deep learning models still face challenges related to high computational

requirements, large dataset needs, and variations in plant appearance under real-world environmental conditions.

II. RESEARCH METHOD

This research was conducted to develop an intelligent system for herbal plant classification based on leaf images using deep learning. The methodology consists of five main stages: data acquisition, preprocessing and augmentation, model development, model evaluation, and system implementation. The workflow is illustrated in **Figure 1**.

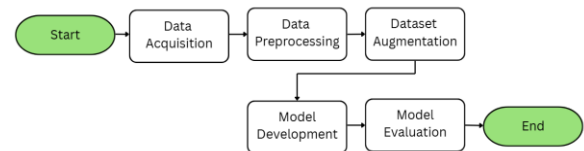


Fig. 1. Research workflow of the proposed herbal plant classification system using MobileNetV2.

A. Data Acquisition

The dataset used in this study consisted of 47 classes of Indonesian herbal plants, with each class containing 300 leaf images, resulting in a total of 14,100 images in .jpg format. The images were collected directly from the Botanical SmartPark UII, Indonesia, under natural lighting conditions to capture realistic visual variations.

Two smartphones were used for image acquisition to ensure diversity in camera characteristics and resolution, namely the Redmi Note 13 Pro 4G equipped with a Super Pixel 16-in-1 2.24 μm sensor, and the Realme 13 Pro+ featuring a Sony LYT-600 camera module. The data collection process covered various leaf orientations, backgrounds, and lighting intensities to improve dataset variability. Figure 2 presents sample visualizations of the collected images, and Table 1 Presents the Class distribution.



Fig.2. Sample visualizations of the collected images.

Table 1. Class distribution across training, validation, and testing datasets showing balanced proportions for all 47 herbal plant classes.

No	Herbal Plant Class	Training (270)	Validation (18)	Testing (12)	Total (300)
1	<i>Adas</i>	270	18	12	300
2	<i>Andong Merah</i>	270	18	12	300
3	<i>Begagang</i>	270	18	12	300
4	<i>Beluntas</i>	270	18	12	300
5	<i>Betadin</i>	270	18	12	300
6	<i>Cincau Perdu</i>	270	18	12	300
7	<i>Daun Afrika</i>	270	18	12	300
8	<i>Daun Cabe Jawa</i>	270	18	12	300
9	<i>Daun Cocor Bebek</i>	270	18	12	300
10	<i>Daun Kumis Kucing</i>	270	18	12	300
11	<i>Daun Mangkokan</i>	270	18	12	300
12	<i>Daun Suji</i>	270	18	12	300
13	<i>Daun Ungu</i>	270	18	12	300
14	<i>Dewa Ndaru</i>	270	18	12	300
15	<i>Garut</i>	270	18	12	300
16	<i>Honje</i>	270	18	12	300
17	<i>Iler</i>	270	18	12	300
18	<i>Insulin</i>	270	18	12	300
19	<i>Jahe</i>	270	18	12	300
20	<i>Jeruk Nipis</i>	270	18	12	300
21	<i>Kapulaga</i>	270	18	12	300
22	<i>Kayu Putih</i>	270	18	12	300
23	<i>Kecibling</i>	270	18	12	300
24	<i>Kemangi</i>	270	18	12	300
25	<i>Kembang Sepatu</i>	270	18	12	300
26	<i>Kenanga</i>	270	18	12	300
27	<i>Kunyit</i>	270	18	12	300
28	<i>Lampes</i>	270	18	12	300
29	<i>Legundi</i>	270	18	12	300
30	<i>Lidah Buaya</i>	270	18	12	300
31	<i>Mahkota Dewa</i>	270	18	12	300
32	<i>Melati</i>	270	18	12	300
33	<i>Meniran</i>	270	18	12	300
34	<i>Mint</i>	270	18	12	300
35	<i>Murbey</i>	270	18	12	300
36	<i>Nilam</i>	270	18	12	300
37	<i>Pacing Petul</i>	270	18	12	300
38	<i>Pagoda</i>	270	18	12	300
39	<i>Pandan</i>	270	18	12	300

