ENHANCED FLOWER IMAGE CLASSIFICATION USING MOBILENETV2 WITH OPTIMIZED PERFORMANCE

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Abstract— *Flower classification is an essential activity in multiple fields, including healthcare, cosmetics, agriculture, and environmental monitoring. Deep learning has achieved notable success in intricate picture categorization problems, especially through the utilization of lightweight convolutional neural network (CNN) architectures like MobileNet and MobileNetV2. This work assesses and contrasts the efficacy of four prevalent optimizers Adam, RMSProp, SGD, and Nadam on datasets of flower and herbal leaf images. Experiments were performed using a uniform training configuration on a CPU-based system devoid of GPU acceleration, evaluating both model efficacy and computational efficiency. Evaluation criteria including accuracy, precision, recall, F1-score, and loss were utilised, augmented by confusion matrix analysis. The findings indicate that MobileNetV2 regularly surpasses the baseline MobileNet, with RMSProp attaining the highest accuracy (99.52%) and the lowest loss (0.0126) on the herbal dataset. In the flower dataset, RMSProp achieved the highest accuracy of 96.67%. Moreover, MobileNetV2 necessitated increased memory and extended training duration, while delivering superior classification performance overall. These findings underscore the significance of optimizer selection and model architecture in lightweight deep learning applications, especially for deployment on resource-limited devices.*

Keywords: *deep learning, flower classification, MobileNetV2, optimization algorithms*

Intisari— *Klasifikasi bunga adalah kegiatan penting di berbagai bidang, termasuk perawatan kesehatan, kosmetik, pertanian, dan pemantauan lingkungan. Deep Learning telah mencapai kesuksesan luar biasa dalam masalah kategorisasi gambar yang rumit, terutama melalui penggunaan arsitektur CNN ringan seperti MobileNet dan MobileNetV2. Dalam penelitian ini, empat pengoptimal yang sering digunakan (Adam, RMSProp, SGD, dan Nadam) dievaluasi dan dibandingkan untuk kumpulan data gambar bunga dan daun herbal. Eksperimen ini dilakukan dengan konfigurasi pelatihan seragam pada sistem berbasis CPU tanpa akselerasi GPU untuk menilai efektivitas model dan efisiensi komputasi. Kriteria evaluasi seperti akurasi, presisi, recall, skor F1, dan loss digunakan, dilengkapi dengan analisis Confusion Matrix. Penelitian ini menunjukkan bahwa MobileNetV2 secara konsisten melampaui MobileNet dasar, dengan RMSProp mencapai*

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akurasi tertinggi (99,52%) dan loss terendah (0,0126) pada dataset herbal. Dalam dataset bunga, RMSProp mencapai akurasi tertinggi yaitu 96,67% dan loss (0.1071). Selain itu, MobileNetV2 memerlukan peningkatan memori dan durasi pelatihan yang lebih lama, sambil memberikan kinerja klasifikasi yang unggul secara keseluruhan. Hasil ini menunjukkan bahwa arsitektur model dan pemilihan optimizer sangat penting untuk aplikasi pembelajaran mendalam ringan, terutama pada perangkat dengan sumber daya terbatas.

Kata Kunci: *pembelajaran mendalam, klasifikasi bunga, MobileNetV2, algoritma optimisasi*

INTRODUCTION

Flower classification is an essential activity in multiple fields, including healthcare, cosmetics, agriculture, and environmental monitoring [1], [2]. Manual classification is difficult because of significant intra-class heterogeneity in color, shape, and texture [3], [4]. Automated recognition systems employing visual attributes can augment plant growth monitoring and facilitate early disease identification, hence enhancing production and decision-making [5], [6].

The increasing interest in flower picture classification has prompted the development of innovative methodologies such as parameter selection and optimization methods in intricate image classification tasks to improve model performance and accuracy [7], [8]. Precise identification facilitates several applications, including agricultural surveillance, species delineation, and the development of botanical products [9], [10]. The implementation of autonomous flower classification systems will enhance digitization and efficiency across various industries, thereby providing support to them [11], [12].

Because of their strong feature extraction capabilities, Convolutional Neural Networks (CNNs) have demonstrated remarkable effectiveness in picture categorization tasks [13], [14]. The efficacy of CNNs is significantly affected by training setups, especially the selection of optimizer [15], [16]. Optimizers are algorithms that adjust neural network weights to reduce the loss function during training [17]. Every optimizer employs a distinct methodology for weight modification, influencing convergence rate, stability, and overall model efficacy [18]. Frequently utilized optimizers are Stochastic Gradient Descent (SGD), Adam (Adaptive Moment Estimation), Nadam (Nesterov-accelerated Adam), and RMSProp (Root Mean Square Propagation), each providing unique benefits in learning rate modulation and momentum management [19].

MobileNet and MobileNetV2 are streamlined convolutional neural network designs intended for mobile and embedded vision applications [20]. MobileNet employs depthwise separable convolutions to minimize computing expenses [21], [22], but MobileNetV2 enhances performance by integrating inverted residual blocks and linear bottlenecks, so promoting improved gradient flow and feature learning without augmenting model complexity [23], [24].

