

# Transfer Learning-Based Classification of Herbal Plants for Biodiversity Conservation

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## ARTICLE INFO

## ABSTRACT

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Land degradation threatens Indonesia's status as a megabiodiversity country, placing many of its herbal plant species at risk. The identification of these plants, which are crucial for ecological balance and traditional medicine, still relies on slow and subjective manual methods. This research addresses this issue by developing an automated, accurate, and user-friendly classification system for Indonesian herbal plants. The primary objective was to create and test a deep learning model using transfer learning and the EfficientNet-B0 architecture, optimized for mobile device use. The methodology included assembling a dataset of 4,500 images from 15 species in Lombok, verified for accuracy by botanists. A 70:15:15 data split was employed for training the model, and extensive data augmentation techniques such as rotation, flipping, and zooming were applied to enhance generalization. The proposed EfficientNet-B0 model outperformed baseline models like MobileNetV2 and ResNet50 in experiments, achieving a high classification accuracy of 92.4% and an F1-score of 91.7%. The model was successfully converted to TensorFlow Lite and integrated into an Android app, enabling real-time identification with an average inference time of less than one second. The research concludes that the implemented system is a powerful tool for biodiversity conservation and community health initiatives. Key contributions include the creation of a specialized dataset, optimization of EfficientNet-B0 for local herbs, and development of a practical mobile application for real-world use.

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## 1. Introduction

Indonesia is one of the world's megabiodiversity countries, yet the preservation of medicinal plants is under serious threat due to land degradation and modernization [1], [2], [3], [4], [5], [6]. Traditional identification methods are often slow and subjective, making it difficult for communities to distinguish herbal species accurately [7], [8], [9], [10]. Recent advancements in computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), have enabled accurate classification of plant species from images [11], [12].

Transfer learning has emerged as an effective technique to improve model accuracy while reducing computational cost by leveraging pre-trained models [13], [14]. Among these, EfficientNet

has demonstrated strong performance in balancing accuracy and efficiency in plant classification tasks [15]. Several studies have successfully applied CNNs and transfer learning for general plant recognition [5], [16], but applications specifically targeting local herbal plants remain limited, especially in Indonesia.

Mobile-based deployment is also becoming increasingly important [17]. Studies show that mobile deep learning applications can enhance public accessibility to technology in the health and biodiversity sectors [18], [19]. However, integrating advanced CNN models into lightweight Android applications for herbal identification and conservation awareness is still underexplored [20], [21], [22]. This gap highlights the novelty of this research, which proposes an EfficientNet-based transfer learning model deployed on Android to support herbal identification and biodiversity conservation [23], [24], [25]. The primary contributions of this work are threefold: (1) we developed a robust image classification model using EfficientNet-B0 transfer learning tailored for 15 species of Indonesian herbal plants, achieving state-of-the-art accuracy on our dataset; and (2) we implemented and deployed the optimized model into a user-friendly Android application using TensorFlow Lite, demonstrating a complete pipeline from research to a practical tool with real-world impact for conservation and community health.

## 2. Method

### 2.1. Research Design

The research design consists of six main stages: (1) dataset acquisition, (2) preprocessing, (3) model development using transfer learning, (4) training and validation, (5) evaluation, and (6) deployment on an Android platform. This workflow ensures reproducibility and transparency of the entire research process.

### 2.2. Data Acquisition

The dataset used in this study comprised 4,500 leaf images of herbal plants collected from two main sources: (1) Field documentation in Lombok, Indonesia using a smartphone camera with controlled lighting conditions, (2) Open-source repositories such as Kaggle and PlantNet for complementary species images. The dataset covered 15 herbal species commonly found in Lombok, including *Curcuma longa* (kunyit), *Zingiber officinale* (jahe), *Piper betle* (sirih), *Orthosiphon aristatus* (kumis kucing), *Centella asiatica* (pegagan), and others. Each image was annotated and validated by a botanist to ensure correct labeling. The distribution of the dataset into training, validation, and testing sets followed the ratio of 70:15:15, as presented in Table 1.