No	Herbal Plant Class	Training (270)	Validation (18)	Testing (12)	Total (300)
40	<i>Patah Tulang</i>	270	18	12	300
41	<i>Pecut Kuda</i>	270	18	12	300
42	<i>Secang</i>	270	18	12	300
43	<i>Sereh</i>	270	18	12	300
44	<i>Sirih</i>	270	18	12	300
45	<i>Srikaya</i>	270	18	12	300
46	<i>Tin</i>	270	18	12	300
47	<i>Zigzag</i>	270	18	12	300

B. Image Preprocessing and Augmentation

All captured images were resized to 224×224 pixels to standardize the input dimensions and optimize computational efficiency during training. This resizing process also ensured compatibility with the Roboflow platform, which was later used for dataset management and augmentation.

To enhance model generalization and prevent overfitting, data augmentation was performed using the Roboflow augmentation engine. The following transformations were applied:

- Flip (Horizontal and Vertical): to simulate variations in viewing direction.
- Rotate (90° , $\pm 15^\circ$): clockwise, counterclockwise, and upside-down rotations to accommodate different camera angles.
- Crop (Zoom 0–20%): to simulate partial visibility of leaves.
- Saturation ($\pm 25\%$) and Brightness ($\pm 15\%$): to mimic diverse lighting conditions.
- Exposure ($\pm 10\%$): to adjust global illumination levels.
- Noise ($\leq 0.1\%$): to improve robustness against visual distortions such as blur or sensor noise.

After augmentation, the total dataset expanded to 35,250 images, ensuring greater variability and improved model learning stability. The dataset was divided into three subsets following standard deep learning partitioning practices, as shown in Table 2. The training set accounted for 90% of the data (31,725 images), while validation and testing sets consisted of 6% (2,115 images) and 4% (1,410 images), respectively.

Table 2. Dataset Distribution After Data Augmentation

Dataset Type	Number of Images	Percentage (%)
Training	31,725	90
Validation	2,115	6
Testing	1,410	4
Total	35,250	100

Representative samples of the augmented dataset are illustrated in Figure 3, showcasing variations in rotation, brightness, zoom level, and color intensity. These transformations effectively simulate real-world conditions, allowing the model to learn more

discriminative leaf features across different visual perspectives.



Fig. 3. Sample visualizations of augmented herbal leaf images.

C. Model Development

The herbal plant classification model was developed using a transfer learning approach based on the MobileNetV2 architecture shown in **Figure 4**, which is known for its high computational efficiency and suitability for mobile deployment. The development process involved three main stages: model initialization, customization and fine-tuning, and training configuration.

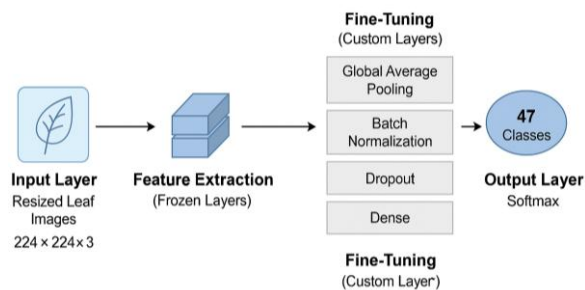


Fig. 4. Architecture of the MobileNetV2-based herbal plant classification model, showing input preprocessing, frozen feature extraction layers, fine-tuning layers, and the final Softmax output with 47 classes.

1) Model Initialization

The base model used in this research was MobileNetV2, pre-trained on the ImageNet dataset. This model was chosen because of its balance between accuracy and low computational cost, making it highly compatible with Android-based applications.

To preserve the general visual features learned from ImageNet, the first 100 layers of MobileNetV2 were frozen (non-trainable). This allowed the model to retain fundamental edge and texture detection capabilities, while the upper layers were modified for the specific task of herbal plant classification.