Notwithstanding architectural enhancements, the choice of optimization algorithm continues to be a pivotal element influencing CNN performance [25], particularly for compact architectures designed for implementation on resource-limited device [26], [27]. Furthermore, whereas several research have utilized CNNs for flower classification [28]. few have rigorously examined the effects of various optimizers on performance using standardized datasets and controlled training environments [29].

Flower classification is among the most coveted subjects in older literature. For example, the research in [30], using CNN and SVM for flower image classification. The CNN model performed well achieving 91.6% accuracy and 78.3% for SVM. Another research One of the most sought-after topics regarding earlier works is flower classification. For instance, the work in [31], applied CNN with Nadam optimization for flower classification, the performance of both from-scratch and transfer learning methodologies on the Oxford17 and Oxford102 datasets attained 60%, 84%, and 42%, 64%, respectively.

A further experiment focused on herbal plant leaf categorization is provided to better assess the model's generalization capabilities. This comparative assignment evaluates the model's robustness across various plant morphologies, despite flower categorization being the primary focus [32], [33].

This paper examines the efficacy of four optimization algorithms SGD, Adam, Nadam, and RMSProp utilized in MobileNet and MobileNetV2 architectures. The goal is to evaluate how optimizer selection affects generalization abilities, convergence traits, and classification accuracy. To evaluate robustness, experiments are performed on two datasets: a floral image dataset and a bespoke herbal leaf dataset. The incorporation of herbal leaves facilitates additional examination of the model's adaptation to analogous but morphologically diverse classification tasks [34].

Given this context, this work examines different optimizer and architecture combinations, offering insights into the trade-offs between computational efficiency and performance as well as useful recommendations for deploying lightweight deep learning models in actual categorization scenarios.

MATERIALS AND METHODS

This study sought to assess the efficacy of MobileNetV2 in classifying flower images by employing optimization strategies to enhance model accuracy. This research aims to produce a more precise, stable, and efficient flower classification model, thereby advancing deep learning technology for object recognition through image classification.

Data Collection

This study leveraged data from the Kaggle platform, consisting of a dataset of 1,200 flower photos classified into three categories: daisy, rose, and tulip, used for algorithm training. This work incorporates supplementary data obtained from the Mendeley Data platform, featuring a dataset of 1,050 herbal leaf photos classified into three categories: kemangi (basil), jambu biji (guava), and nangka (jackfruit).

Data Preprocessing

This study employed a dataset of flower images classified into three categories, daisy, rose, and tulip, as well as a dataset of herbal leaf images categorized into three groups: kemangi (basil), jambu biji (guava), and nangka (jackfruit).

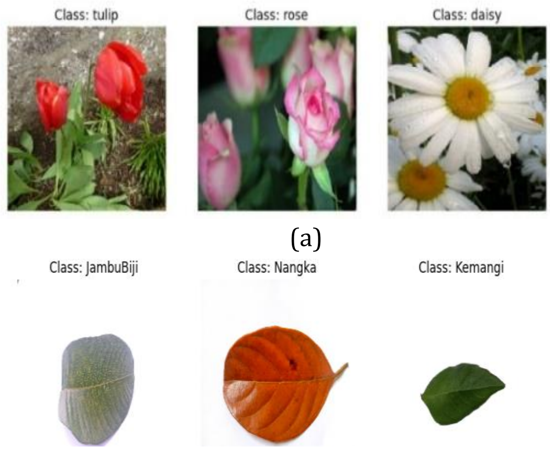
The total number of flower images used is 1,200, and the total number of herbal leaf used is 1,050, with the distribution presented in Table 1.

Table 1. Number of Images

No	Images Type	Number of Images
1	Flower daisy	400
2	Flower rose	400
3	Flower tulip	400
Total	1,200	
1	Herbal leaf kemangi (basil)	350
2	Herbal leaf jambu biji (guava)	350
3	Herbal leaf nangka (jackfruit)	350
Total	1,050	

Source : (Research Result, 2025)

Table 1 displays flowers data obtained from Kaggle:(https://www.kaggle.com/datasets/imsparsh/flowers-dataset) and herbal leaf data from Mendeley Data (https://data.mendeley.com/datasets/s82j8dh4rr/1), with the data pre-categorized by type. The images represent of each type of flower images and herbal leaf images, is shown in Figure 1.



Source : (a) (Kaggle.com, 2021)
(b) (Mendelay Data.com, 2022)

Figure 1. Sample of Image Flowers & Herbal Leaves

Figure 1 displays samples of floral photos from the collection, specifically daisy, rose, and tulip. The dataset additionally comprises herbal leaves for comparison, specifically kemangi (basil), jambu biji (guava), and nangka (jackfruit). The dataset is equitably distributed among six classes and exhibits considerable diversity in color and shape. This combination facilitates a more comprehensive evaluation of the model's generalization capability across diverse plant species.

