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# Multiclass Herbal Plant Classification Using CNN Architectures: A Comparative Study of MobileNetV2, EfficientNetV2B0, NASNetMobile, and InceptionV3

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**Abstract−**Indonesia is a country with an exceptionally rich biodiversity; herbal plants offer a wide range of benefits in the fields of health and traditional medicine. However, the process of identifying herbal leaves is still done manually and is often prone to errors due to similarities in shape, color, and texture among leaves. This study aims to develop a multi-class herbal plant leaf image classification system based on a Convolutional Neural Network (CNN) by comparing four transfer learning architectures: MobileNetV2, EfficientNetV2B0, NASNetMobile, and InceptionV3. The dataset used consists of 10 classes of herbal plant leaves. The contributions of this study include a comparative analysis of four CNN architectures for multi-class classification, an evaluation of the effectiveness of preprocessing and data augmentation on a limited dataset, and recommendations for the most optimal model based on accuracy and computational efficiency. The experimental results show that all models achieved validation accuracy above 98%. InceptionV3 delivered the best performance with a test accuracy of 97%, precision of 90%, and accuracy, recall, and F1-score of 89% respectively, demonstrating good generalization ability. Meanwhile, MobileNetV2 offers the best balance between accuracy and computational efficiency, making it a promising candidate for herbal plant identification systems based on mobile devices or in environments with limited computational resources.

**Keywords**: Multiclass; Herbal Plant; Classification; Comparative; CNN Architectures

## 1. INTRODUCTION

Indonesia is a country with an exceptionally rich biodiversity[1], [2]. Various types of herbal plants have long been used in traditional medicine [2], [3]. Herbal plants contain secondary metabolites such as flavonoids, tannins, saponins, alkaloids, and essential oils [4]. These compounds have been shown to possess antioxidant, antibacterial, anticancer, and anti-allergic properties [5]. Herbal plants have a long tradition in Indonesian culture and are an integral part of the public health system. Indonesia's rich flora makes the country one of the primary repositories of useful medicinal plants, with various species such as guava, curry, basil, turmeric, mint, papaya, betel, soursop, aloe vera, and green tea commonly used in traditional medicine [3].

However, the identification of herbal plants faces significant challenges. Traditional identification methods relying on visual inspection are time-consuming and require expertise that not everyone possesses [6]. Additionally, the similarity in shape, color, and texture among herbal plant species makes the identification process difficult and requires specialized expertise [7]. Challenges, such as variations in lighting, image backgrounds, leaf shapes, object orientation, and visual similarities between classes of herbal leaves [8]. This highlights the complexity of visually analyzing herbal plants. These challenges can hinder the sustainable, appropriate, and safe use of herbal plants. Identification errors can result in the use of plants that are unsuitable or even harmful to health [9], [10].

Early and accurate detection of medicinal plants is crucial [11], advancements in computer vision technology based on machine learning or deep learning offer solutions that facilitate the efficient identification of medicinal plants [12] [7]. Previous studies have used machine learning approaches to classify herbal plant leaves [13] [14]. CNN are capable of learning complex visual patterns that are essential for distinguishing between classes. Approaches such as Convolutional Neural Networks (CNNs) offer solutions to these challenges [15]. Convolutional Neural Networks (CNNs) models perform well and can be improved [16].

In addition, traditional CNN models are generally large in size and require high computational power. To address these limitations, architectures such as MobileNet, EfficientNet, NASNetMobile and InceptionV3 have been introduced as lightweight CNNs that deliver satisfactory accuracy [17], [18], [19], [20]. These architectures offer clear advantages due to their computational efficiency and high compatibility, making them suitable for use on devices with limited computational resources [21], [22], [23]. These architectures are designed with a simple yet effective structure to reduce computational load, memory usage, and overfitting [24].

