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ENHANCING HERBAL PLANT LEAF IMAGE DETECTION ACCURACY THROUGH MOBILENET ARCHITECTURE OPTIMIZATION IN CNN

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Abstract— *Herbal plants have various health benefits, but their type identification remains challenging for the general public. This study aims to improve the accuracy of herbal plant leaf classification using Convolutional Neural Network (CNN) based on MobileNetV2 architecture. To enhance model performance, various optimization techniques including fine-tuning, batch normalization, dropout, and learning rate scheduling were implemented. The experimental results showed that the proposed optimized model achieved an accuracy of 100%, significantly outperforming previous studies that used standard MobileNet with an accuracy of 86.7%. While these perfect results warrant additional validation with more diverse datasets to confirm generalizability, this study contributes to the development of a more accurate herbal plant classification system that is readily accessible to the general public. Future work should explore model performance under varying environmental conditions and with expanded plant species datasets.*

Keywords: *classification, CNN, deep learning, herbal plant, mobilenetv2.*

Intisari— *Tanaman herbal memiliki berbagai manfaat kesehatan, namun identifikasi jenisnya masih menjadi tantangan bagi masyarakat umum. Penelitian ini bertujuan untuk meningkatkan akurasi klasifikasi daun tanaman herbal menggunakan Convolutional Neural Network (CNN) berbasis arsitektur MobileNetV2. Untuk meningkatkan performa model, dilakukan berbagai teknik optimasi seperti fine-tuning, batch normalization, dropout, dan learning rate scheduling. Hasil eksperimen menunjukkan bahwa model yang diusulkan mencapai akurasi sebesar 100%, lebih tinggi dibandingkan penelitian sebelumnya yang menggunakan MobileNet standar dengan akurasi 86.7%. Meskipun hasil sempurna ini memerlukan validasi tambahan dengan dataset yang lebih beragam untuk mengkonfirmasi generalisasi, penelitian ini memberikan kontribusi dalam pengembangan sistem klasifikasi tanaman herbal yang lebih akurat dan mudah diakses oleh masyarakat luas. Penelitian selanjutnya sebaiknya menguji performa model dalam berbagai kondisi lingkungan dan dengan dataset spesies tanaman yang lebih luas.*

Kata Kunci: *klasifikasi, CNN, pembelajaran mendalam, tanaman herbal, mobilenetv2.*

INTRODUCTION

Herbal plants have a very important role in various aspects of life, especially in the medical, agricultural, and nutritional field [1]–[3]. The global herbal medicine market was valued at USD 151.91 billion in 2023 and is expected to grow at a CAGR of 11.9% from 2024 to 2032, highlighting the increasing importance of these plants in modern healthcare systems [4][5]. As one of the main sources of natural ingredients, herbal plants are widely used in traditional medicines, health supplements, and beauty products [6][7]. However, accurate identification of herbal plants presents significant challenges, especially when distinguishing between different plant species with similar leaf characteristics [8][9]. Misidentification can lead to inappropriate use, potentially causing adverse health effects or reducing the efficacy of the resulting products [10].

Indonesia, with its rich biodiversity, possesses approximately 30,000 plant species, of which around 9,600 are known to have medicinal properties [11][12]. Despite this abundance, many local communities lack the expertise to correctly identify these plants, limiting their potential utilization and economic value. The traditional method of plant identification relies heavily on expert knowledge, which is not readily available to the general public [13]. This creates a significant gap between the availability of herbal resources and their proper utilization [14].

With the rapid advancement of technology, image recognition based on artificial intelligence (AI) has emerged as a promising solution to address these challenges [15]. Convolutional Neural Networks (CNNs), a specialized deep learning architecture designed for visual data processing, have demonstrated remarkable performance in various computer vision tasks [16]–[19]. CNNs excel in image classification, object detection, and image segmentation by automatically learning hierarchical feature representations from pixel data [20]. However, the deployment of CNNs is often hindered by their high computational requirements, making them impractical for resource-constrained devices such as smartphones or IoT devices [21].