Research Framework

This study was conducted through several systematic stages. Each stage was designed to ensure that the model development process was structured, efficient, and aligned with deep learning best practices. The research process has multiple primary steps, as depicted in Figure 2 below.

Figure 2 illustrates that the research workflow commences with the acquisition of two datasets: a flower and herbal leaf dataset obtained. All images undergo preprocessing processes before comparing the two architectures, MobileNet and MobileNetV2. The grid search method sought to assess the influence of each optimizer on validation accuracy, with the ideal model chosen according to the highest validation performance. Four optimizers Adam, RMSProp, Stochastic Gradient Descent (SGD), and Nadam are assessed to evaluate the influence of optimization strategies on model performance. The conventional classification metrics of accuracy, precision, recall, and F1-score are utilized to assess the trained models. The model's performance was

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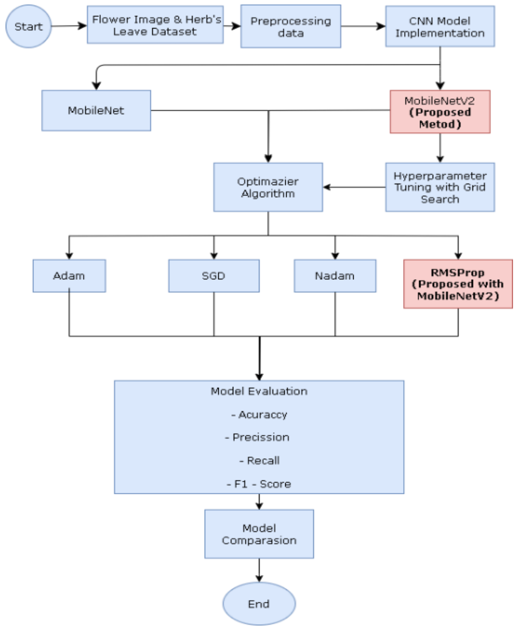
subsequently assessed, analyzed, interpreted, and conclusions derived from the results.



Source : (Research Result, 2025)
Figure 2. Research Framework

1. Data Collection

The dataset of flower images classified into three categories, daisy, rose, and tulip was collected from reliable sources. Besides the flower image collection, this work provides a supplementary dataset consisting herbal leaf images sorted into three categories, kemangi (basil), jambu biji (guava), and nangka (jackfruit). The dataset underwent a verification process to ensure quality for model training

2. Preprocessing Data

All images undergo preprocessing phases, which encompass resizing, normalization of pixel values, and the use of data augmentation techniques, including rotation, zooming, and horizontal flipping, prior to model implementation. These measures aim to diversify the dataset and mitigate the risk of overfitting during training. The dataset was subsequently partitioned into training, validation, and testing sets.

3. Model Achitecture Design

This research compares two lightweight convolutional neural network architectures: MobileNet and MobileNetV2. MobileNet and MobileNetV2 are lightweight convolutional neural network (CNN) architectures designed for efficient image categorization, especially on mobile and embedded devices. Their primary aim is to attain great precision with minimum computing expense, rendering them appropriate for real-time applications.

4. Optimizer Configuration and Hyperparameter Tuning

This study evaluated four optimizers: Adam, RMSProp, SGD, and Nadam. All optimizers were configured by a manual grid search with a learning rate of 0.0001, utilizing SGD with a momentum of 0.9, and a batch size of 32. These setups guaranteed uniform assessment across optimizers and architectures.The identical model architecture and training pipeline were employed to evaluate each combination of optimizer and learning rate. This method allows for a fair and consistent comparison of all optimizer settings [35].

5. Optimizer Algorithm

An optimizer is an algorithm employed in the training phase of a neural network to adjust the model's weights and reduce the loss function. Diverse optimizers employ distinct methodologies to modify learning rates and gradients. The MobileNetV2 model was constructed using a modified architecture designed for multi-class classification tasks to enhance accuracy while maintaining computational efficiency.

Adam (Adaptive Moment Estimation) integrates the advantages of two additional variants of Stochastic Gradient Descent: Momentum and RMSProp. It calculates adaptive learning rates for each parameter by preserving exponentially decaying averages of previous gradients (momentum) and squared gradients. Adam is extensively utilized for its rapid convergence and resilience across many issues [36].

RMSProp (Root Mean Square Propagation) adjusts the learning rate for each parameter by dividing the gradient by a running average of its previous magnitudes. This mitigates oscillations and enhances convergence in a non-stationary environment [37]. RMSProp is very proficient at training recurrent or deep networks, particularly when dealing with noisy or sparse input.

Stochastic Gradient Descent (SGD) is the most fundamental and conventional optimization algorithm. It adjusts model weights according to the gradient of the loss function relative to each parameter for a randomly chosen batch [38].