CNNs were used in 64.5% of the studies as a deep learning method for classifying medicinal plants, with transfer learning applied in 83.8% of the studies [25]. Although CNNs demonstrate high performance in the medical domain and some agricultural applications, they achieve classification accuracy of up to 100% for 2-class classification and 87.14% for 5-class classification in medical images [26]. In other research, CNN performance reached 94.20% for 4-class and 90.10% for 8-class breast cancer classification [27]. The results of the study show that the CNN-based approach consistently demonstrates high performance for 2 to 8 classes, although its performance generally declines as the number of classes increases. Multi-class classification of herbal plants still has limitations, including inter-class and intra-class similarity issues, where different plant species have similar leaf characteristics[28]. Therefore, further research is needed to optimize the identification process.

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Previous research has identified issues related to occluded leaves and the complexity of feature extraction, highlighting the importance of considering the background in the classification process [28]. This research indicates that there is still room for improvement in multi-feature fusion and characteristic extraction, and that the application of advanced data augmentation techniques can result in more accurate and robust systems [8].

Based on a literature review, there remains a lack of research comparing the performance of various Convolutional Neural Network (CNN) architectures in the multiclass classification of herbal plants using limited-size datasets. Therefore, this study conducts a comprehensive evaluation of four transfer learning models (MobileNetV2, EfficientNetV2B0, InceptionV3, and NASNetMobile) for classifying images of herbal plant leaves. The main contributions of this study are the presentation of a systematic comparative analysis of the four CNN architectures in a multi-class classification scenario, the identification of the model that offers the best balance between accuracy and computational efficiency, and the presentation of empirical evidence that can serve as a reference in the development of artificial intelligence-based herbal plant identification systems. The performance of each model was evaluated using accuracy, precision, recall, and F1-score metrics to provide a comprehensive assessment of their classification capabilities.

# 2. RESEARCH METHODOLOGY

## 2.1 Research Stages

This research uses several CNN models to classify a multi-class set of herbal leaf images consisting of guava leaves, curry leaves, basil leaves, turmeric leaves, mint leaves, papaya leaves, betel leaves, soursop leaves, aloe vera, and green tea. The training process was conducted using several experimental scenarios, such as image background on CNNs-based models. The research stages include Data Collection, Model Design, Experimental Scenarios, and Model Evaluation. The overall research stages are illustrated in Figure 1.

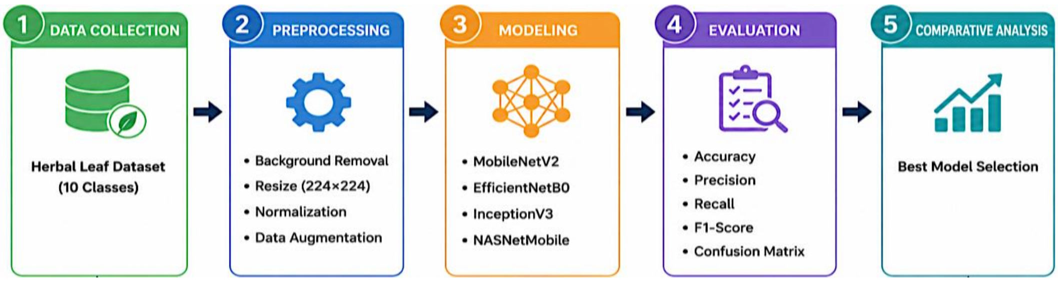


**Figure 1.** Research Stages

## 2.2 Data Collection

In this study, the data used were images of herbal plant leaves obtained from the public dataset Kaggle. The data comprised images of leaves representing various types of herbal plants with distinct visual characteristics. This study included ten classes: guava, curry, basil, turmeric, mint, papaya, betel leaf, soursop, aloe vera, and green tea. All collected image data were then organized into a dataset structured by class. Each class possesses distinct visual characteristics, making them suitable as the basis for image classification using deep learning methods. Figure 2 shows examples of the herbal leaf images used in this study. Figure 2 presents a examples of Herbal Plants.


