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Comparison of Transfer Learning Strategies Using MobileNetV2 and ResNet50 for Ecoprint Leaf Classification

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Abstract

This research focuses on the classification of leaf types used in ecoprint production through the steaming technique by applying transfer learning on two widely recognized convolutional neural network (CNN) architectures, MobileNetV2 and ResNet50. Leaves have diverse applications in various sectors such as medicine, nutrition, and handicrafts. The study utilized a total of 600 leaf images from 15 species were collected from the surrounding environment and divided into 80% training and 20% testing sets. The aim of this study is to classify leaf types suitable for ecoprint quickly and efficiently, based on transfer learning with two CNN architectures, while incorporating fine-tuning. MobileNetV2 was selected for its computational efficiency, while ResNet50 was chosen for its ability to address the vanishing gradient problem and deliver high accuracy. Fine-tuning was employed to optimize model performance. Experimental results demonstrate that both architectures achieved strong performance, with MobileNetV2 reaching 94.12% accuracy and ResNet50 slightly outperforming it at 94.96%. Confusion matrix evaluation further confirmed these results, yielding accuracy, precision, recall, and F1-score values of 0.94, 0.95, 0.95, and 0.94, respectively. These findings highlight ResNet50's superior performance over MobileNetV2 while affirming the effectiveness of both models in ecoprint leaf classification.

Keywords: *Ecoprint, MobileNetV2, ResNet50, Transfer Learning, types of leaves.*

1. INTRODUCTION

Leaves are not only essential elements in photosynthesis, but they also have diverse uses across various sectors, including medicine, nutrition, and crafts. They exhibit a variety of shapes, colors, and textures that make them ideal for ecoprint. Ecoprint is an artistic technique that utilizes natural materials, especially leaves, to create unique patterns and images on fabric [1]. In recent years, the ecoprint technique has become one of the major innovations in the creative industry, focusing on natural printing methods that extract pigments from leaves and flowers to produce distinctive, artistic, and eco-friendly motifs. This technique offers a sustainable alternative in the fashion industry by minimizing the use of synthetic chemicals and hazardous waste [2].

In practice, not all leaves can be used to produce optimal patterns in ecoprint, especially with the steaming method [3]. Suitable leaves typically have physical characteristics such as prominent leaf veins, slightly rough surfaces, neither too stiff nor too soft, non-slippery, and do not contain excess moisture. These characteristics are crucial to ensure that the pigments within the leaves can transfer properly onto the fabric surface, resulting in clear and long-lasting patterns.

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However, the process of producing ecoprint patterns still heavily relies on manual identification of the types of leaves used, which is not only time-consuming but also prone to error. To overcome this challenge, computer vision and deep learning technologies are being explored as potential solutions to automate the leaf classification process by utilizing deep learning image recognition algorithms, such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN) with transfer learning techniques [4], [5], and [6]. This innovation aims to improve efficiency, accuracy, and consistency in the ecoprint production process. Although conventional methods can recognize visual features such as shape and color, the results are often inconsistent under complex or varied image conditions. In contrast, deep learning methods using two popular CNN architectures, MobileNetV2 and ResNet50, based on transfer learning, have proven to be more effective in extracting complex features from leaf images and achieving higher classification accuracy [7], [8]. Nevertheless, implementing CNN from scratch requires large datasets and long training times, which presents a practical obstacle [9].

To address these limitations, transfer learning approaches have increasingly been adopted in natural image classification tasks, helping to accelerate the training process [10], while also utilizing existing architectures. By leveraging pre-trained models such as MobileNetV2 and ResNet50 [11], and applying fine-tuning as an advanced stage after transfer learning [12], classification can be performed efficiently even with limited datasets. Studies by [13] demonstrate that both models are capable of achieving high accuracy in plant classification tasks, including leaves. Furthermore, MobileNetV2 has shown advantages in lightweight, mobile-based applications due to its high computational efficiency [14], [15], . However, there remains limited research that specifically applies transfer learning for leaf classification in the context of ecoprint production, which has unique visual and local characteristics. The central question, therefore, is: How well do MobileNetV2 and ResNet50 perform under transfer learning [16], [17], and [18] in classifying leaf types used in ecoprint techniques? This study aims to answer that question through experimental evaluation and comparative analysis of both models based on leaf image classification performance.