Nadam (Nesterov-accelerated Adaptive Moment Estimation) is an enhancement of Adam that incorporates Nesterov momentum into its update mechanism. This enables it to anticipate the gradient's direction, enhancing stability and possibly accelerating convergence speed. Nadam occasionally outperforms Adam, particularly in scenarios with sparse or highly dynamic gradients. Despite its computational efficiency, it frequently converges slowly and may become trapped in local minima, particularly in intricate deep learning problems [39].

6. Evaluate Model Performance

The model's performance was evaluated using accuracy, confusion matrix, and classification report. In comparison to the original MobileNetV2 architecture and the baseline MobileNet, the proposed MobileNetV2 model, which incorporates additional layers and modifications, demonstrated superior accuracy [40].

7. Model Comparisson

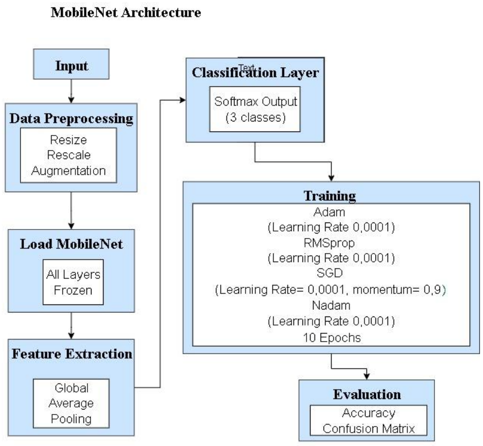
We assess the effectiveness of two lightweight convolutional neural network (CNN) architectures, MobileNet and MobileNetV2, using two datasets: one containing images of flowers (daisy, rose, and tulip) and the other comprising images of herbal leaves (kemangi (basil), jambu biji (guava), and nangka (jackfruit)). The evaluation criteria encompass the confusion matrix, which illustrates the efficacy of a classification model by presenting true positives, false positives, true negatives, and false negatives. The F1-score, recall, accuracy, precision, and loss function as evaluative metrics [41].

MobileNet Architecture

MobileNet introduces the concept of depthwise separable convolution, which divides a standard convolution into two separate operations: depthwise convolution and pointwise convolution. This significantly reduces the parameter count and processing cost compared to traditional convolutions, while preserving a similar level of accuracy.

Depthwise convolution employs a single filter for each input channel, enabling the acquisition of spatial information. Pointwise convolution employs (1×1) filters and subsequently integrates the outputs across channels.

This architectural decision decreases the computational expense by roughly 8 to 9 times in comparison to conventional CNNs. Nonetheless, MobileNet exhibits certain constraints in its deeper layers owing to the absence of shortcut (residual) connections, which may impede gradient flow and the acquisition of intricate patterns [42], [43]. Figure 3 depicts the architecture.



Source : (Research Result, 2025)

Figure 3. MobileNet Architecture

Figure 3. exemplifies a fundamental transfer learning strategy, characterized by rapid training, utilization of unaltered pretrained models, and appropriateness as a benchmark for comparison with the suggested technique.

Proposed Method

This study utilizes the pretrained MobileNetV2 model (omitting the top classification layers) and incorporates custom layers, including Global Average Pooling (GAP), a Dropout layer for regularization, a fully connected (Dense) layer with ReLU activation, and a softmax layer for multi-class classification.

MobileNetV2 was introduced with two notable architectural innovations: the linear bottleneck and the inverted residual block [44]. The inverted residual structure employs shortcut connections to link narrow layers (bottlenecks) while temporarily augmenting the number of channels in the intermediate layers. Simultaneously, to retain essential feature information in a low-dimensional space, the linear bottleneck removes non-linearity at the last projection layer of each block. Due to these enhancements, MobileNetV2 surpasses its predecessor while utilizing fewer parameters [45].

This architecture is trained using four optimizers (SGD, Adam, Nadam, RMSProp) to evaluate their effect on convergence and classification performance. A visual comparison of MobileNet, and the proposed method MobileNetV2 is shown in Figure 4, illustrating architectural evolution and enhancement in feature extraction and efficiency.

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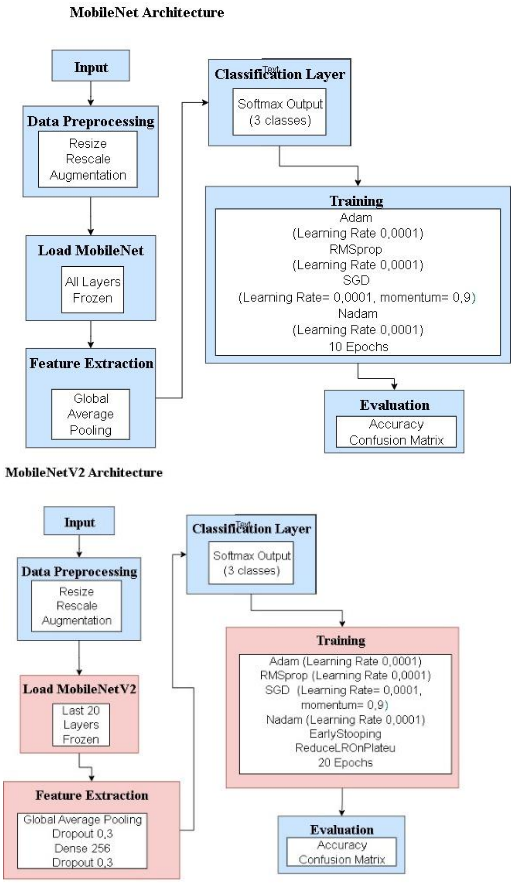