**Figure 2.** Images examples of Herbal Plants

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### 2.3 Preprocessing

The data preprocessing stage is a crucial step in this study, aimed at improving image quality before the data is used in the model training process. The acquired herbal plant leaf images generally vary in size, lighting, background, and orientation; therefore, adjustments are necessary to make the data more uniform and suitable for the model's requirements. The first step is image resizing, which involves resizing all images to 224 × 224 pixels to match the input size required by the CNNs architecture. Next, normalization is performed, which involves converting pixel values into the range of 0 to 1 by dividing each pixel value by 255. Additionally, data augmentation techniques are applied to increase dataset diversity and reduce the risk of overfitting. The augmentation techniques used include image rotation, horizontal and vertical flipping, brightness adjustments, and zooming. With these augmentations, the model is expected to recognize objects under various conditions and from different viewpoints. After the augmentation process is completed, each image is converted into a tensor and normalized before being fed into the model. The augmentation process is applied dynamically to each batch during training, so the variations in images received by the model can differ in each training iteration. This approach aims to improve the model's ability to recognize visual patterns of herbal leaves under various lighting conditions, orientations, and leaf shapes, thereby making the classification performance more stable and capable of generalizing well to new data.

### 2.4 Modelling

This study was conducted using a deep learning approach based on a Convolutional Neural Network (CNN) architecture specifically designed to produce lightweight and efficient models, making them suitable for use on devices with limited computational resources [22][23]. Feature extraction was performed using pre-trained lightweight models, namely MobileNetV2, EfficientNetB0, InceptionV3, and NASNetMobile. These architectures fall under the category of deep neural networks with high computational efficiency, enabling implementation on devices with limited computational power [23]. Convolutional neural networks are capable of automatically extracting features from images without requiring manually crafted features [29]. These architectures are designed with a simple yet effective structure to reduce computational load, memory usage, and overfitting [24]. Subsequently, the images are processed by a pre-trained CNN base model using the ImageNet dataset, so that the model has the initial ability to recognize common visual features.

MobileNetV2 is a convolutional neural network (CNN) architecture specifically designed for mobile applications and resource-constrained devices, yet it is still capable of delivering high accuracy in multi-class image classification. This algorithm is an evolution of a mobile-first architecture that optimizes computational efficiency without significantly compromising performance [30]. MobileNetV2 can automatically extract image features that identify important patterns and characteristics of images for the classification process [8]. MobileNetV2 has proven successful in handling various multi-class classification domains with impressive accuracy levels, classifying 7 categories of swallow nests with 94.07% accuracy [31].

EfficientNetB0 is a highly effective CNN architecture for multi-class image classification, achieving performance of 91% and 99% in various applications. Research shows it achieves 99.14% accuracy in 10-class skin disease classification [32], 97% in six-class tea leaf disease classification [33], 99.79% in six-class rice leaf disease classification [34], and 99.69% in tropical fruit classification [35].

InceptionV3 is a powerful Convolutional Neural Network (CNN) architecture for multi-class image classification, with excellent feature extraction capabilities through transfer learning, such as ImageNet [36]. The model generates rich features from images and is able to capture both local and global aspects effectively[37]. InceptionV3 demonstrates high performance, achieving 99.50% – 99.65% for 4 class classification of ocular OCT images [37]. 96.07% for multi-class breast cancer classification [38], and the model also successfully classified 6 coloboma subtypes effectively [39].

NASNetMobile is an effective deep learning architecture for multi-class image classification, consistently demonstrating high accuracy across various applications. Studies show strong performance, with an accuracy of 89.88% in classifying 4 cat breeds [40], and 91.6% for 3 skin diseases[41], NASNetMobile is the most accurate in plant leaf disease recognition. Its lightweight architectural design makes it suitable for deployment on mobile devices [42].