The main contribution of this research is to provide a baseline for automatic classification performance of ecoprint leaves using two popular transfer learning models [5], which can serve as a foundation for developing smarter and more efficient support systems for the ecoprint industry. The results are also expected to be a starting reference in developing automatic leaf identification systems that can be easily integrated into the ecoprint production process by sustainable fashion SMEs. Specifically, this study aims to evaluate the efficiency, accuracy, and generalization capability of the MobileNetV2 and ResNet50 models [19] by optimizing the fine-tuning process [20], [21] on a local leaf dataset commonly used in ecoprint.

This study is limited to two-dimensional leaf image classification using a dataset of 600 samples from 15 types of leaves collected from the surrounding environment. The study does not consider factors such as leaf age, and instead enriches the exploration of transfer learning methods in leaf classification for ecoprint, focusing on applications within small to medium-scale ecoprint production. It is hoped that this research will be useful for future studies in leaf classification for ecoprint purposes.

2. METHOD

This research method employs a comparative approach, beginning with the process illustrated in Figure 1, which shows the workflow of the leaf classification method using deep learning and transfer learning approaches, divided into three main stages.

Referring to Figure 1, this process aims to facilitate the selection of leaf types to be used for the ecoprint technique (steaming method) in a fast and accurate manner. The process begins with observation, followed by a literature review, then preprocessing which includes data collection and

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processing. It continues with the model development phase using transfer learning enhanced with fine-tuning [22], followed by model testing, and concludes with the evaluation of classification performance [23], [24]. This series of stages will produce an accuracy value, after which the leaf type can be identified and used for ecoprint.

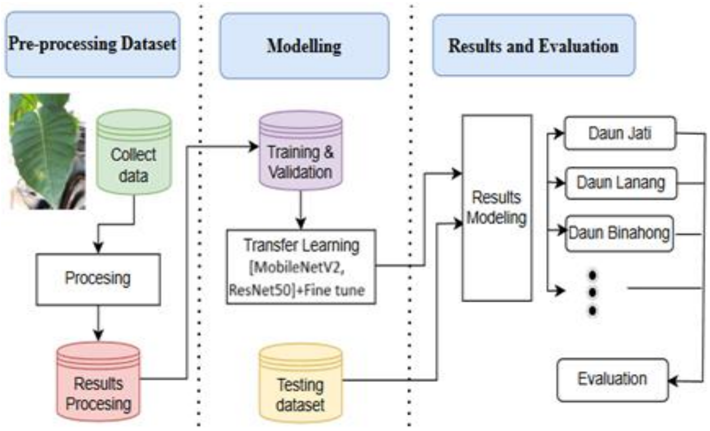

Figure 1. Research methods

2.1. Pre-processing

This initial stage aims to prepare the leaf image data that will be used in the model training and testing processes. It is divided into three phases: Collect Data, Processing, and Results Processing, before proceeding to the modeling phase. The types of leaves can be seen in Figure 2.