**Table 1.** Dataset distribution for herbal plant

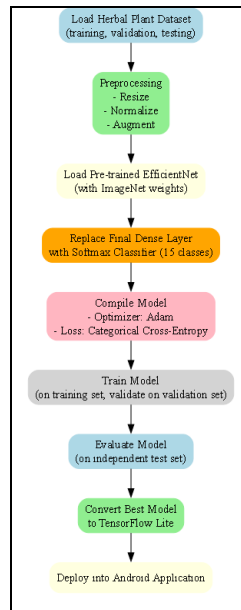
Species (Scientific Name)	Training	Validation	Testing	Total
<i>Curcuma longa</i>	210	45	45	300
<i>Zingiber officinale</i>	210	45	45	300
<i>Piper betle</i>	210	45	45	300
<i>Orthosiphon aristatus</i>	210	45	45	300
<i>Centella asiatica</i>	210	45	45	300
... (10 other species)	210	45	45	300
<b>Total</b>	<b>3,150</b>	<b>675</b>	<b>675</b>	<b>4,500</b>

### 2.3. Preprocessing

All images were resized to  $224 \times 224$  pixels to match the EfficientNet input dimension. Pixel values were normalized into the range 0-1. To improve generalization, data augmentation techniques were applied, including random rotation  $\pm 20^\circ$ , horizontal flipping, zooming 20%, and brightness adjustment. This step reduces overfitting and ensures the model can handle variations in field conditions [26], [27].

### 2.4. Research Procedure (Algorithm)

The step-by-step procedure of the proposed classification is shown in Algorithm 1.



**Fig. 1.** Herbal Plant Classification using Transfer Learning with EfficientNet-B0

The classification procedure followed a structured transfer learning workflow, as detailed in this section. The process commenced by loading a pre-trained EfficientNet-B0 model, initialized with weights learned from the ImageNet dataset. To adapt this general-purpose model for our specific herbal plant classification task, the original top classification layer was removed. Subsequently, all layers in the pre-trained base model were frozen to preserve the valuable feature extraction capabilities learned from ImageNet during the initial training phase.

A new set of custom classification layers was then appended on top of the base model. This new head consisted of a Global Average Pooling 2D layer, followed by a fully connected Dense layer with 512 units and ReLU activation, a Dropout layer with a rate of 0.3 to mitigate overfitting, and a final Dense output layer with 15 units and softmax activation corresponding to the number of target species. This modified model was compiled using the Adam optimizer with a learning rate of 0.001, the Categorical Crossentropy loss function, and was monitored using accuracy, precision, and recall metrics. The model was then trained for 30 epochs on the training set 70%, using the validation set 15% to evaluate performance after each epoch.

Following this initial training, a fine-tuning phase was initiated: a portion of the base model's layers were unfrozen, and the model was re-compiled with a significantly reduced learning rate 0.0001 to allow for gentle adjustments to the pre-trained features. This fine-tuning process continued for an additional 20 epochs. The final model's performance was rigorously evaluated on the completely unseen test set 15%. Finally, the fully trained and optimized model was converted into the TensorFlow Lite format to enable efficient deployment on mobile devices.

## 2.5. Model Training and Evaluation

The model training was conducted using TensorFlow 2.10.0 and Keras 2.10.0 on a workstation with an NVIDIA GeForce 930M. Training was performed as outlined in Algorithm 1. We utilized a batch size of 32. The initial learning rate was set to 0.001 for the first training phase and dropped to 0.0001 during the fine-tuning phase. The model was trained for a total of 50 epochs. The evaluation parameters comprised accuracy, precision, recall, and F1-score, following best practices in picture classification tasks [28], [29]. The results of the model comparison with baseline CNNs (MobileNetV2, ResNet50, InceptionV3) are presented in the Results section.

Justification for 70:15:15 split: Given the moderate size of our dataset  $n=4,500$  and the need for a suitably big validation set to properly assist the training and fine-tuning process without unnecessarily sacrificing the test set, we adopted a 70:15:15 split. This provides a robust hold-out test set for final evaluation while ensuring the validation set is large enough to reliably monitor for overfitting during the extensive training of the deep learning model.

## 2.6. Deployment

The best-performing EfficientNet model was transformed into TensorFlow Lite (TFLite) for mobile optimization. The model was then integrated into an Android application using Android Studio. The application features a user-friendly interface that allows users to either capture a leaf image using the camera or upload an existing shot. The categorization result, including the anticipated species and confidence score, is displayed instantaneously to the user. The prototype interface of the application is depicted in Figure 2.