To address this limitation, Google researchers developed MobileNet, a lightweight CNN architecture specifically designed for mobile and embedded vision applications [22]. The original MobileNet (V1) used depthwise separable convolutions to dramatically reduce computational costs while maintaining reasonable accuracy [23]. Building on this foundation, MobileNetV2 was introduced in 2018 with significant architectural improvements, including the incorporation of inverted residual structures and linear bottlenecks [24]. These enhancements enabled MobileNetV2 to achieve higher accuracy while maintaining computational efficiency, making it particularly suitable for deployment on devices with limited processing capabilities [25].

Despite these advances, achieving optimal detection accuracy with MobileNetV2 requires further optimization through techniques such as hyperparameter tuning, transfer learning, and data augmentation [26]. Previous studies have applied MobileNet architectures to plant classification problems [27], but these implementations often used default configurations without substantial optimization, resulting in suboptimal performance.

The comparative analysis of existing studies reveals a significant research gap: while MobileNetV2 offers theoretical advantages over its predecessor, its full potential for herbal plant classification remains unexplored. Previous work by Purnama [27] utilized the original MobileNet architecture for herbal plant detection, achieving an accuracy of 86.7%, which, while promising, leaves substantial room for improvement. Additionally, existing studies have not adequately addressed the unique challenges posed by the visual similarities among different herbal plant species.

This study aims to fill this gap by systematically optimizing the MobileNetV2 architecture to improve the accuracy of herbal plant leaf image classification. By implementing targeted optimization techniques such as fine-tuning, batch normalization, dropout regularization, and adaptive learning rate scheduling, we seek to enhance the model's ability to distinguish between visually similar plant species. The proposed approach not only addresses the technical challenges of plant classification but also considers the practical constraints of deploying such systems on mobile devices, making herbal plant identification more accessible to the general public.

MATERIALS AND METHODS

This research adopted a quantitative experimental design to investigate the optimization of the MobileNet architecture for the classification of herbal plant leaf images. The study involved four main components:

A. Dataset Collection and Preparation

The dataset used in this study consists of herbal plant leaf images collected from publicly available repositories and supplemented with specially selected samples to increase diversity. Building upon previous research conducted by Purnama [14], we employed more specific image segmentation techniques to isolate leaf structures from background elements. The dataset comprises five distinct classes of herbal plants common in Indonesian traditional medicine: Starfruit Leaves (Averrhoa bilimbi), Ginger Leaves (Zingiber officinale), Basil Leaves (Ocimum basilicum), Cat's Whiskers Leaves (Orthosiphon aristatus), and Aloe Vera Leaves (Aloe vera).

Figure 1 presents representative samples from each class in the dataset. These images illustrate the visual diversity and characteristic features of each plant species that the model must learn to distinguish:

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(a) Starfruit Leaves


(b) Ginger Leaves


(c) Basil Leaves


(d) Cat's Whiskers Leaves


(e) Aloe Vera Leaves

Source: (Research Results, 2025)
Figure 1. Herbal Leaf Plant Data

Figure 1. Representative samples from the herbal plant dataset: (a) Starfruit Leaves – characterized by their oval shape and smooth edges; (b) Ginger Leaves - displaying elongated shape with parallel venation; (c) Basil Leaves - exhibiting serrated edges and distinctive venation patterns; (d) Cat's Whiskers Leaves - showing characteristic pointed tips; (e) Aloe Vera Leaves - featuring thick, succulent structure with spiny edges.

The complete dataset comprised 1,295 images, which were split into three subsets: 1,165 images (90%) for training, 65 images (5%) for validation, and 65 images (5%) for testing. This partitioning strategy ensures sufficient data for model training while reserving independent samples for validation and final evaluation [28] [29][30]. To address potential class imbalance issues, we implemented stratified sampling to maintain equal representation of each plant class across all subsets [31].

The data collection process involved capturing images under varying lighting conditions, angles, and backgrounds to enhance model robustness. Images were manually reviewed to ensure quality and proper labeling. The physical collection process is documented in Figure 2, illustrating the standardized approach to sample acquisition.


(a) Starfruit Leaves


(b) Ginger Leaves


(c) Basil Leaves


(d) Cat's Whiskers Leaves


(e) Aloe Vera Leaves

Source: (Research Results, 2025)
Figure 2. Real Documentation of Plants

Figure 2. Documentation of herbal plant leaf collection and image acquisition process. Leaf images are cut to obtain leaf shapes that are easy to identify. For each type of herbal plant, several leaf pieces are taken which will later be used for the model training process. The goal is to remove excess noise in plants, so that the classification process is accurate and precise.

