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Automatic identification of herbal medicines using deep learning on leaf images

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ABSTRACT

Indonesia has a high diversity of medicinal plants that are widely used in traditional healthcare practices. Identification of medicinal plants is commonly based on leaf morphology; however, similarities in leaf shape, texture, and color often cause misidentification, particularly among non-experts. This limitation highlights the need for an automated and reliable identification approach. The primary objective of this study is to develop and evaluate a deep learning–based system for the automatic identification of medicinal plants using leaf images, with a specific focus on comparing the performance and efficiency of MobileNetV2 and ResNet50V2 architectures. The research design adopts an experimental approach using an internally collected dataset of medicinal plant leaf images representing multiple plant classes. The dataset is divided into training and testing sets to evaluate model generalization. The methodology involves image preprocessing steps, including resizing, normalization, and data augmentation, followed by the application of transfer learning using MobileNetV2 and ResNet50V2 as feature extractors. Both models are trained under the same experimental settings and evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The main outcomes and results indicate that both deep learning models achieve high classification performance. MobileNetV2 achieves an accuracy of 98.77%, precision of 98.84%, recall of 98.77%, and F1-score of 98.77%, while ResNet50V2 achieves an accuracy of 97.53%, precision of 97.87%, recall of 97.53%, and F1-score of 97.58%. The results demonstrate that MobileNetV2 provides slightly superior performance with lower computational complexity. In conclusion, lightweight deep learning architectures such as MobileNetV2 are effective and efficient for medicinal plant leaf identification and are suitable for implementation in mobile or resource-constrained environments.

1. Introduction

Indonesia is recognized as one of the world's biodiversity hotspots, hosting a vast number of plant species with medicinal potential [1], [2]. Traditional medicine remains an integral part of healthcare practices in many Indonesian communities, where herbal plants are commonly sourced from home gardens and surrounding natural environments [3], [4]. It is estimated that Indonesia is home to approximately 30,000 plant species, with around 1,200 species documented for their medicinal properties [5], [6]. Leaves are among the most frequently used plant parts in herbal medicine due to their accessibility, renewability, and rich bioactive compound content [7], [8].

Despite their widespread use, accurate identification of medicinal plants based on leaf morphology poses significant challenges. Many plant species exhibit highly similar leaf shapes, venation patterns, textures, and color distributions, making visual discrimination difficult, particularly for non-experts [9], [10], [11]. Such morphological similarities substantially increase the likelihood of misidentification, which may result in inappropriate usage, reduced therapeutic effectiveness, or unintended adverse effects [12], [13]. Conventional plant identification methods rely heavily on expert knowledge and manual observation of morphological characteristics. While effective in controlled settings, these approaches are time-consuming, subjective, and difficult to scale for broader public use [14], [15].

To overcome these limitations, image-based plant identification systems have attracted increasing attention in recent years [16], [17]. Advances in computer vision and machine learning have enabled automated analysis of plant images for species recognition with higher robustness and accuracy [18], [19]. In particular, deep learning approaches, especially convolutional neural networks (CNNs) have demonstrated superior performance in image classification by automatically learning hierarchical feature representations directly from raw image data [20], [21], [22]. Consequently, CNN-based methods have been widely adopted in intelligent informatics applications, including visual pattern recognition, decision-support systems, and automated classification, highlighting their effectiveness for complex image analysis tasks [23], [24], [25].

Compared with traditional machine learning techniques that rely on handcrafted features, CNN-based models provide higher adaptability and better generalization capability in complex visual recognition problems, such as plant leaf classification [26], [27]. However, the performance of deep CNN models is strongly influenced by dataset size, model architecture, and training strategy [28], [29]. Transfer learning has therefore emerged as an effective solution by leveraging knowledge from models pre-trained on large-scale datasets such as ImageNet, enabling improved performance even when training data are limited [30], [31], [32].

Lightweight CNN architectures, such as MobileNetV2, are specifically designed to reduce computational complexity and memory usage while maintaining competitive classification accuracy [33], [34]. These characteristics make lightweight models particularly suitable for deployment in mobile devices and resource-constrained environments [35], [36]. In contrast, deeper architectures such as ResNet50V2 utilize residual connections to facilitate stable training of very deep networks and have demonstrated strong performance in complex image classification tasks [37], [38]. Nevertheless, deeper models generally require higher computational resources and larger datasets to fully exploit their representational capacity [39], [40].