### 2.5 Split Dataset

The experimental scenarios in this study were designed to evaluate the performance of model in performing multi-class classification of herbal plant images and to determine the effect of data augmentation techniques on improving model performance. The experiments were conducted using three different testing scenarios to identify the model configuration with the best generalization ability. The first scenario used the hold-out validation method, in which the dataset was divided into 80% training data and 20% validation data. Additionally, the study utilized 200 image data points as a test set to evaluate the model's final performance on previously unseen data.

**Table 1.** Distribution of data sets

| Training Data 80% | Validation Data 20% | Test Data |
|---|---|---|
| 640 | 160 | 200 |

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### 2.6 Model Evaluation

The evaluation was conducted to measure the performance of the CNNs model in performing multi-class classification of herbal plant images. The purpose of the model evaluation was to determine the model's ability to accurately recognize each class of herbal leaves and to analyze the model's stability across various experimental scenarios. The testing was conducted using validation and test data that had not been used in the model training process. In this study, evaluations were conducted across three experimental scenarios hold-out validation, K-fold cross-validation with K = 5, and a comparison between a baseline model without data augmentation and a model with data augmentation. All test results were compared to determine the impact of data augmentation and cross-validation techniques on improving the performance of the classification model.

Multiple evaluation metrics are used to measure model performance, namely accuracy, precision, recall, and F1-score. The accuracy score is used to determine the percentage of correct predictions relative to the entire test dataset. Precision is used to measure the model's accuracy in predicting a specific class, while recall is used to assess the model's ability to identify all instances within a specific class. Additionally, the F1-score serves as a measure of the balance between precision and recall. The evaluation equations used can be expressed as follows [43]:

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

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$F1 - Score = \frac{2\ X\ Precision\ X\ Recall}{Precision + Recall} \tag{4}$$

## 3. RESULT AND DISCUSSION

This study aims to analyze the impact of image background processing and attention mechanisms on the classification performance of herbal plant leaves. The study uses a multi-class dataset consisting of ten categories of herbal plant leaves including guava leaves, curry leaves, basil leaves, turmeric, mint leaves, papaya leaves, betel leaves, soursop leaves, aloe vera, and green tea leaves. Four CNN architectures MobileNetV2, EfficientNetB0, InceptionV3, and NASNetMobile were implemented and evaluated across several CNN models Performance evaluation was conducted using accuracy, precision, recall, and F1-score metrics, enabling the identification of the optimal model architecture and experimental configuration for herbal leaf image classification. The hyperparameters used in Table 1.

**Table 2.** Hyperparameters Used

| Parameter | Value / Configuration | Description |
|---|---|---|
| Model Architecture | MobileNetV2, EfficientNetB0, InceptionV3, NASNetMobile | Model for image classification |
| Transfer Learning | Enabled | Using pretrained model |
| Pretrained Weights | ImageNet | Initial model weights |
| Input Image Size | 224 × 224 pixels | Input image size |
| Number of Classes | 10 Classes | Multi-class herbal leaf classification |
| Optimizer | Adam | Training optimization algorithm |
| Learning Rate | 0.001 | Learning rate value |
| Batch Size | 32 | Number of samples per batch |
| Epoch | 30 | Training iterations |
| Loss Function | Categorical Crossentropy | Multi-class classification loss |
| Activation Function | Softmax | Output layer activation |
| Hidden Layer Activation | ReLU | Hidden layer activation |
| Validation Method | Hold-Out (80:20) | 80% training, 20% validation |
| Test Data | 200 Images | Final unseen test data |
| Cross Validation | K-Fold = 3 | Generalization evaluation |
| Fine-Tuning | Partial Unfreeze | Unfreeze selected MobileNetV2 layers |
| Image Resizing | 224 × 224 | Image resizing process |
| Remove Background | Applied and Non | Background removal preprocessing |
| Data Normalization | ImageNet Standardization | Pixel normalization |
| Early Stopping | Enabled | Reduce overfitting |
| Dropout | 0.5 | Regularization technique |
| Evaluation Metrics | Accuracy, Precision, Recall, F1-Score | Performance evaluation |
| Visualization Metrics | ROC Curve, Confusion Matrix | Classification analysis |
| Framework | TensorFlow / Keras | Deep learning framework |
| Hardware | GPU Acceleration | Training acceleration |