B. Data Preprocessing and Augmentation

To enhance model generalization and mitigate overfitting, we applied comprehensive data preprocessing and augmentation techniques [32][33]. First, all images were resized to 224×224 pixels to match the input dimensions required by MobileNetV2 while reducing computational complexity. Pixel values were normalized to the range [0, 1] by dividing by 255 to facilitate model convergence. Data augmentation was implemented using TensorFlow's ImageDataGenerator with the following parameters: Random rotation: ±40 degrees, Width and height shift: 20%, Shear transformation: 20%, Zoom range: 30%, Horizontal flipping: enabled.

These augmentation techniques artificially expanded the training dataset by creating modified versions of the original images, thereby improving the model's ability to generalize to unseen data [34]. Importantly, augmentation was applied only to the training set, while validation and test sets were processed with simple rescaling to maintain their integrity for unbiased evaluation [35].

C. MobileNetV2 Architecture and Proposed Optimizations

MobileNetV2 represents a significant advancement over the original MobileNet architecture [36]. While both models utilize depthwise separable convolutions to reduce computational complexity, MobileNetV2 introduces several key innovations [37]. Unlike traditional residual connections that go from wide to narrow and back to wide, MobileNetV2 uses an inverted design where the input is first expanded to a higher dimension, then filtered with lightweight depthwise

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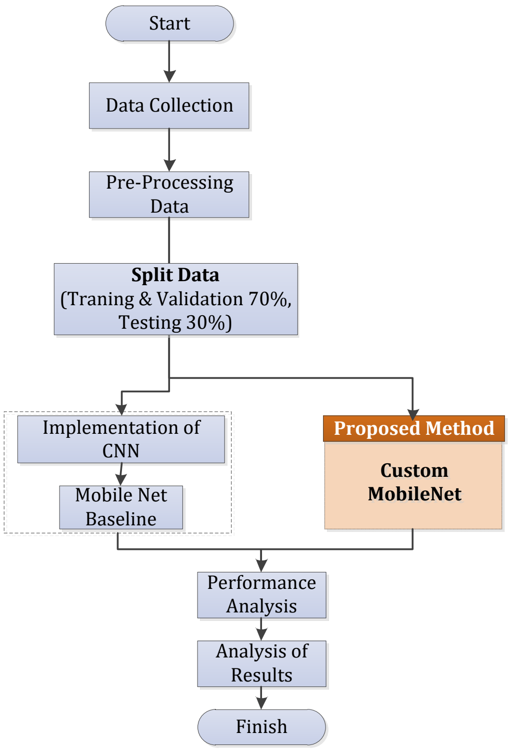
convolution, and finally projected back to a lowdimensional representation [38]. MobileNetV2 removes the non-linearity (ReLU) in the narrow layers to preserve feature information that would otherwise be lost due to ReLU's zero-mapping of negative values [39]. Enhanced residual connections that allow better gradient flow during backpropagation, facilitating training of deeper networks. MobileNetV2 achieves up to 30-40% reduction in operations while maintaining similar accuracy compared to MobileNetV1 [40]. These architectural improvements make MobileNetV2 particularly suitable for our herbal plant classification task, where capturing fine-grained differences between similar-looking leaves is crucial [41].