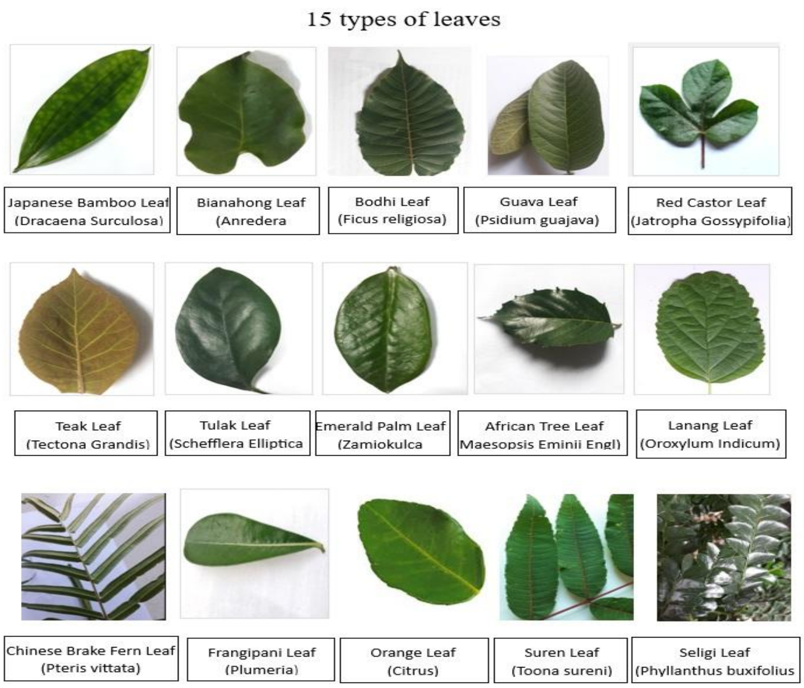

Figure 2. Leaf types used as research objects

Collect Data: The data were collected in the form of images (photos) taken directly from the surrounding environment, with a total of 600 photos from 15 types of leaves. Namely: Japanese Bamboo Leaf, Bianahong Leaf, Bodhi Leaf, Guava Leaf, Red Castor Leaf, Teak Leaf, Orange Leaf, Frangipani Leaf, African Tree Leaf, Lanang Leaf, Chinese Brake Fern Leaf, Emerald Palm Leaf, Seligi Leaf, Suren Leaf, and Tulak Leaf. The photos were taken from the surrounding environment, and online datasets

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were used when necessary. In practice, not all types of leaves can be used to produce optimal patterns in the ecoprint technique, especially when using the steaming method.

Suitable leaves generally have physical characteristics such as prominent leaf veins, slightly rough surfaces, not too stiff or too soft, non-slippery, and do not contain excess moisture. These characteristics are essential as they allow the leaves to release pigments effectively onto the fabric during the steaming process. It is observed that leaves with slightly rough textures and clearly defined veins tend to produce sharper and more durable patterns, while leaves that are too soft or slippery tend to result in blurred motifs.

Procesing: The image data were then processed through several stages, including normalization, data augmentation (such as rotation, flipping, zooming, etc.) to enrich dataset variations, and image labeling according to leaf type. The transformation processes of random rotation and random flipping can be seen in Figure 3.

Figure 3. Augmented Image Samples of Emerald Palm Leaf

Results Processing: The dataset resulting from the image augmentation preprocessing contains 40 original images per leaf type, which were augmented into 400 images each. The total number of datasets increased from 600 to 6,000, representing 15 different types of leaves. The data were split into two main parts: training dataset and testing dataset.

2.2. Modelling

The dataset obtained from the preprocessing stage was then used in the modeling phase, utilizing MobileNetV2 and ResNet50 models based on transfer learning, combined with fine-tuning [25]. This stage represents the core of the classification process, which involves building an artificial intelligence model capable of recognizing and classifying leaves into appropriate categories using an 80:20 dataset ratio, and trained over 15 epochs. This process consists of two main parts: the Training & Validation phase (80%) and the Testing phase (20%).

Training & Validation: This stage involves training the model to recognize patterns from 4,800 labeled leaf images, followed by evaluating how well the model can understand and correctly interpret the data.

Transfer Learning: utilizes the weights from a pre-trained model to recognize general features, which are then adapted to the leaf dataset in the final layers. The use of transfer learning involves applying deep learning architectures that have undergone initial training on large-scale datasets (such as ImageNet), followed by fine-tuning using the available leaf image data. This study employs two popular pre-trained CNN architectures.

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MobileNetV2: is a model optimized for efficiency and speed. It is well-suited for use on mobile devices or edge computing. Despite its lightweight architecture, it is still capable of delivering good accuracy in classification tasks. The ResNet50 architecture is illustrated in Figure 4.