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### 3.1 Training Performance

Comparison of the training accuracy and validation accuracy curves for these models, Figure 4 shows the training curves for (a) MobileNetV2, (b) EfficientNetV2B0, (c) NASNetMobile, and (d) InceptionV3 over 30 training epochs. In general, all models show a significant increase in accuracy during the early training phase, then converge and reach a stable state in subsequent epochs. MobileNetV2 and InceptionV3 exhibit more consistent training patterns with a relatively small difference between training and validation accuracy, indicating good generalization ability. EfficientNetV2B0 showed the fastest convergence rate with validation accuracy approaching 100% from the early epochs, while NASNetMobile experienced a more gradual increase in accuracy but still achieved high performance by the end of training. Overall, all models achieved validation accuracy above 98%, demonstrating that each architecture is highly capable of learning data characteristics and producing optimal classification performance.

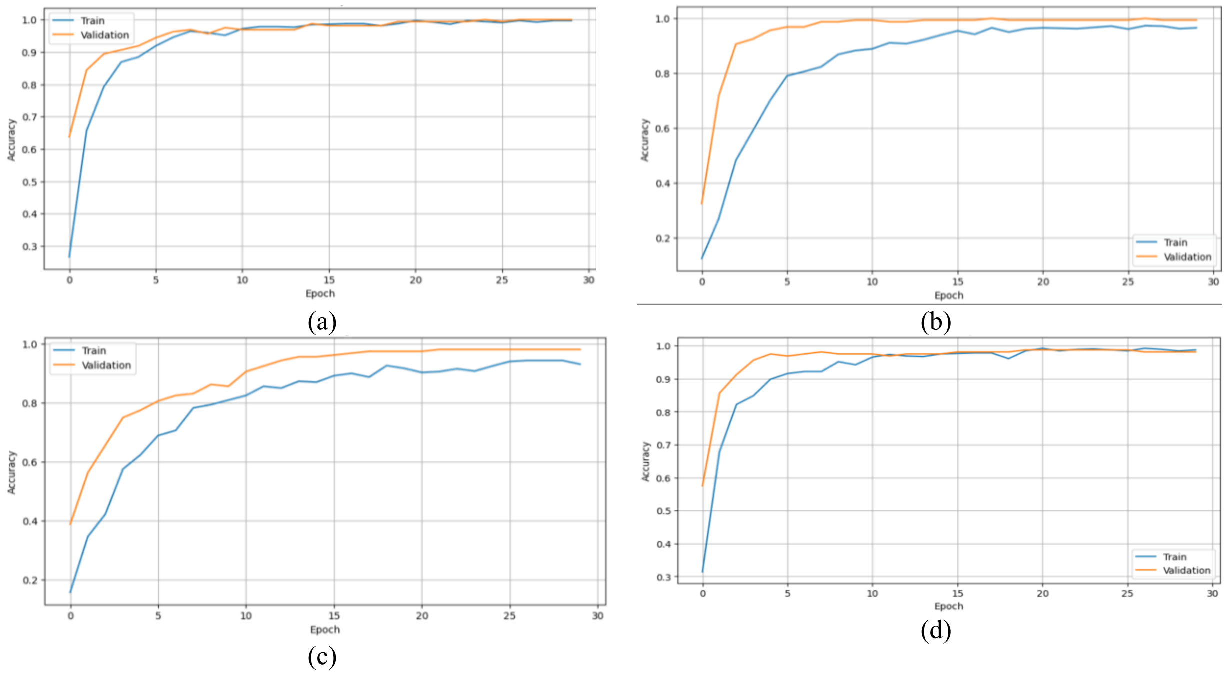


**Figure 4.** Comparison of training

### 3.2 Comparison Performance Model

The experimental results show that all models achieved an accuracy of over 98% on the internal test data. MobileNetV2 achieved the highest accuracy of 100%, followed by EfficientNet at 99.37%, while InceptionV3 and NASNetMobile each achieved 98.12%. However, evaluation on external test data consisting of 200 new images revealed a different pattern. InceptionV3 achieved the highest accuracy of 97.00%, followed by MobileNetV2 at 93.00%, EfficientNet at 92.50%, and NASNetMobile at 85.50%. The difference between internal and external accuracy highlights