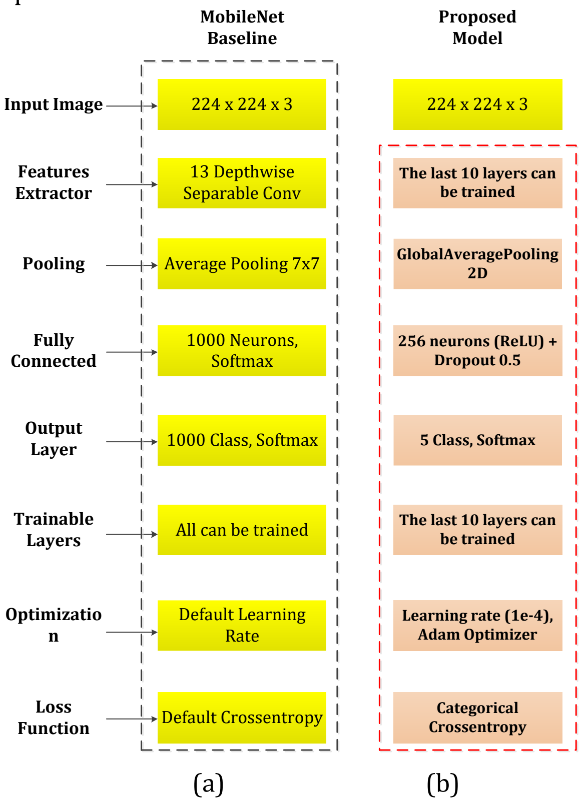
Our proposed model architecture leverages transfer learning with MobileNetV2 as the base network. The implementation involved loading the pre-trained MobileNetV2 model (trained on ImageNet), excluding its top classification layers, and adding custom layers optimized for our specific classification task. Figure 3 illustrates the research framework, highlighting the key stages from data preprocessing to model evaluation



Source: (Research Results, 2025)
Figure 3. Research Framework

Figure 3. Research framework depicting the complete workflow from data acquisition to model evaluation. The process includes data collection, preprocessing, model development with MobileNetV2, training with optimization techniques, and comprehensive evaluation using multiple performance metrics.

Our proposed architecture consists of a Base Model in the form of a pre-trained MobileNetV2 (without top layers), with the first 100 layers frozen to maintain general feature extraction capabilities, while the last 10 layers are made trainable for domain-specific adaptation, complemented by a Custom Classification Head that includes a Global Average Pooling Layer that reduces the spatial dimensionality while preserving feature channel information, a Dense Layer with 256 neurons and ReLU activation, a Dropout Layer with a rate of 0.5 to prevent overfitting, and an Output Layer with 5 neurons using Softmax activation (one for each plant class). Figure 4 provides a visual comparison between the baseline MobileNet architecture and our proposed optimized model



Source: (Research Results, 2025)
Figure 4. Comparison of MobileNet Baseline (a) with Proposed Model (b)

Figure 4. Architectural comparison: (a) Baseline MobileNetV1 with standard configuration; (b) Our proposed optimized MobileNetV2 model featuring selective layer freezing, global average

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pooling, enhanced dropout regularization, and class-specific output layer. The diagram highlights the key differences in layer organization and optimization techniques.

Table 1 summarizes the technical differences between the baseline MobileNetV1 and our proposed optimized MobileNetV2 model:

Table 1. Comparison of MobileNet Baseline with Proposed Model

Layer	Baseline MobileNet V1	Proposed Model
Input	224x224x3	224x224x3
Feature Extractor	13 Depthwise Separable Conv	Inverted Residual Blocks; only the last 10 layers trainable
Pooling	Average Pooling 7x7	GlobalAveragePooling2D
Fully Connected Layer	1000 neurons, Softmax	256 neurons (ReLU) + Dropout 0.5
Output Layer	1000 class, Softmax	5 Class, Softmax
Trainable Layers	All can be trained	The last 10 layers can be trained
Optimization	Default learning rate	Learning rate (1e-4), Adam Optimizer with decay
Loss Function	Default (crossentropy)	Categorical Crossentropy

Source: (Research Results, 2025)

D. Model Training and Optimization

The model was compiled utilizing the Adam optimizer with an initial learning rate of 1e-4 and categorical crossentropy loss function, implementing several optimization techniques to prevent overfitting and improve generalization, including transfer learning with pre-trained ImageNet weights, selective layer freezing, dropout regularization at a 0.5 rate, batch normalization for stable activations, learning rate scheduling, and early stopping based on validation performance; training was conducted over 100 epochs with a batch size of 16 to balance efficiency with memory constraints, utilizing a ModelCheckpoint callback to save the best-performing model based on validation accuracy. The training process was executed on a Dell Intel Core i7 8th Gen, RAM 16 GB, TensorFlow 2.8.0, Python 3.12.