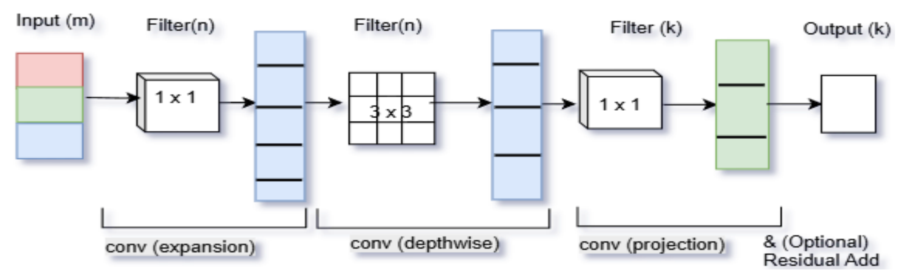

Figure 4. MobileNetV2 architecture

ResNet50: It is a deeper network architecture consisting of 50 layer [26]. It is capable of avoiding the vanishing gradient problem and adopts the concept of residual learning, which makes the training process more stable and enables it to handle larger and more complex data. The ResNet50 architecture is illustrated in Figure 5.

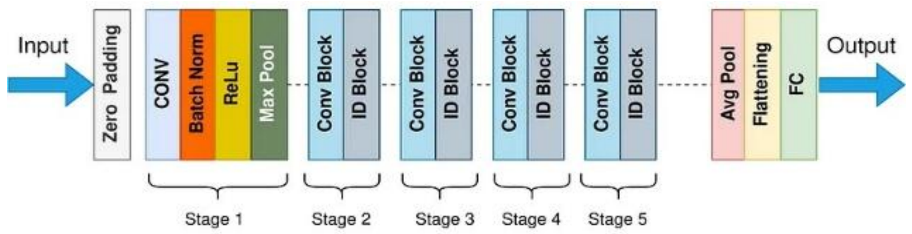

Figure 5. ResNet50 Architecture

Fine Tune: This is an advanced stage in transfer learning, in which some or all of the weights from a previously trained (pretrained) model are unfrozen and retrained using the specific dataset being used. The goal is to adapt the model to the characteristics of the new dataset in order to achieve more accurate classification results.
Testing: After training using MobileNetV2 and ResNet50 with fine-tuning, the models were tested using a testing dataset that had not been seen by the models before, in order to evaluate classification accuracy, using Python. A total of 1,200 datasets were used for testing, selected from the entire dataset.

2.3. Results and Evaluation

This stage represents the results of modeling and the evaluation process, where the trained model was tested using the testing data. After obtaining all classification results, the process continues to the Evaluation stage, which assesses the model's performance in terms of accuracy, precision, and reliability in distinguishing different types of leaves. Accuracy represents the proportion of correct predictions using the Confution matrix [27], [28], between the model's classification results and the actual conditions [29] both for leaf categories that can and cannot be used for ecoprint. A high accuracy score indicates that the model has strong identification capabilities regarding leaf characteristics in the context of ecoprint technique application. The evaluation was conducted using the following metrics:

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (1)$$

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Accuracy in a confusion matrix is a measure of how many model predictions are correct compared to the total number of test data, where the diagonal values represent the number of data correctly classified for each class (1).

$$Precision = \frac{(TP)}{(TP+FP)} \quad (2)$$

Precision is important for assessing the quality of prediction accuracy for each class, indicating how precise the model's positive predictions are (2).

$$Recall = \frac{(TP)}{(TP+FN)} \quad (3)$$

Meanwhile, recall focuses on the completeness of positive predictions, meaning how well the model identifies all the actual positive data (3).

$$F1\ Score = \frac{2x(Recall\ x\ Precision)}{(Recall+\ Precision)} \quad (4)$$

Meanwhile, the F1-Score is an evaluation metric that functions to measure the balance between precision and recall. For example, if precision = 90% and recall = 60%, then F1 = 72%, indicating that the model's performance cannot be considered very good even though precision is high, because recall is low (4).