Several recent studies have explored CNN-based approaches for plant and medicinal leaf classification; however, most existing works emphasize accuracy improvement without sufficient discussion of model efficiency and deployment feasibility [41], [42]. Moreover, comparative investigations examining the trade-offs between lightweight and deep residual architectures for medicinal plant leaf classification, particularly using locally collected datasets, remain limited [43], [44].

Previous studies conducted by the authors have explored intelligent systems and data-driven approaches for pattern recognition and classification, providing a methodological foundation for applying deep learning techniques to visual recognition problems [45], [46]. Building upon this line of research, the present study focuses on applying CNN-based transfer learning models for medicinal plant identification using leaf images.

Therefore, this study aims to compare the performance of MobileNetV2 and ResNet50V2 architectures for the classification of medicinal plants based on leaf images. The main contributions of this study are threefold: (1) the development of a CNN-based medicinal plant identification framework using an internally collected leaf image dataset, (2) a comparative evaluation of lightweight and deep CNN architectures in terms of classification accuracy and computational efficiency, and (3) an assessment of the suitability of lightweight deep learning models for deployment in real-world, resource-constrained applications.

2. Method

This study adopts an experimental research methodology to classify medicinal plants based on leaf images using deep learning techniques. The overall research workflow consists of data preprocessing, model implementation, training, testing, and performance evaluation, as illustrated in Fig. 1.

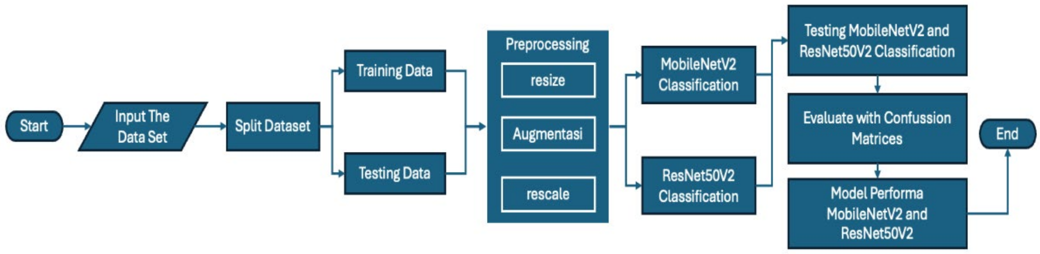

Fig. 1. Research Stages.

2.1. Data Preprocessing

Data preprocessing is conducted to improve data quality and ensure consistency prior to model training. The original leaf images are converted into a standard image format and resized to match the input requirements of the deep learning models. Image normalization is applied to rescale pixel intensity values, enabling stable and efficient training processes [47].

To enhance model generalization and reduce overfitting, data augmentation techniques are applied to the training dataset, including rotation and horizontal flipping. Data augmentation has been shown to improve performance in image-based deep learning models, particularly when working with limited datasets [48], [49].

2.2. Deep Learning Framework

Deep learning is employed in this study due to its capability to automatically learn hierarchical feature representations from raw image data. Unlike traditional machine learning approaches that rely on handcrafted features, deep learning models learn discriminative features through multiple layers of abstraction, making them suitable for complex image classification tasks [50].

2.3. Convolutional Neural Network Models

Convolutional neural networks (CNNs) are used as the core architecture for image classification. CNNs are effective in extracting spatial features from images through convolutional and pooling operations, followed by classification layers that map learned features to output classes [51]. The input image is processed through convolutional layers that extract visual features such as edges, textures, and shapes, forming three-dimensional feature maps (width, height, and depth). The process begins with the input layer, which receives the raw image data in the form of pixel matrices. Unlike traditional fully connected neural networks, CNNs preserve the spatial structure of images by organizing pixel information along three dimensions: width, height, and depth (channels). The input image is passed through a series of convolutional layers, where multiple learnable filters slide over the image to extract meaningful features such as edges, textures, and shapes. These filters produce feature maps, which represent different visual patterns detected from the input. As illustrated on the Fig. 1, the convolution process transforms a 2D image into a three-dimensional feature representation composed of width, height, and depth, where depth corresponds to the number of filters applied. Following convolution, activation functions and pooling layers are typically applied to introduce non-linearity and reduce spatial dimensions, allowing the network to focus on the most important features while reducing computational complexity. The extracted feature maps are then flattened and forwarded to fully connected layers, as depicted on the left side of Fig. 1, which perform high-level reasoning and classification. Finally, the output layer produces the predicted class labels, representing the identified medicinal plant species based on the learned visual patterns. This hierarchical structure enables CNNs to automatically learn both low-level and high-level features directly from leaf images, making them highly effective for visual recognition tasks such as medicinal plant identification.