2) Customization and Fine-Tuning

After freezing the base layers, several new layers were added to adapt the model for the 47 herbal plant classes. The modified architecture is summarized in

Table 3, which details the added layers, activation functions, and key parameters.

Table 3. Custom Layers and Parameters for the Modified MobileNetV2 Model

Layer Type	Description / Function	Activation Function	Parameters / Notes
Global Average Pooling 2D	Convert feature maps into a single vector per feature channel	-	Reduces overfitting and improves generalization
Batch Normalization	Normalizes activations to stabilize training	-	Help accelerate convergence
Dropout	Randomly drops neurons during training	-	Dropout rate = 0.3
Dense Layer 1	Fully connected layer	ReLU	256 neurons
Dense Layer 2	Fully connected layer	ReLU	128 neurons
Output Layer	Final classification layer	Softmax	47 output classes

This architectural enhancement allows the model to extract both generalized visual features (from the frozen layers) and domain-specific representations of herbal leaf patterns (from the fine-tuned layers).

3) Training Configuration

The model was compiled using the Adam optimizer with a learning rate of 1×10^{-5} and trained using the categorical cross-entropy loss function since the dataset involves multi-class classification (47 classes).

The training process was performed for 25 epochs, with an early stopping mechanism applied when validation accuracy did not improve for 3 consecutive epochs to prevent overfitting. The batch size was set to 32, and model weights were saved at the point of best validation performance, **Table 4** present the training parameters.

Table 4. Training Parameters

Parameter	Value
Optimizer	Adam
Learning Rate	1×10^{-5}
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	25
Early Stopping	Patience = 3
Validation Split	10% of training data
Output Classes	47

D. Model Evaluation

The performance of the proposed model was evaluated using the testing dataset to measure its classification accuracy and robustness. Four common performance metrics were used: Accuracy, Precision, Recall, and F1-Score. These metrics provide a comprehensive assessment of the model's ability to correctly classify herbal plant species based on leaf images.

Let TP (True Positive) represent correctly classified images, TN (True Negative) represent correctly rejected images, FP (False Positive) represent misclassified images of other classes, and FN (False Negative) represent unrecognized images of the correct class.

The formulas for each evaluation metric are expressed as follows (1), (2), (3) and (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Accuracy measures the overall proportion of correctly classified images, **Precision** evaluates how many predicted positive samples are correct, **Recall** measures the model's ability to detect all relevant instances, and **F1-Score** provides the harmonic mean of Precision and Recall to balance both aspects.

E. Inference Testing on Application

While model evaluation was conducted using the testing dataset to measure classification performance, an additional inference testing was performed through the mobile application to validate the model's real-world usability.

III. RESULT AND DISCUSSION

A. Model Performance Evaluation

Figure 5 illustrates the training and validation loss curves of the MobileNetV2-based herbal plant classification model over 25 epochs. Both curves show a steady decrease in loss values as the number of epochs increases, indicating that the model successfully learns meaningful features from the training data.

During the initial training phase (epochs 0–5), the training loss rapidly drops from around 3.5 to below 1.0, and it gradually converges toward zero after epoch 20. The validation loss follows a similar trend, demonstrating that the model generalizes well to unseen

data. The close alignment between the training and validation loss curves suggests stable convergence with minimal overfitting.

Overall, this learning behavior confirms that the fine-tuned MobileNetV2 model effectively adapts to the herbal leaf dataset and achieves reliable optimization performance throughout the training process.

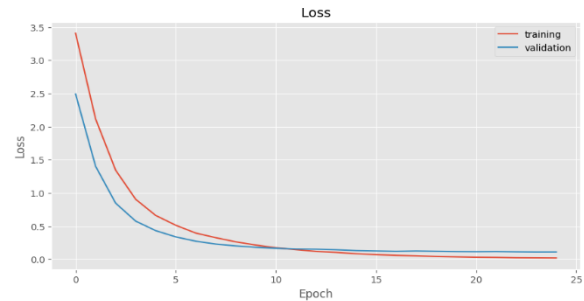


Fig. 5. Training and validation loss curves of the MobileNetV2 herbal plant classification model showing smooth convergence and minimal overfitting across 25 epochs.