Source : (Research Result, 2025)

Figure 4. Comparison Architecture of MobileNet With MobileNetV2 (Proposed Method)

Figure 4 depicts a more aggressive and adaptable transfer learning technique, encompassing: fine-tuning of initial layers, application of dropout and dense layers, and execution of regularization and training oversight to mitigate overfitting. The outcomes are expected to exceed the baseline owing to the model's enhanced adaptability to the target dataset, especially in the categorization of complex visual patterns such as flowers andherbal leaves.

RESULTS AND DISCUSSION

This section delineates and examines the experimental outcomes derived from the training and assessment of the MobileNet and MobileNetV2 architectures employing diverse optimization strategies. The assessment centers on contrasting model efficacy between two distinct datasets: floral images and herbal leaf images. Essential performance parameters, including as accuracy, precision, recall, and F1-score, are employed to evaluate the efficacy of each optimizer Adam, RMSProp, SGD, and Nadam across both CNN architectures. Furthermore, the convergence behavior of training is analyzed via accuracy and loss plots, while confusion matrices are employed to assess model generalization and misclassification patterns. This investigation aims to identify the ideal mix of design and optimizer that maximizes classification performance while ensuring computing economy.

Image Data Pre-Processing Results

This section delineates the outcomes of the preprocessing phase, encompassing the distribution of the datasets. The dataset was partitioned into testing (20%), validation (20%), and training (80%), as illustrated in Table 2.

Table 2. Images Data Splitting

No	Data Spliting	Class	Amount
1	*Training*	*Daisy*	320
2		*Rose*	320
3		*Tulip*	320
4		*Kemangi*	280
5		*Jambu Biji*	280
6		*Nangka*	280
7	*Validation*	*Daisy*	80
8		*Rose*	80
9		*Tulip*	80
10		*Kemangi*	70
11		*Jambu Biji*	70
12		*Nangka*	70
13	*Testing*	*Daisy*	80
14		*Rose*	80
15		*Tulip*	80
16		*Kemangi*	70
17		*Jambu Biji*	70
18		*Nangka*	70

Source : (Research Result, 2025)

Table 2 delineates the allocation of image data among training, validation, and testing sets for both floral and herbal leaf classifications.

The dataset is composed of six classes, three from the flower category daisy, rose, and tulip and three from the herbal leaf category kemangi (basil), jambu biji (guava), and nangka (jackfruit).

For the training set, each flower class contains 320 images, while each herbal class includes 280 images. The validation set consists of 80 images per flower class and 70 images per herbal class. Similarly, the testing set includes 80 images for each flower class and 70 images for each herbal class.

This allocation results ensures a balanced and representative distribution across all classes, enabling reliable model evaluation and generalization assessment during experiments.

Image Data Classification Result

This section delineates the outcomes of the classification tasks executed utilizing the MobileNet

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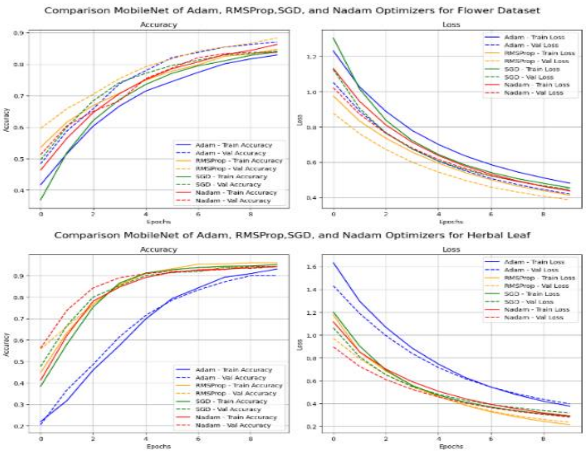
and MobileNetV2 designs across two distinct datasets: floral and herbal leaves.