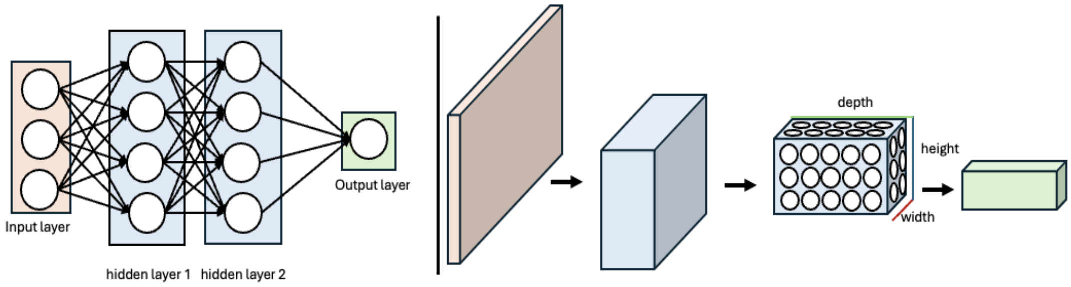

Fig. 2. Architecture of CNN.

Two CNN architectures are implemented in this study: MobileNetV2 and ResNet50V2. Both models are applied using a transfer learning strategy, where weights pre-trained on large-scale image datasets are utilized as initial feature extractors and subsequently fine-tuned using the medicinal plant leaf dataset.

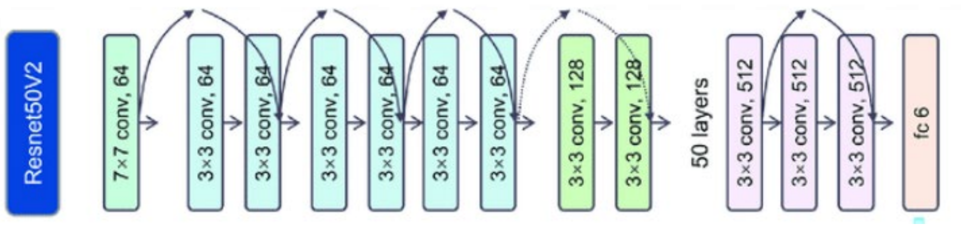

Fig. 3. Architecture of ResNet50V2.

MobileNetV2 is selected due to its lightweight architecture, which employs depthwise separable convolutions and linear bottleneck layers to reduce computational complexity while maintaining high classification accuracy. ResNet50V2 is chosen as a deep residual network that utilizes identity-based skip connections to facilitate stable training of deep architectures and mitigate the vanishing gradient problem.

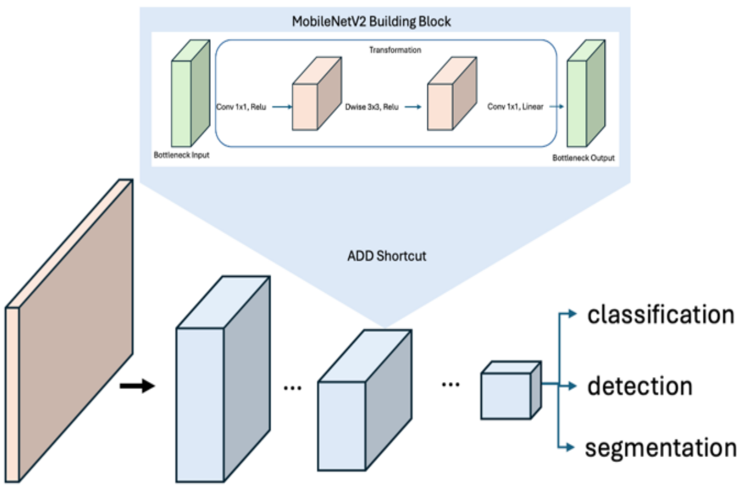

Fig. 4. Architecture of MobileNetV2.