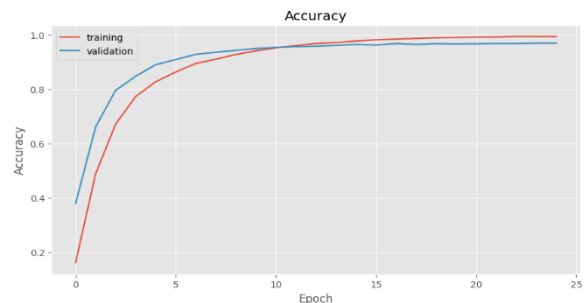


Fig. 6. Training and validation accuracy curves of the MobileNetV2 herbal plant classification model showing stable convergence and high generalization performance across 25 epochs.

Figure 6 presents the training and validation accuracy curves of the MobileNetV2 herbal plant classification model across 25 epochs. Both curves exhibit a rapid increase in accuracy during the early training phase (epochs 0–5), indicating that the model quickly learns discriminative features from the dataset.

After epoch 10, the accuracy stabilizes, with both curves converging near 100%, demonstrating excellent model performance and strong generalization to unseen validation data. The close alignment between training and validation accuracy confirms that the model effectively avoids overfitting and achieves balanced learning.

This consistent performance across both datasets indicates that the fine-tuned MobileNetV2 architecture is well-suited for herbal plant classification tasks, achieving high accuracy through efficient feature extraction and robust optimization.

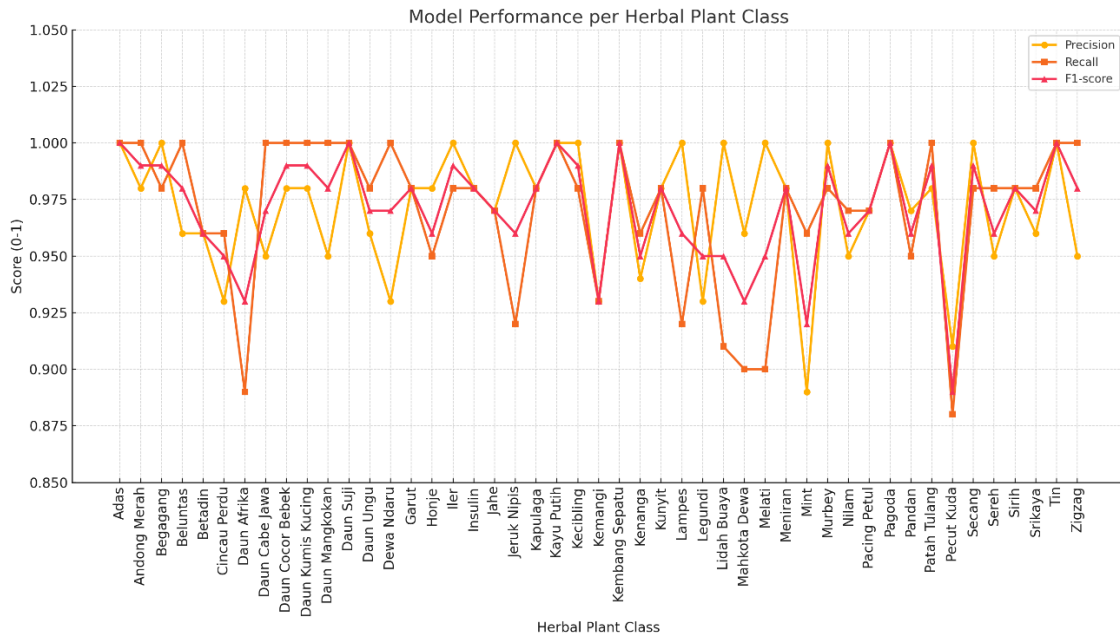


Fig. 7. Class-wise performance metrics (Precision, Recall, and F1-score) of the MobileNetV2 herbal plant classification model showing consistently high performance across 47 herbal species with minimal variation among classes.