Explain that TP (True Positive): The number of leaves correctly predicted as positive (e.g., leaves that can be used for ecoprint and are correctly predicted as such). TN (True Negative): The number of leaves correctly predicted as negative (leaves that cannot be used for ecoprint and are correctly predicted as such). FP (False Positive): Leaves incorrectly predicted as positive (leaves that cannot be used, but the model mistakenly predicts they can be used). FN (False Negative): Leaves incorrectly predicted as negative (leaves that can be used, but the model mistakenly predicts they cannot be used).

3. RESULT

This study evaluates the performance of two CNN architectures based on transfer learning, namely MobileNetV2 and ResNet50, under two training scenarios: with and without fine-tuning, and also evaluated using a confusion matrix. Each scenario was tested on a leaf image dataset for classifying leaves suitable for ecoprint.

3.1. Experimental Results with MobileNetV2

In this scenario, all layers of the pre-trained model were frozen (not retrained), so only the final classification layer was trained using the new dataset, with and without fine-tuning. The training results demonstrated excellent performance.

The MobileNetV2 model without fine-tuning achieved the highest validation accuracy of 92.44% with the lowest validation loss of 0.2750 at the 8th epoch. Meanwhile, the MobileNetV2 model with fine-tuning achieved a higher validation accuracy of 94.12%, with a validation loss of 0.2768 at the 3rd epoch. Further details can be seen in Table 1.

Table 1. Results Accuracy with MobileNetV2

Model	*Epoch*	*Accuracy*	*Loss*	*Val-accuracy*	*Val-loss*
Not fine-tuning	8	98.86%	0.0894	92.44%	0.2750
With fine-tuning	3	93.56%	0.2619	94.12%	0.2768

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Both models underwent a fast and stable training process, even without applying fine-tuning. This indicates that the features obtained from the initial training using ImageNet were sufficiently relevant and capable of capturing the characteristics of the leaf dataset used.

The visualization of changes in accuracy and loss values during the training process is shown in Figure 6, which presents the performance graph of the MobileNetV2 training with fine-tuning.

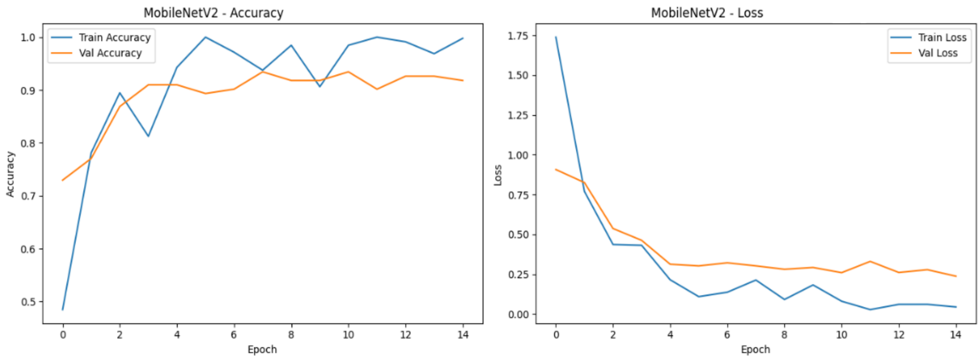

Figure 6. Results Accuracy MobileNetV2

Referring to Figure 6, the graph shows that MobileNetV2 experienced a relatively consistent increase in validation accuracy, while the ResNet50 method showed a tendency to plateau.

The testing results using the confusion matrix also achieved high accuracy, with an F1-score reaching 92%. Further details can be seen in Figure 7 and Table 2.