2.4. Model Training and Testing

The dataset is divided into training and testing subsets. Both MobileNetV2 and ResNet50V2 models are trained using identical experimental settings to ensure a fair comparison. The training process is conducted for a fixed number of epochs, and the Adam optimizer is employed to update model weights due to its effectiveness in accelerating convergence during deep neural network training. The categorical cross-entropy loss function is used to optimize multi-class classification performance.

After training is completed, the testing dataset is used to evaluate the classification performance of each model independently.

2.5. Performance Evaluation

Model performance is evaluated using confusion matrix–based metrics, including accuracy, precision, recall, and F1-score. Confusion matrices are generated to analyze classification results and identify misclassification patterns. These evaluation metrics are commonly used to assess the performance of image classification models.

3. Results and Discussion

This section presents and analyzes the experimental outcomes of medicinal plant leaf classification using MobileNetV2 and ResNet50V2. The discussion integrates dataset characteristics, learning behavior, and quantitative results to evaluate the suitability of each architecture for this application.

3.1. Dataset Distribution and Learning Implications

The distribution of medicinal plant leaf images across training and testing datasets is illustrated in Fig. 5, while the numerical details are summarized in Table 1. The dataset contains 376 training images and 162 testing images distributed across eight medicinal plant classes.

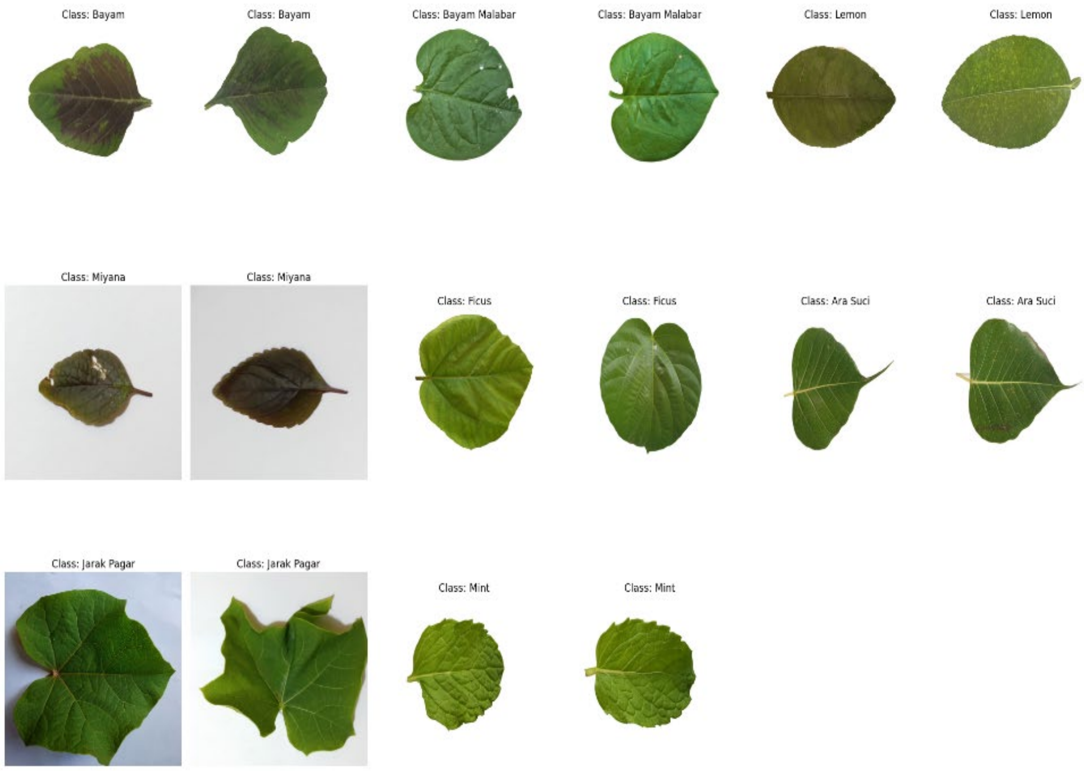

Fig. 5. Results of Grouping Data for Each Class.