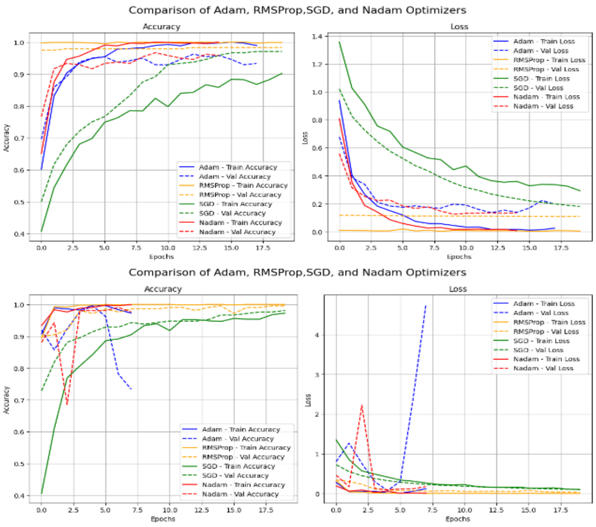
Loss and Accuracy Curve

Prior to model training, all picture data underwent a sequence of preprocessing procedures to ensure uniformity and improve the model's generalization capability. The procedures involved downsizing all photos to 224×224 pixels, normalizing pixel values to a range of [0,1], and implementing data augmentation methods including rotation, zooming, and horizontal flipping.

The objective of preprocessing was to standardize the input data, mitigate the danger of overfitting, and enhance classification efficacy. The results demonstrate the significance of optimization strategies for classification tasks employing deep learning, as evidenced by the model convergence illustrated in Figure 5.



(a) Accuracy/Loss MobileNet



(b) Accuracy/Loss MobileNetV2

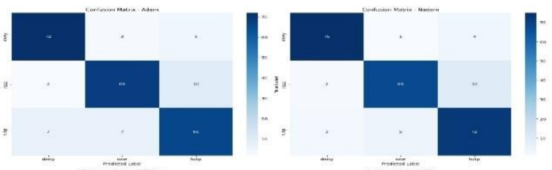
Source : (Research Result, 2025)

Figure 5. Training And Validation Accuracy/Loss for Flower using MobileNet & MobilenetV2

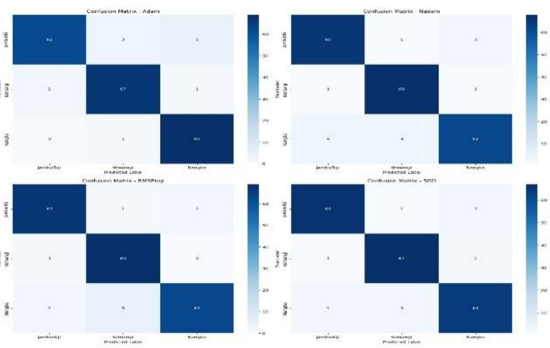
Figure 5 illustrates the accuracy and loss trajectories of MobileNet & MobileNetV2 employing four distinct optimizers. The training and validation curves for both datasets demonstrate that RMSProp consistently delivers superior performance across all metrics. It achieves faster convergence, minimal loss, and stable validation accuracy, especially on the herbal dataset where other optimizers exhibited fluctuations or divergence. Adam and Nadam also perform well but are prone to validation instability. SGD, while slower, eventually converges but underperforms compared to adaptive methods. These results affirm the effectiveness of adaptive optimizers, particularly RMSProp, in fine-tuning lightweight CNN architectures like MobileNetV2 for multiclass plant classification tasks.

Confusion Matrix

The confusion matrix offers essential insights into the efficacy of a classification model, emphasizing potential mistake areas. Analyzing the confusion matrix reveals false positives, false negatives, and correct classifications, all essential for improving the model's accuracy. If the model consistently produces false negatives, it suggests that the classification threshold may need adjustment, or that additional techniques like data augmentation could be advantageous, as illustrated in Figure 6.



(a) Confusion Matrix MobileNet Flower



(b) Confusion Matrix MobileNet Herbal Leaf

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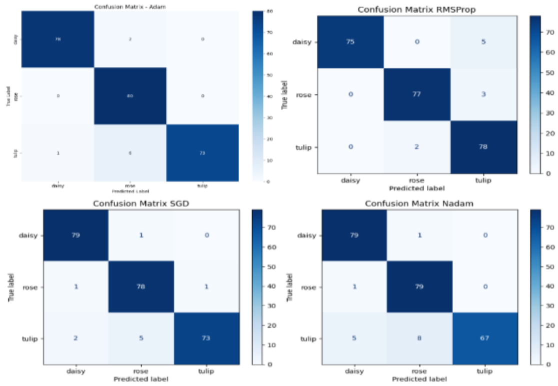
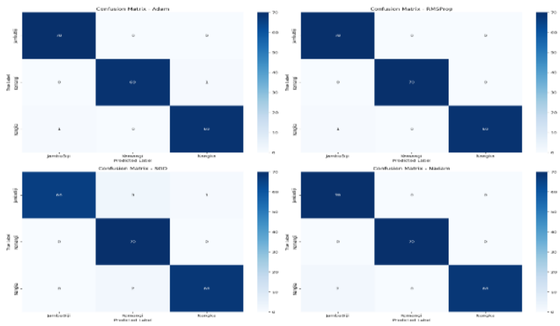


(c) Confusion Matrix MobileNetV2 Flower



(d) Confusion Matrix MobileNetV2 Herbal Leaf

Source : (Research Result, 2025)

Figure 6. ConfusionMatrix MobileNet & MobilenetV2 (a,b,c,d)

Figure 6 presents a comparison of classification accuracy per class based on the confusion matrix outputs for both MobileNet and MobileNetV2 models, using four different optimizers. Overall, MobileNetV2 consistently shows higher correct classification counts across most classes, especially for flower datasets. RMSProp and Adam optimizers exhibit strong and stable performance in both datasets, while Nadam shows some instability, particularly on the herbal dataset for the nangka (jackfruit) class. This underscores the significance of optimizer selection in attaining consistent performance across various data categories.