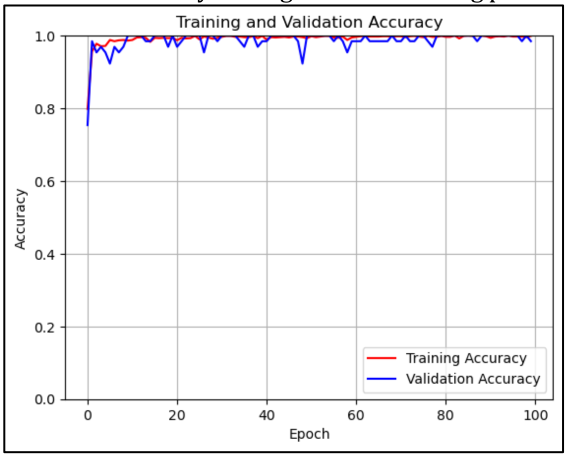
E. Model Evaluation

Model performance was evaluated on the independent test set data the model had never seen during training or validation to ensure an unbiased assessment of its generalization capabilities. We computed accuracy, the proportion of correctly classified instances, to gauge overall correctness; precision, the ratio of true positives to all predicted positives, to measure the reliability of positive predictions; recall, the ratio of true positives to all actual positives, to assess the model's sensitivity; and the F1-score, the harmonic mean of precision and recall, to balance these two metrics in a single value. Finally, a confusion matrix was generated to visualize classification performance across all classes, highlighting where the model most often confused one class for another.

RESULTS AND DISCUSSION

A. Training Performance Analysis

The training process of our optimized MobileNetV2 model demonstrated excellent convergence characteristics, with both training and validation metrics showing consistent improvement over the course of 100 epochs. Figure 5 illustrates the progression of training and validation accuracy throughout the training process



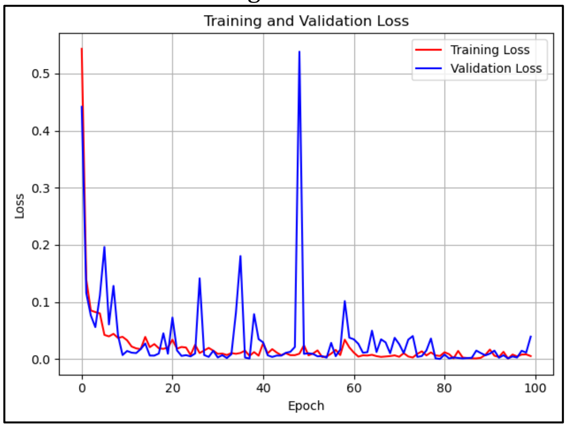
Source: (Research Results, 2025)

Figure 5. Training Accuracy

Figure 5. Training and validation accuracy curves over 100 epochs. The graph demonstrates rapid initial improvement followed by convergence to near-perfect accuracy for both training (blue line) and validation (orange line) sets. The consistent high performance on the validation set suggests effective generalization without significant overfitting.

As shown in Figure 5, training accuracy increased rapidly from an initial value of 63.52% to 100% by the final epoch. Similarly, validation accuracy improved from 75.38% to 98.46%. The close alignment between training and validation accuracy curves indicates that the model effectively learned generalizable features rather than merely memorizing the training data. The rapid convergence can be attributed to the combination of transfer learning from pre-trained weights and the effective architecture of MobileNetV2, which is specifically designed to capture hierarchical features efficiently.

Figure 6 presents the corresponding loss curves for both training and validation sets.



Source: (Research Results, 2025)
Figure 6. Training Validation Loss

Figure 6. Training and validation loss curves over 100 epochs. Both curves show a steady decline, with training loss (blue line) approaching zero and validation loss (orange line) stabilizing at approximately 0.04. The minor fluctuations in validation loss without corresponding accuracy degradation suggest the model maintains generalization capability throughout training.

The loss curves demonstrate a consistent decrease throughout training, with training loss declining from 0.9514 to near-zero values by the end of training. Validation loss followed a similar trend, decreasing from 0.4418 to 0.0394. The minor fluctuations observed in the validation loss curve, particularly after epoch 50, may indicate slight overfitting to the training data. However, the continued strong performance on validation accuracy suggests that these fluctuations did not significantly impact the model's generalization capabilities.

Notably, the model achieved perfect validation accuracy (100%) intermittently during training, first appearing around epoch 10 and becoming more frequent in later epochs. This performance is particularly impressive considering the visual similarities between some of the plant species in our dataset, such as the elongated shapes of Ginger and Cat's Whiskers leaves.