Fig. 5 visually highlights the imbalance among classes, where Bayam, Bayam Malabar, and Mint dominate the dataset, whereas Jarak Pagar and Miyana are represented by substantially fewer samples. The figure shows representative samples of medicinal plant leaf images used in this study across eight classes: Bayam, Bayam Malabar, Lemon, Miyana, Ficus, Ara Suci, Jarak Pagar, and Mint. Each class exhibits distinct visual characteristics in terms of leaf shape, size, vein structure, and surface texture. Despite these differences, several classes display similar color tones and morphological patterns, which increases the difficulty of manual identification. This visual diversity and inter-class similarity make the dataset suitable for evaluating the effectiveness of deep learning models in recognizing and distinguishing medicinal plant species based on leaf images.

Table 1. Number of Train Data and Test Data for Each Class.

Data	Class	Total	Data	Class	Total
Training	Ara Suci	46	Testing	Ara Suci	17
	Bayam	83		Bayam	40
	Bayam Malabar	74		Bayam Malabar	29
	Ficus	36		Ficus	14
	Jarak Pagar	14		Jarak Pagar	18
	Lemon	43		Lemon	14
	Mint	65		Mint	33
	Miyana	15		Miyana	7
Total		376	Total		162

This imbalance reflects realistic data acquisition conditions in herbal plant documentation, where certain species are more readily available or frequently collected than others. From a learning perspective, such imbalance introduces additional challenges because classification models tend to be biased toward majority classes, while minority classes receive fewer samples for learning discriminative features. Consequently, this dataset provides a meaningful and realistic benchmark for evaluating the robustness and generalization capability of the deep learning models used in this study.

3.2. Learning Behavior of MobileNetV2

The MobileNetV2 architecture, summarized in Table 2, contains approximately 2.34 million parameters, making it a lightweight model.

Table 2. The MobileNetV2 architecture.

Layer (Type)	Output Shape	Param
Mobilev2_1.00_244 (Functional)	(none,7,7,1280)	2.257.984
Global_average_pooling	(none, 1280)	0
dense	(none, 64)	81.984
dropout	(none, 64)	0
dense_1	(none, 8)	520
Total Params	2.340.488	
Trainable Params	82.504	
No-Trainable Params	2.257.984	

In addition, MobileNetV2 introduces inverted residual blocks with linear bottlenecks, enabling efficient information flow through the network without unnecessary nonlinear transformations. This architectural feature helps preserve essential feature representations and mitigates information loss, particularly when learning subtle morphological differences among visually similar medicinal plant leaves. The training and validation accuracy curves in Fig. 6 show that MobileNetV2 converges smoothly, reaching 99.74% training accuracy and 98.15% validation accuracy. The corresponding loss curves in Fig. 7 decrease steadily to low final values, indicating stable optimization and good generalization. The strong performance of MobileNetV2 observed in this study can be attributed to its architectural design, which is optimized for efficient feature extraction under limited data conditions. MobileNetV2 employs depthwise separable convolutions, decoupling spatial filtering from channel-wise feature extraction. This design significantly reduces the number of trainable parameters while preserving the model's ability to capture discriminative spatial patterns in leaf images.

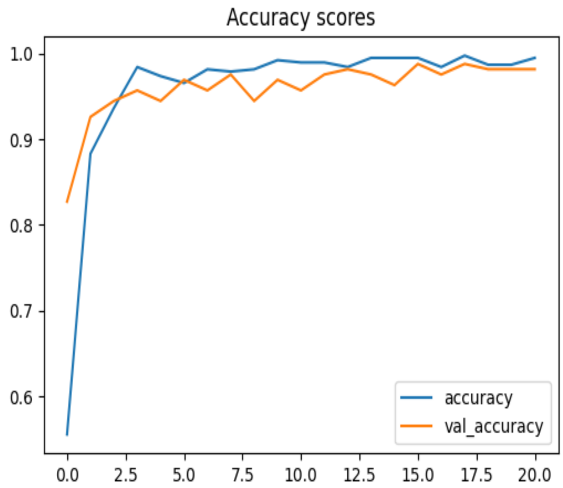

Fig. 6. MobileNetV2 Architecture Accuracy Results.