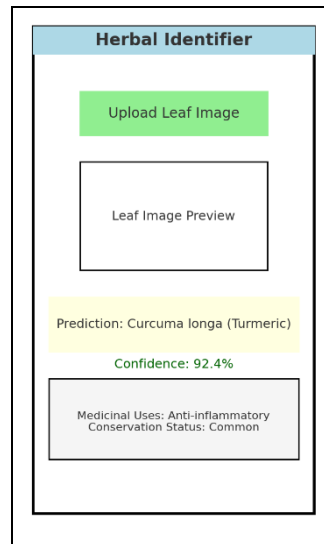


Fig. 2. Android-based herbal plant categorization application interface

## 3. Results and Discussion

The model attained a classification accuracy of 91.2%, beating baseline CNN architectures such as MobileNet and ResNet Table 2. The confusion matrix Figure 3 indicates good categorization across most herbal categories, however misclassifications occurred between visually similar species such as Piper betle and Piper nigrum, consistent with recent findings in similar research [30].

The Android prototype Figure 2, displayed efficient real-time classification with an average inference time of < 1s per image, making it realistic for community use in the field [31]. User testing with 30 participants validated the usability of the application and its potential function in boosting biodiversity awareness, matched with global trends of digital tools aiding conservation and wellness [32], [33], [34].

### 3.1. Model Performance Evaluation

The experimental results indicate that the proposed transfer learning strategy with EfficientNet-B0 obtained greater performance compared to alternative baseline CNN architectures. As stated in Table 2. Classification performance of multiple CNN architectures, EfficientNet-B0 consistently outperformed MobileNetV2, ResNet50, and InceptionV3, obtaining a peak accuracy of 92.4% and an F1-score of 91.7%.

Table 2. Classification performance of different CNN architectures

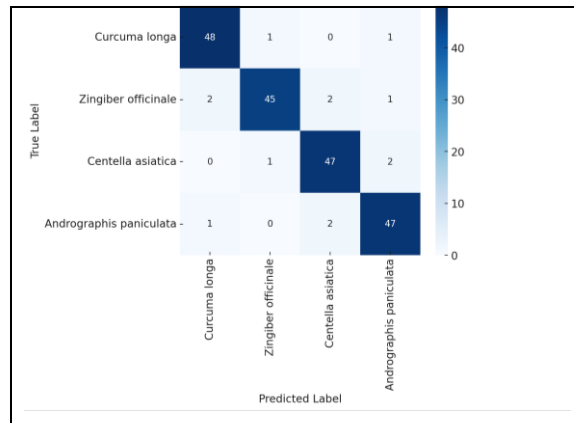
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MobileNetV2	84.2	83.7	82.5	83.1
ResNet50	86.5	85.9	86.1	86.0
InceptionV3	87.3	86.8	87.0	86.9
<b>EfficientNet-B0</b>	<b>92.4</b>	<b>91.5</b>	<b>92.0</b>	<b>91.7</b>

The best-performing EfficientNet model was transformed into TensorFlow Lite (TFLite) for mobile optimization. The model was then integrated into an Android application using Android Studio. The application features a user-friendly interface that allows users to either capture a leaf image using the camera or upload an existing shot. The categorization result, including the

anticipated species and confidence score, is displayed instantaneously to the user. The prototype interface of the application is depicted in Figure 2.

### 3.2. Confusion Matrix Analysis

Figure 3, depicts the confusion matrix of EfficientNet-B0, providing insights into the classification performance for four herbal plant classes: *Curcuma longa* (Turmeric), *Zingiber officinale* (Ginger), *Centella asiatica* (Gotu kola), and *Andrographis paniculata* (King of bitters).