Figure 7 illustrates the class-wise performance metrics — Precision, Recall, and F1-score — of the MobileNetV2-based herbal plant classification model across 47 herbal species. Overall, the model demonstrates high and consistent performance, with most classes achieving scores close to 1.0, indicating accurate and reliable classification results.

The metrics show only minor fluctuations among classes, which is typical in fine-grained image classification problems where certain species share similar visual features. For example, classes such as Lampes, Mahkota Dewa, Kemangi, and Mint display slightly lower values (around 0.90–0.93) across the three metrics. This decline is likely due to morphological similarities among leaves, such as overlapping shape patterns, color tones, or vein structures.

In contrast, species like Adas, Daun Suji, Kayu Putih, Pagoda, and Tin achieve perfect scores (1.00) across all metrics, reflecting the model’s strong capability to identify plants with distinctive leaf patterns and textures. The minimal gap between precision and recall across classes suggests that the model maintains a well-balanced ability to both correctly detect and accurately classify most herbal species without significant bias.

These results confirm that the proposed deep learning model achieves robust generalization and can reliably distinguish between a large number of visually similar herbal plant classes, making it suitable for practical implementation in botanical recognition systems.

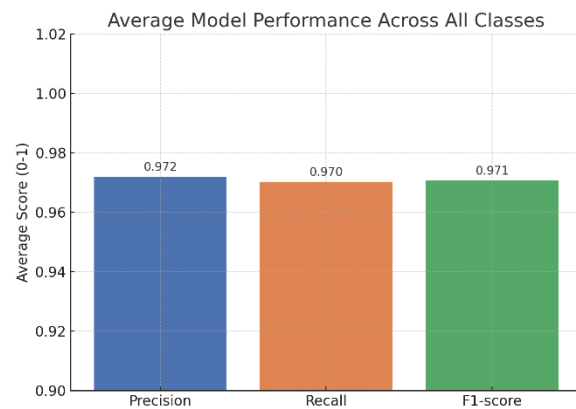


Fig. 8. Average Precision, Recall, and F1-score of the MobileNetV2 herbal plant classification model showing consistently high overall performance across all classes.

Figure 8 shows the average model performance across all 47 herbal plant classes based on Precision, Recall, and F1-score. The model achieves consistently high results, with an average precision of 0.972, recall of 0.970, and F1-score of 0.971. These values indicate excellent balance between accuracy and generalization, confirming the model’s strong capability in distinguishing various herbal species effectively.

Figure 9 presents the accuracy test results for each herbal plant species in the dataset. The model demonstrates high and consistent performance, with most classes achieving perfect accuracy (100%). Only a few species, such as Lampes (60%), Mahkota Dewa (70%), Kemangi and Mint (80%), and Begagang, Cincau Perdu, Daun Cabe Jawa, Daun Mangkokan, and Kapulaga (90%), show slightly lower accuracy due to morphological similarities among their leaves.

Overall, the model achieves an average accuracy of 96.6%, indicating excellent classification capability and reliable generalization across a diverse set of 47 herbal

plant classes. This high performance confirms the effectiveness of the MobileNetV2 architecture in

handling complex visual variations within natural leaf datasets.