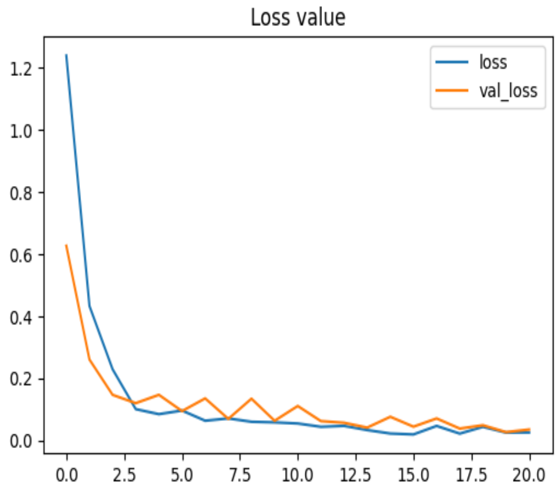

Fig. 7. MobileNetV2 Architecture Loss Results.

These architectural advantages explain why MobileNetV2 achieves superior generalization performance despite its substantially smaller model size. In the context of this study, where the dataset is moderately sized and imbalanced, the lightweight yet expressive nature of MobileNetV2 enables it to learn robust features without overfitting, making it well suited for practical medicinal plant identification tasks. The confusion matrix in Fig. 8 further supports this observation. MobileNetV2 correctly classifies all samples of Ara Suci, Ficus, Lemon, and Miyana, with only minor misclassifications occurring mainly between visually similar classes such as Bayam and Mint. This suggests that MobileNetV2 is able to capture subtle morphological differences in leaf images, despite the presence of class imbalance.

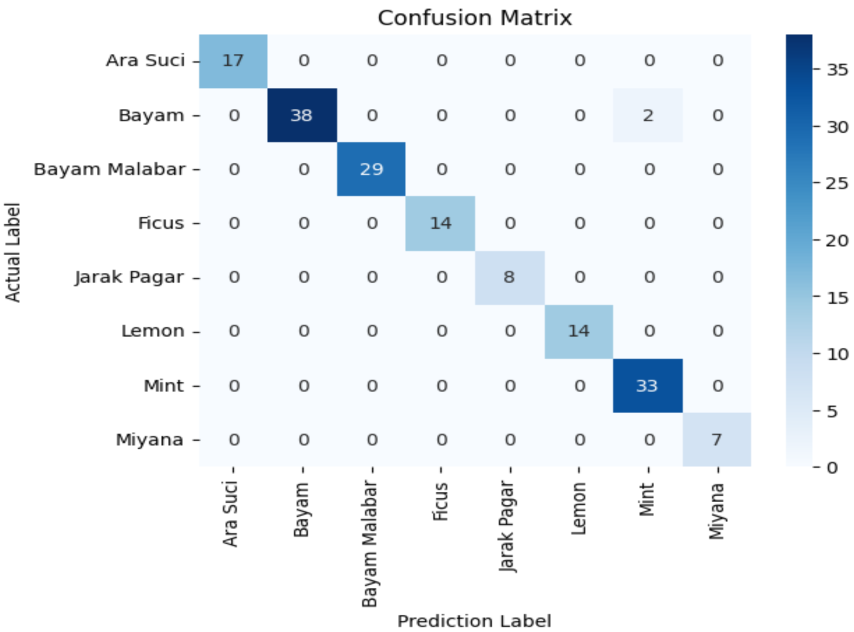

Fig. 8. The Result of *the Confusion Matrix Architecture of* MobileNetV2.

The strong performance of MobileNetV2 can be attributed to its depthwise separable convolutions and linear bottleneck design, which enable efficient feature extraction while limiting the risk of overfitting. As a result, MobileNetV2 demonstrates both high accuracy and strong generalization, making it particularly suitable for datasets of moderate size.

3.3. Learning Behavior of ResNet50V2

ResNet50V2, as shown in Table 3, contains more than 23 million parameters, providing substantially greater representational capacity than MobileNetV2. The performance of ResNet50V2 observed in this study is closely related to its deep residual learning architecture. ResNet50V2 employs identity-based skip connections, which allow gradients to flow directly through the network and enable the training of very deep architectures.

Table 3. Model ResNet50V2.