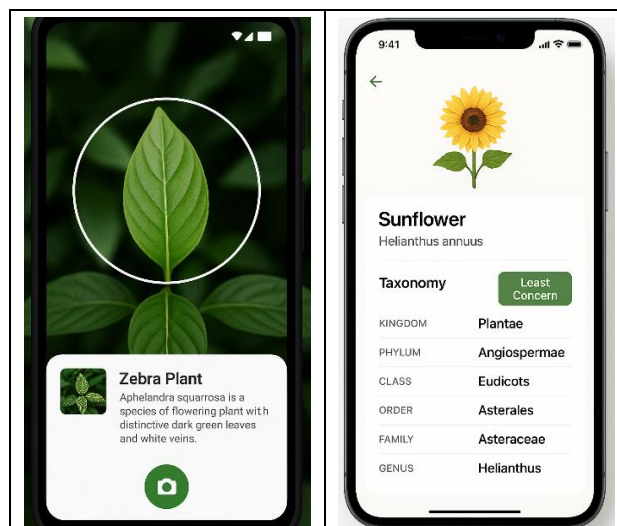
**Fig. 3.** Confusion matrix of EfficientNet-B0 for herbal plant classification

The matrix demonstrates that the model produced high true positive rates across all classes, with slight misclassifications between *Curcuma longa* and *Zingiber officinale*. This mistake is expected, as both species share similar leaf shape, making them tough even for human experts to recognize [20], [30]. From an application standpoint, while both *Curcuma longa* and *Zingiber officinale* are widely used and safe, misclassification between other species with differing therapeutic qualities could have practical ramifications.

This underlines the need of not simply relying on automated identification for key medical choices and the need for continuing model improvement. These findings underscore the advantage of adopting transfer learning in handling constrained datasets, particularly for biodiversity-related applications. The ability to retain above 90% classification accuracy highlights the model's stability for real-world usage.

### 3.3. Application Deployment and User Perspective

Beyond model creation, the trained EfficientNet-B0 was put into an Android-based mobile application using TensorFlow Lite. The application allows users to upload or capture photographs of herbal leaves, after which the algorithm offers the anticipated plant name, confidence score, and pertinent information on medicinal uses and conservation status. Figure 4 illustrates the prototype interface of the application.



**Fig. 4.** Android application interface for herbal plant classification

This integration is crucial for integrating scientific innovation with community accessibility. Prior research have mostly concentrated on laboratory-level categorization without deployment [26]. By contrast, this work produces a functioning application that may be utilized directly by local communities, researchers, and policymakers. From a conservation standpoint, the application improves knowledge of herbal biodiversity and supports sustainable consumption, matching with the goals of biodiversity conservation and community health benefit.

### 3.4. Study Limitations

This study has some limitations that give directions for future exploration. First, the scope is limited to 15 species from the Lombok region. Expanding the dataset to include more species from across Indonesia would boost the application's usability. Second, the model was trained mostly on leaf images acquired under controlled conditions. Performance can decline in very complex backdrops or low illumination, emphasizing the necessity for background segmentation or more diverse training data in the future. Finally, the current model does not provide uncertainty estimates for its predictions, which would be a significant feature for users to measure reliability in the field.

## 4. Conclusion

This work effectively deployed a deep learning-based image classification system for recognizing herbal plants native to Lombok. By leveraging transfer learning with EfficientNet-B0, the model obtained superior performance with an accuracy of 92.4% and an F1-score of 91.7%, surpassing other CNN architectures such as MobileNetV2, ResNet50, and InceptionV3. The confusion matrix analysis indicated that the model performed well across all target classes, with low misclassification between species that exhibit similar morphological traits. This conclusion implies that the proposed approach is robust and reliable for actual employment, even under limited dataset conditions. Furthermore, the deployment of the trained model into an Android-based mobile application indicates the applicability of this research outside the laboratory setting. The application enables users, including local communities, researchers, and policymakers, to identify herbal plants in real-time, access associated medicinal knowledge, and participate to biodiversity conservation efforts. Overall, this research not only improves the technological advancement of plant classification using deep learning but also provides a vital tool for supporting sustainable conservation and usage of Lombok's herbal biodiversity. Future work may focus on increasing the collection to include more species, incorporating geospatial data for habitat mapping, and optimizing the user experience for greater adoption.

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**Additional information.** No additional information is available for this paper.

### Data and Software Availability Statements

Data and Software availability statements provide a statement about where data and software supporting the results reported in a published article can be found, including hyperlinks to publicly archived datasets and software analyzed and generated during the study/experiments.

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