each model's generalization capability. InceptionV3 experienced a drop of only 1.12%, far smaller than MobileNetV2 (7.00%), EfficientNet (6.87%), and NASNetMobile (12.62%). These results indicate that the multi-scale convolution structure in InceptionV3 is capable of extracting leaf features of various sizes more effectively, making it more robust against variations in new data. Table 3 presents a performance comparison of the four models.

**Table 3.** Comparison of Results

| Model | Validasi | Loss | Test | Loss | Training Time (s) |
|---|---|---|---|---|---|
| EfficientNetV2 | 99.37% | 0.0073 | 92.50% | 0.1780 | 150 ± 5 |
| NASNetMobile | 98.12% | 0.0110 | 85.50% | 0.1998 | 180 ± 7 |
| MobileNetV2 | 100% | 0.0348 | 93% | 0.1049 | 50 ± 2 |
| InceptionV3-Mobile | 98.12% | 0.0950 | 97% | 0.3932 | 120 ± 4 |

The confusion matrix in Figure 5 shows differences in generalization ability among the models when tested. (a) MobileNetV2 and (b) EfficientNetB0 are able to classify most classes well, but still make errors with the Basil Leaves, Guava Leaf Buds, and Green Tea Leaves classes, which have similar visual characteristics. (c) NASNetMobile exhibits the highest error rate, particularly for the Guava Leaf Buds class, which is frequently misclassified as Green Tea Leaves, indicating lower feature discrimination capability. Conversely, (d) InceptionV3 produces the most dominant diagonal distribution with minimal errors, demonstrating superior feature extraction and generalization capabilities compared to other models. These findings are consistent with the testing accuracy results, where InceptionV3 achieved the highest performance 97%, making it the most effective model for multi-class classification of herbal plant leaves in this study.