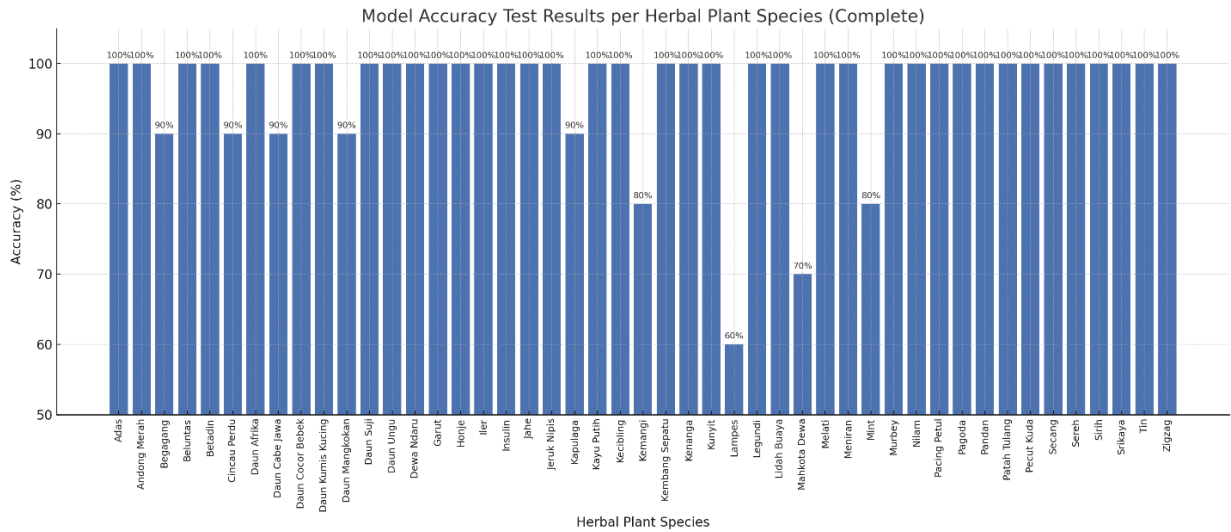


Fig. 9. Model accuracy test results per herbal plant species showing an average accuracy of 96.6% with most classes achieving perfect classification performance.

B. Inference Testing on Application (Direct User Test) Result

Figure 10 illustrates the average accuracy results from real-world testing conducted by four different users using the developed mobile herbal plant identification application. In this testing scenario, each user was assigned five specific herbal plant species and instructed to perform five image captures per plant, resulting in 25 total test samples per user. The goal was to evaluate how well the model performs in realistic conditions — including variations in lighting, camera quality, and image angles.

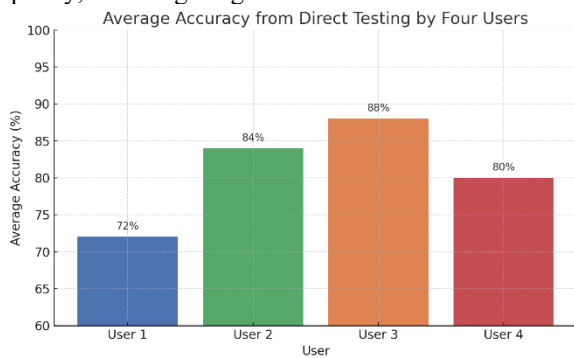


Fig. 10. Average classification accuracy from direct testing by four users, each testing five herbal plant species with five image captures per plant, showing consistent model performance under real-world conditions.

The results show that the system maintained stable performance across users, with User 3 achieving the highest average accuracy (88%), followed by User 2 (84%), User 4 (80%), and User 1 (72%). The variation in accuracy indicates that external environmental factors — such as lighting conditions, background noise, and differences in smartphone cameras — slightly influenced model predictions. Despite these variations, the model consistently

demonstrated strong recognition capability, proving its effectiveness for practical, real-world usage.

C. System Performance (Respon Time)

Figure 11 presents the system response time results measured during multiple image capture tests across ten different herbal plant species. Each test recorded the time required by the mobile application to process an image and return a classification result.