Model Performance Evaluation

The report encompasses essential evaluation measures including Precision, Recall, F1-Score, and Support for each class. These indicators elucidate the efficacy of each model in differentiating across classes, managing class imbalances, and ensuring consistency in forecasts. Through the analysis of these variables, we may more effectively evaluate the strengths and limitations of each optimizer for class-wise performance, particularly in practical classification contexts where balanced precision and recall are essential. The classification outcomes presented in Table 3.

Table 3. Classification Result of MobileNet & with MobileNetV2

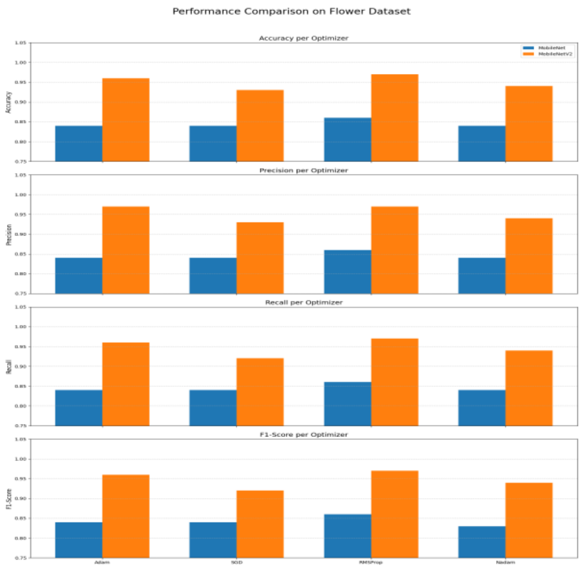
MobileNetV2 Flower Dataset					
Optimizer	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Loss**
RMSProp	96.67	96.90	96.67	96.68	0.1071
Adam	96.25	96.42	96.25	96.26	0.1535
Nadam	93.75	94.24	93.75	93.65	0.1140
SGD	92.50	93.34	92.50	92.45	0.2189
Herbal Leaf Dataset					
Optimizer	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Loss**
RMSProp	99.52	99.53	99.52	99.52	0.0126
Adam	99.05	99.05	99.05	99.05	0.0209
Nadam	99.05	99.07	99.05	99.05	0.0209
SGD	97.14	97.29	97.14	97.15	0.1781
MobileNet Flower Dataset					
Optimizer	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Loss**
RMSProp	85.83	85.81	85.83	85.79	0.3868
Nadam	85.42	85.37	85.42	85.38	0.4225
Adam	83.75	83.89	83.75	83.72	0.4113
SGD	83.33	83.33	83.33	83.33	0.4341
Herbal Leaf Dataset					
Optimizer	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Loss**
RMSProp	94.76	94.88	94.76	94.74	0.2527
Adam	94.29	94.41	94.29	94.25	0.3573
SGD	93.81	93.80	93.81	93.80	0.3140
Nadam	93.33	93.35	93.33	93.30	0.3470

Source : (Research Result, 2025)

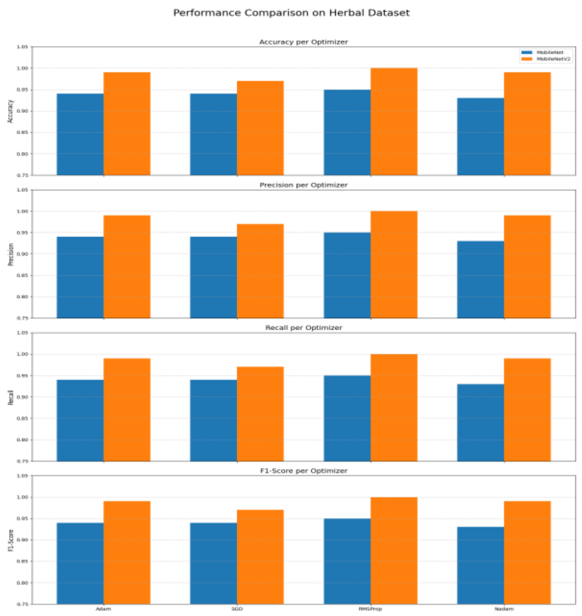
The classification results in Table 3 illustrates that across both MobileNet and MobileNetV2 architectures, RMSProp consistently achieved the best overall performance, especially in terms of accuracy and loss. The MobileNetV2 model performed significantly better than the MobileNet baseline across all evaluation metrics, particularly on the Herbal Leaf Dataset. Additionally, training on the herbal dataset yielded higher accuracies compared to the flower dataset across all configurations, suggesting that the herbal dataset may be easier to classify or more consistent in features.