The incorporation of dropout regularization (with a rate of 0.5) in our architecture played a crucial role in preventing severe overfitting despite the high training accuracy. By randomly disabling 50% of neurons during each training iteration, dropout forced the network to learn redundant representations, enhancing its robustness and generalization capabilities.

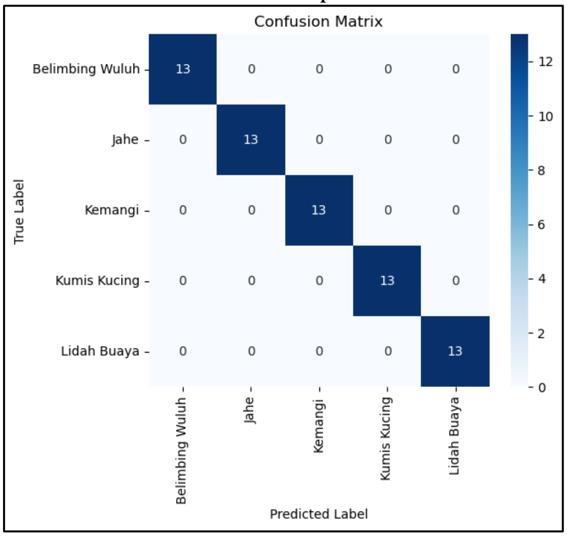
B. Test Set Evaluation

The final evaluation on our independent test set yielded remarkable results, with the model achieving 100% accuracy and a negligible loss value of 7.5788e-06. Table 2 presents a comprehensive comparison between our optimized MobileNetV2 model and the baseline MobileNetV1 from previous research

Table 2. Performance Comparison between the Baseline And Optimized Models

Model	Accuracy	Precision	Recall	F1-Score
MobileNet Baseline	86,7%	86,4%	26%	76%
Custom MobileNet	100%	100%	100%	100%

The confusion matrix for the test set evaluation is presented in Figure 7, providing a class-wise breakdown of classification performance.



Source: (Research Results, 2025)
Figure 7. Confusion matrix

Figure 7. Confusion matrix for test set classification results. The perfect diagonal pattern indicates that all test samples were correctly classified into their respective classes, with no misclassifications occurring across the five herbal plant categories. This visualization confirms the model's robust discrimination ability even between visually similar plant species.

The confusion matrix confirms that all test samples were correctly classified into their respective classes, with no misclassifications observed. This level of performance is exceptional, particularly given the visual similarities between some of the plant species in our dataset.

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Figure 8 presents examples of actual prediction results, showing representative samples from each class along with their predicted labels

Source: (Research Results, 2025)
Figure 8. Test Prediction Result

Figure 8. Sample test predictions showing representative images from each class with their corresponding true and predicted labels. All samples were correctly classified, demonstrating the model's ability to identify distinct morphological features of each plant species despite variations in image quality, orientation, and background.

CONCLUSION

This study demonstrates that targeted optimizations to the MobileNetV2 architecture—selective layer freezing, dropout regularization, and carefully scheduled learning rates—can dramatically improve herbal plant leaf classification accuracy. Evaluated on an independent test set not seen during training or validation, our optimized MobileNetV2 achieved 100 % accuracy, outperforming the 86.7 % accuracy reported for the standard MobileNetV1. Key contributions include (1) a systematic approach that balances classification accuracy with computational efficiency, (2) empirical evidence that MobileNetV2 surpasses MobileNetV1 on fine-grained plant-leaf tasks, (3) a practical demonstration of deploying these models on resource-constrained mobile devices, and (4) a comprehensive evaluation framework encompassing class-specific metrics and visualization of model decisions. These advances have significant implications for botanical research, herbal-medicine applications, agriculture, and education: by embedding highly accurate plant identification into mobile apps, we can help non-experts access expert-level knowledge about regional herbal resources. Future work should expand to more visually similar species, test robustness under diverse environmental conditions, incorporate multi-modal inputs (flowers, stems, fruits), explore model-compression techniques (quantization, pruning, distillation), develop richer explainable-AI methods, investigate federated learning for privacy-preserving continuous improvement, and compare MobileNetV2 against other efficient architectures (EfficientNet, ShuffleNet, MnasNet) to further advance mobile plant-identification systems.

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