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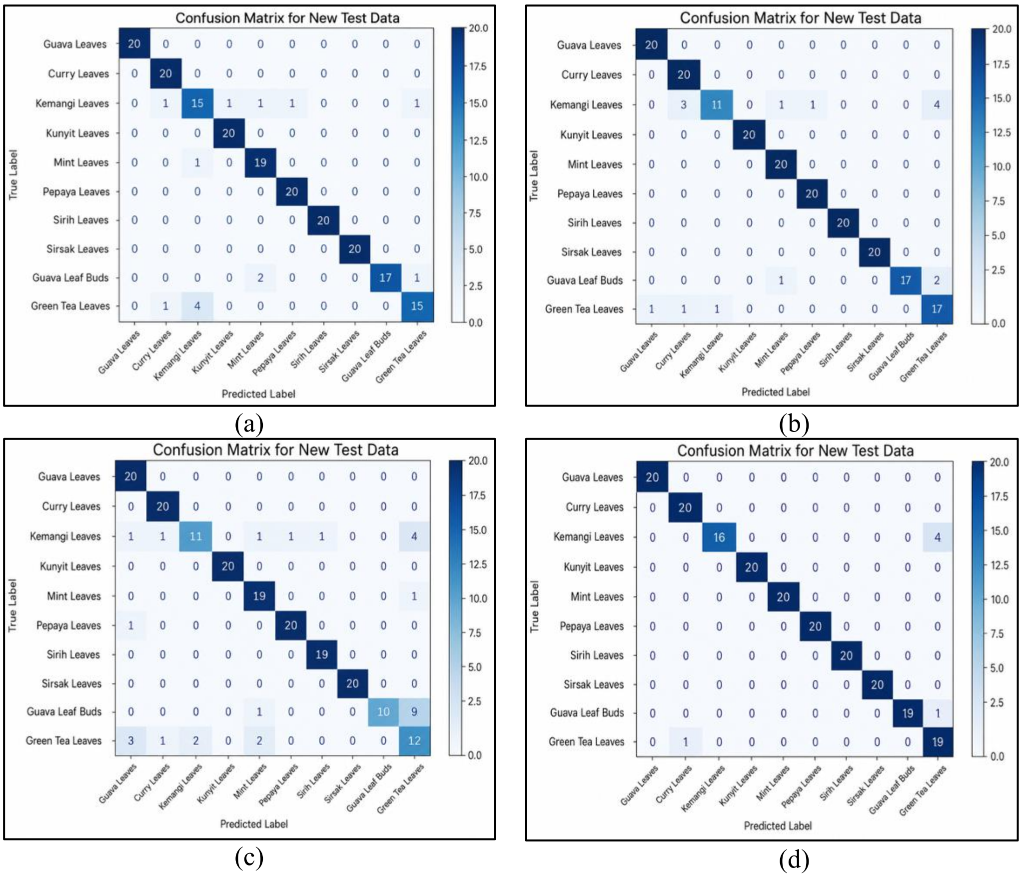


**Figure 5.** Confusion Matrix Results

Based on the results of the classification report and confusion matrix, some classes performed worse than others. Figure 6 presents a comparison of evaluation metrics for the classes with the lowest performance as determined by each model. The analysis results show that Sweet Basil Leaf is the class with the lowest performance on MobileNetV2, EfficientNet, and InceptionV3, while Green Tea Leaf is the class with the lowest performance on NASNetMobile. These findings indicate that these two classes have visual characteristics that are relatively similar to other classes, making them more prone to misclassification.

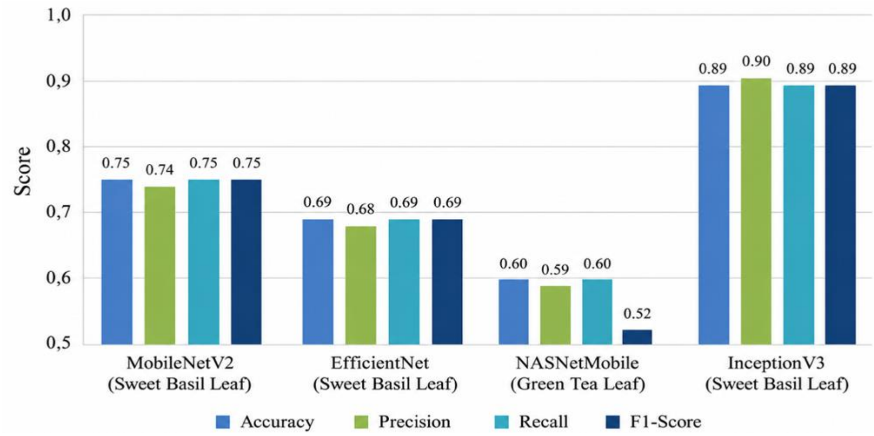


**Figure 6.** Comparison of Lowest Performing Classes

### 3.3 Discussion

Compared to previous studies, the results of this study show a significant improvement in performance. The study in reference [14] applied the Support Vector Machine (SVM) algorithm for medicinal plant classification and reported an accuracy of 77.6%. Although SVM has demonstrated strong classification capability for high-dimensional data, its effectiveness largely depends on the quality of manually extracted features. In contrast, the CNN-based architectures evaluated in this study perform end-to-end feature learning, enabling the models to automatically capture informative characteristics such as leaf texture, venation, shape, and color distribution. As a result, all CNN models evaluated in

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this study outperformed the SVM-based approach, with MobileNetV2 and InceptionV3-Mobile exceeding 90% test accuracy.