Model Comparisson

A thorough assessment of the MobileNet and MobileNetV2 models' performance was performed through an investigation of essential classification parameters. The subsequent figures provide a comparative analysis of the performance of the two models on the Flower and Herbal datasets. The parameters of accuracy, precision, recall, and F1-score were evaluated across multiple optimizers, including Adam, SGD, RMSProp, and Nadam, to deliver a comprehensive assessment of their efficacy. The results underscore the trade-offs between model complexity and performance, offering critical insights for the selection of an ideal model in a specific context, as illustrated in Figure 7.



(a) Comparison Performance of Flower Dataset

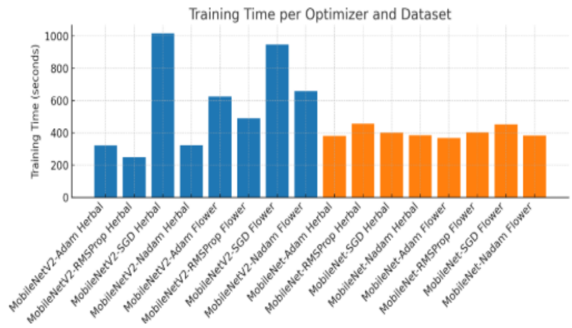


(b) Comparison Performance of Herbal Dataset

Source : (Research Result, 2025)
Figure 7. Comparison Performance of MobileNet & MobileNetV2 (a,b)

Figure 7 displays the accuracy, precision, recall, and F1-score for both models in classifying images of daisy, rose, tulip, kemangi (basil), jambu biji (guava), and nangka (jackfruit). The performance is categorized by the optimizer employed during training, demonstrating MobileNetV2's exceptional performance across all criteria. The findings unequivocally illustrate MobileNetV2's superior performance, attaining near-optimal scores with specific optimizers, particularly RMSProp.

All training tests were executed on a CPU-only computer utilizing an Intel Core i3-1115G4 processor with 8 GB of RAM, devoid of GPU acceleration. Thus, the training durations reported in this study indicate CPU-based execution efficiency. The durations are anticipated to be considerably diminished when utilizing a dedicated GPU system (e.g., NVIDIA CUDA-enabled devices), as illustrated in Figure 8.



Source : (Research Result, 2025)
Figure 8. Training Time per Optimizer & Dataset

Figure 8 illustrates the S, which highlights that MobileNetV2 requires more training time and memory compared to MobileNet. On average, MobileNetV2 takes approximately 610 seconds and utilizes 900 MB of memory, while MobileNet completes training in about 410 seconds with 600 MB of memory. These differences emphasize MobileNetV2's higher model complexity and capacity, but also its greater resource demands, especially in CPU-only environments.

A detailed analysis of the graph shows that performance varies depending on the optimizer and dataset combination. For MobileNetV2, the longest training time was achieved with the SGD optimizer on the Flower dataset (around 950 seconds), while the shortest time was with the RMSProp optimizer on the Herbal dataset (around 250 seconds). In contrast, MobileNet's training times tend to be more consistent and faster, with an average below 500 seconds.

In terms of model size, MobileNetV2 models are larger (approximately 900 MB) due to their deeper and more expressive architecture, whereas MobileNet models are more lightweight (600 MB),

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making them better suited for memory-constrained environments.

These results provide valuable insight into the trade-offs between accuracy, training duration, and memory efficiency. These findings are particularly relevant when deploying deep learning models in resource-limited or edge-computing environments.

CONCLUSION

This work assessed four optimization algorithms Adam, RMSProp, SGD, and Nadam on MobileNet and MobileNetV2 architectures utilizing flower and herbal leaf picture datasets. The investigation, performed on a CPU-only system (Intel i3-1115G4, 8GB RAM), evaluated performance metrics and computational efficiency. MobileNetV2, combined with RMSProp, achieved an accuracy of 99.52% and an insignificant loss of 0.0126. The flower dataset attained an accuracy of 96.67% with a loss of 0.1071 for the identical configuration. MobileNetV2 required an average training time of 9–10 minutes and approximately 900 MB of memory, whereas MobileNet used just 6–7 minutes and about 600 MB of memory, however provided superior classification outcomes, particularly in scenarios with significant intra-class similarity.

The herbal dataset exhibited superior macro F1-scores compared to the floral dataset across all optimizers, indicating it provides more discernible characteristics. he findings highlight the importance of selecting an effective CNN architecture and a suitable optimizer, particularly in resource-constrained environments. Future research may explore hybrid optimizers, learning rate scheduling, Bayesian hyperparameter optimization (e.g., Optuna), and more lightweight models such as EfficientNet or ShuffleNet. Incorporating explainable AI (e.g., Grad-CAM), data augmentation, and real-time deployment on edge devices (e.g., Raspberry Pi, Jetson Nano) would markedly enhance model interpretability and functionality.

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