Layer (Type)	Output Shape	Param
Mobilev2_1.00_244 (Functional)	(none,7,7,2084)	23.564.800
Global_average_pooling	(none, 2048)	0
dense	(none, 64)	131.136
dropout	(none, 64)	0
dense_1	(none, 8)	520
Total Params	23.696.456	
Trainable Params	131.656	
No-Trainable Params	23.564.800	

This design makes ResNet50V2 highly effective for learning complex and highly diverse visual patterns, particularly when large-scale datasets are available. However, in the context of this study, where the dataset is of moderate size and exhibits class imbalance, the very high representational capacity of ResNet50V2 becomes less advantageous. The model tends to learn fine-grained but dataset-specific features, which can reduce its generalization ability when compared to a more compact architecture. This behavior is reflected in the higher validation loss and larger number of misclassifications observed in the confusion matrix. Furthermore, the deeper structure of ResNet50V2 increases the number of trainable parameters and computational complexity, making the model more sensitive to noise and redundant patterns in the training data. As a result, although ResNet50V2 remains a powerful architecture for large-scale image recognition tasks, its depth does not translate into superior performance for medicinal plant leaf classification under the current data conditions. The training and validation curves in Fig. 9 and Fig. 10 indicate that ResNet50V2 converges effectively, achieving 97.21% training accuracy and 96.30% validation accuracy. However, the higher loss values and larger train–validation gap suggest weaker generalization compared to MobileNetV2.

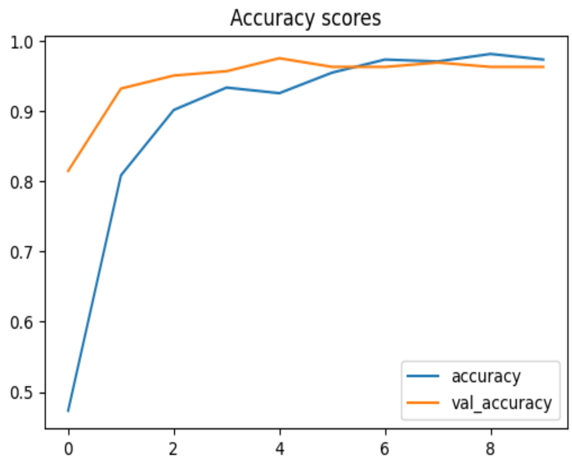

Fig. 9. RestNet50V2 Architecture Accuracy Results.

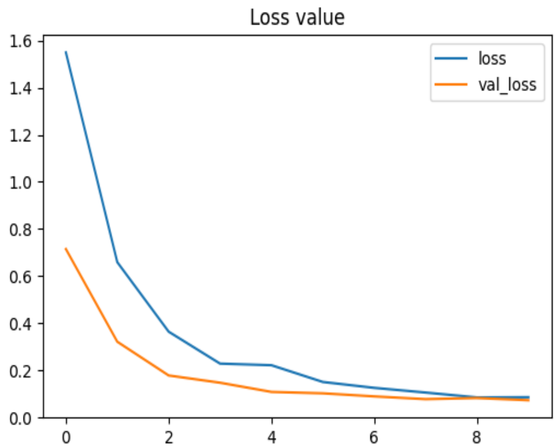

Fig. 10. RestNet50V2Architecture Loss Results.

The confusion matrix in Fig. 10 reveals more misclassification cases, particularly between Bayam Malabar and Ficus as well as Mint and Bayam, which share similar visual characteristics. This indicates that the deeper ResNet50V2 model, while powerful, is more sensitive to overlapping features and limited data availability.