The study reported in [3]. which utilized the AlexNet architecture for classifying ten classes of herbal leaves, achieved a test accuracy of 73.50%. This result is considerably lower than those obtained in the present study. The superior performance achieved by the proposed models can be attributed to the use of more advanced CNN architectures that incorporate improved feature extraction mechanisms and more efficient network designs. In particular, MobileNetV2 employs depthwise separable convolutions and inverted residual blocks to reduce computational complexity while preserving feature representation quality, whereas InceptionV3-Mobile benefits from multi-scale feature extraction that enables more robust discrimination among visually similar leaf classes.

A more recent study reported in [7] employed the ConvNeXt architecture for Indonesian medicinal plant classification and obtained an accuracy of 92.5%. This performance is comparable to the MobileNetV2 model evaluated in this study, which achieved a test accuracy of 93%. However, the proposed InceptionV3-Mobile model further improved the classification performance, reaching 97% test accuracy while simultaneously obtaining the highest evaluation metrics (Accuracy = 0.89, Precision = 0.90, Recall = 0.89, and F1-score = 0.89). These findings indicate that InceptionV3-Mobile provides stronger generalization capability for herbal leaf classification, whereas MobileNetV2 remains an attractive alternative due to its substantially lower computational cost and the shortest training time (50 ± 2 s), making it highly suitable for deployment on mobile and embedded devices.

Furthermore, previous research in [11] on tomato disease recognition using MobileNetV2 also reported classification accuracy exceeding 90% on the PlantVillage dataset. The results of the present study are consistent with these findings, as both MobileNetV2 (93%) and InceptionV3-Mobile (97%) achieved test accuracies above 90%. This consistency reinforces the robustness of modern CNN architectures in plant image analysis tasks. Overall, the experimental results suggest that advanced CNN models are capable of effectively extracting discriminative visual features from plant leaves, including texture patterns, morphological structures, and color variations, thereby providing superior classification performance compared with conventional machine learning techniques.

## 4. CONCLUSION

This study compared the performance of four CNN architectures MobileNetV2, EfficientNetV2B0, NASNetMobile, and InceptionV3-Mobile for multiclass herbal plant classification. The main contribution of this study is to provide a systematic empirical evaluation of the differences in generalization ability, computational efficiency, and classification performance of each architecture on a relatively limited herbal plant dataset, as well as to identify the most suitable model for both high-accuracy requirements and implementation on devices with limited computational resources. The experimental results show that the four CNN architectures have different characteristics in terms of generalization ability, computational efficiency, and classification performance. The training results table shows that all models achieved validation accuracies above 98%, indicating that the learning process proceeded successfully. However, differences in performance on the test data suggest that high validation accuracy does not always correlate directly with a model's generalization ability. Among the evaluated models, InceptionV3-Mobile achieved the best overall performance, with 97% test accuracy and the highest evaluation metrics Accuracy, Recall and F1-score = 89%, Precision 90%, demonstrating superior classification capability. MobileNetV2 provided the best computational efficiency, requiring only 50 ± 2 s of training time while achieving 93% test accuracy and the lowest test loss (0.1049), making it well suited for deployment on mobile and edge devices. EfficientNetV2B0 showed competitive performance 92.5% test accuracy, whereas NASNetMobile achieved the lowest accuracy 85.5% and required the longest training time. Overall, the results indicate that InceptionV3-Mobile is the most suitable model when classification accuracy is the primary objective, while MobileNetV2 offers the best trade-off between accuracy and computational efficiency. Future work will focus on incorporating attention mechanisms, evaluating larger and more diverse herbal plant datasets, and applying model optimization techniques to improve both classification performance and deployment efficiency.

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