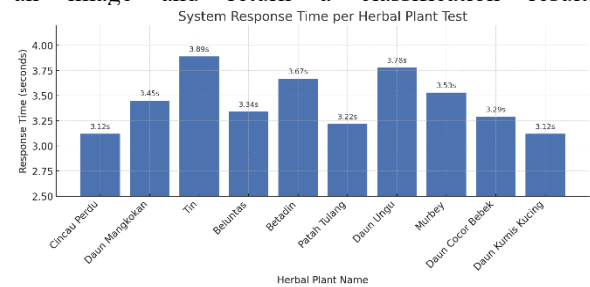


Fig. 11. System response time results for ten herbal plant samples showing consistent processing performance with an average response time of 3.45 seconds per image.

The response times range from 3.12 to 3.89 seconds, with an average of 3.45 seconds, demonstrating that the system performs efficiently for real-time use. The fastest responses were observed for *Cincau Perdu* and *Daun Kumis Kucing* (3.12 s), while the longest processing time occurred for *Tin* (3.89 s). Minor variations in response time are attributed to differences in image size, lighting conditions, and background complexity during image capture.

Overall, these results indicate that the system achieves a stable and responsive performance, maintaining classification speed well within an acceptable range for mobile-based plant identification applications.

D. Discussion

The overall experimental findings demonstrate that the MobileNetV2-based herbal plant classification system exhibits excellent performance in terms of accuracy, efficiency, and generalization. During model training, both the loss and accuracy curves showed stable convergence, confirming effective feature learning and the absence of overfitting. The evaluation metrics indicated a balanced classification capability, with average precision of 0.972, recall of 0.970, and F1-score of 0.971 across all 47 classes. This consistency reflects the model's ability to maintain high accuracy while minimizing both false positive and false negative.

The per-class accuracy analysis revealed an average overall accuracy of 96.6%, with most species achieving 100% correct classification. The minor misclassifications observed in visually similar plants (e.g., *Lampes*, *Kemangi*, *Mint*) highlight the challenge of distinguishing morphologically close species. Real-world testing through mobile application usage yielded an average user accuracy of 81%, confirming that the model performs reliably under diverse environmental conditions such as lighting, background variation, and camera differences.

In terms of efficiency, the system achieved an average response time of 3.45 seconds per image, validating its suitability for real-time mobile inference. Collectively, these findings confirm that the model provides an optimal balance between accuracy and computational performance, demonstrating its potential for real-world applications in botanical education, conservation monitoring, and smart botanical systems like the UII Botanical SmartPark. Table 5 presents the summary of experimental findings.

Table 5. Summary of experimental findings showing the MobileNetV2 model's strong accuracy, robustness, and efficiency across various evaluation aspects.

Aspect	Key Finding	Interpretation
Model Convergence	Stable training, no overfitting	Effective feature learning via transfer learning
Average Metrics	Precision 0.972, Recall 0.970, F1-score 0.971	Balanced prediction capability
Accuracy per Class	96.6% average	Excellent classification consistency
Real-World Testing	81% average accuracy	Robust in uncontrolled environments
Response Time	3.45 seconds average	Efficient for mobile inference

IV. CONCLUSION

This study successfully developed and evaluated a deep learning-based herbal plant classification system using the MobileNetV2 architecture, optimized for real-time implementation in the UII Botanical SmartPark application. The model achieved high overall performance, with an average precision of 0.972, recall of 0.970, and F1-score of 0.971, indicating balanced

predictive capability and robust generalization across 47 herbal plant classes. The average classification accuracy of 96.6% confirms the model's ability to correctly identify diverse species, while the real-world user testing yielded an average accuracy of 81%, demonstrating reliable functionality under practical environmental conditions.

The system also performed efficiently, achieving an average response time of 3.45 seconds per image, validating its feasibility for mobile-based deployment. These findings highlight the effectiveness of transfer learning and data augmentation strategies in enhancing recognition accuracy for complex natural image datasets.

Overall, the research provides a lightweight, accurate, and practical solution for digital plant identification that supports environmental education, botanical research, and tourism in smart botanical parks. Future work will focus on improving the system's robustness under diverse environmental variations, expanding the dataset, and exploring advanced lightweight architectures such as EfficientNetLite or MobileNetV3 to further enhance accuracy and inference speed.

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