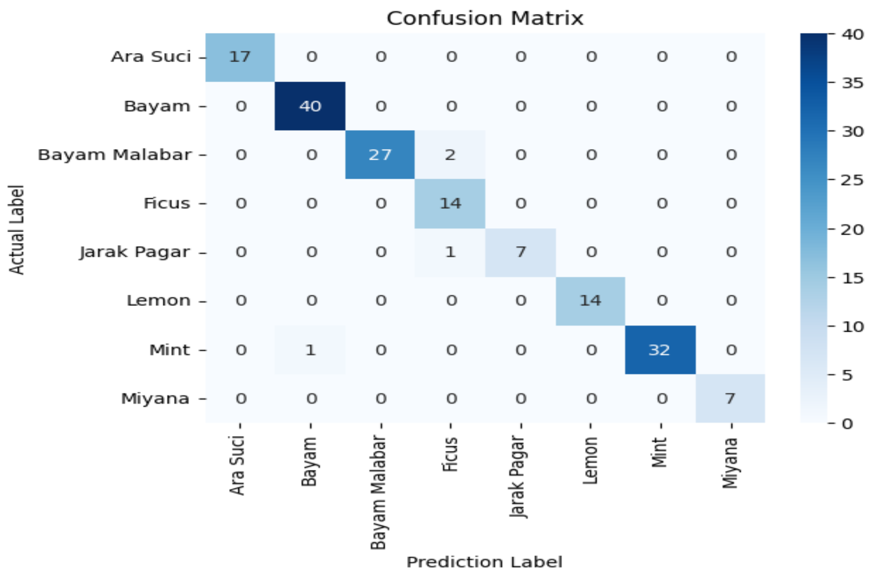

Fig. 11. The Result of *Confusion Matrix* Architecture ResNet50V2.

The overall quantitative comparison in Table 4 confirms this trend. MobileNetV2 achieves 98.77% accuracy and 98.77% F1-score, outperforming ResNet50V2, which achieves 97.53% accuracy and 97.58% F1-score. Although the numerical difference is modest, it is consistent across all metrics. Based on 162 test samples, MobileNetV2 misclassifies approximately 2 images, while ResNet50V2 misclassifies approximately 4 images, resulting in error rates of 1.23% and 2.47%, respectively. A two-proportion comparison indicates that MobileNetV2 has a lower misclassification rate, supporting the conclusion that its superior performance is not due to random variation but reflects a more robust learning behavior.

Table 4. Evaluation Result Comparison.

Layer (Type)	MobileNetV2	ResNet50V2
Accuracy	98.77%	97.53%
Precision	98.84%	97.87%
Recall	98.77%	97.53%
F1-Score_1	98.77	97.58%

Overall, these results demonstrate that while both architectures are effective for medicinal plant leaf classification, **MobileNetV2 provides a better balance between accuracy and efficiency**, making it more suitable for deployment in practical, resource-constrained environments such as mobile or field-based herbal identification systems.

4. Conclusion

This study investigated the use of deep learning for the automatic identification of medicinal plants based on leaf images by comparing two convolutional neural network architectures, MobileNetV2 and ResNet50V2. Using an internally collected dataset of eight medicinal plant species, both models demonstrated strong classification capability, confirming the effectiveness of CNN-based approaches for herbal plant recognition. The experimental results show that MobileNetV2 consistently outperforms ResNet50V2 across all evaluation metrics, including accuracy, precision, recall, and F1-score. Despite having significantly fewer parameters, MobileNetV2 achieves better generalization and lower misclassification rates, indicating that lightweight architectures can be more effective than deeper networks when applied to moderately sized and imbalanced datasets. This finding highlights the importance of selecting models that are not only powerful but also well aligned with data characteristics and deployment constraints. From a practical perspective, the superior performance and computational efficiency of MobileNetV2 make it particularly suitable for real-world applications, such as mobile-based herbal identification systems and community health support tools in rural or resource-limited environments. These applications can help improve the safety, accessibility, and reliability of traditional herbal medicine usage. Nevertheless, this study is limited by the size and scope of the internal dataset and the use of a single train–test split. Future research should expand the dataset, incorporate additional plant organs such as flowers or stems, apply cross-validation techniques, and explore hybrid or ensemble deep learning models to further enhance robustness and generalization. This research provides empirical evidence that lightweight deep learning models, particularly MobileNetV2, offer a promising and practical solution for automated medicinal plant leaf identification, supporting the integration of intelligent informatics into traditional healthcare practices.

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Declarations

Author contribution.
1st Author (Anita Ahmad Kasim): Conceptualization, Methodology, Formal Analysis, Writing – Original Draft
2ndAuthor (Lukman Nadjamuddin): Investigation, Data Curation, Visualization
3rd Author (Muhammad Bakri): Writing – Review & Editing, Supervision
4th Author (Chairunnisa Ar. Lamasitudju): Resources, Funding Acquisition, Project Administration
5th Author (Harry T. Pagiu): Implementation and Coding
6th Author (Puguh Budi Prakoso): Conceptualization, Methodology, Formal Analysis
7th Author (Anindita Septiarini): Conceptualization, Methodology, Formal Analysis
8th Author (Bima Prihasto): Conceptualization, Methodology, Formal Analysis
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