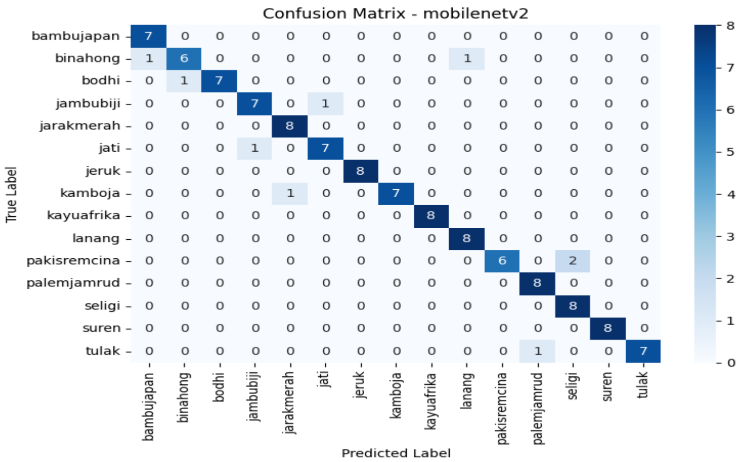

Figure 7. Validation Results Confusion Matrix of MobileNetV2

The evaluation results of the ecoprint leaf classification model are presented in Table 2. Overall, the model achieved an accuracy of 92%, with consistent macro average and weighted average values of 0.92. This indicates that the model is capable of making predictions with high accuracy and balanced performance across all leaf classes.

When analyzed per class, most leaf types obtained Precision, Recall, and F1-Score values above 0.90. The jeruk, kayu afrika, and suren leaves even achieved perfect scores (1.00) on all three metrics, demonstrating that the model can effectively recognize the distinctive characteristics of these leaves. However, some classes showed relatively lower performance, such as binahong (F1-Score 0.80) and pakis remcina (F1-Score 0.86). The lower scores in these classes may be attributed to the similarity in texture patterns or shapes with other classes, making it more challenging for the model to distinguish them.

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Table 2. Results Accuracy Matrix MobileNetV2

Class	*Precision*	*Recall*	*F1-score*
bambujapan	0.88	1.00	0.93
binahong	0.86	0.75	0.80
bodhi	1.00	0.88	0.93
jambubiji	0.88	0.88	0.88
jarakmerah	0.89	1.00	0.94
jati	0.88	0.88	0.88
jeruk	1.00	1.00	1.00
kamboja	1.00	0.88	0.93
kayuafrika	1.00	1.00	1.00
lanang	0.89	1.00	0.94
pakisremcina	1.00	0.75	0.86
palemjamrud	0.89	1.00	0.94
seligi	0.80	1.00	0.89
suren	1.00	1.00	1.00
tulak	1.00	0.88	0.93
Accuracy			0.92
Macro avg	0.93	0.93	0.92
Weighted avg	0.93	0.92	0.92

3.2. Experimental Results with ResNet50

In this scenario, several of the final layers of the pre-trained model were unfrozen and retrained along with the classification layers. This process, conducted with and without fine-tuning, aimed to refine the feature representations to better match the specific characteristics of ecoprint leaf images. As a result, the model's performance showed an improvement.

It performed better in handling complex datasets, despite its larger size compared to MobileNetV2. Further details can be seen in Table 3.

Table 3. Results Accuracy with ResNet50

Model	*Epoch*	*Accuracy*	*Loss*	*Val-accuracy*	*Val-loss*
Not fine-tuning	5	96.61%	0.1364	93.28%	0.2991
With fine-tuning	1	97.37%	0.1295	94.96%	0.2025

Meanwhile, ResNet50 demonstrated slightly better performance, achieving a validation accuracy of 93.28% and a minimum validation loss of 0.2991 at the 5th epoch. The ResNet50 model also showed improved performance starting from the first epoch, reaching a maximum validation accuracy of 94.96% with a validation loss of 0.2025.

In Figure 8, the training performance graph of the ResNet50 method with fine-tuning is shown, although the results are not significantly different from the accuracy achieved without fine-tuning.

Referring to Figure 8, the graph shows that MobileNetV2 experienced a relatively consistent improvement in validation accuracy after fine-tuning, while ResNet50 showed a tendency to plateau. This pattern indicates that the effectiveness of fine-tuning is highly influenced by the model's level of complexity and the amount of data used during training.

In the testing results using the confusion matrix, a high accuracy was also achieved, with an F1-score reaching 94%. Further details can be seen in Figure 9 and Table 4.

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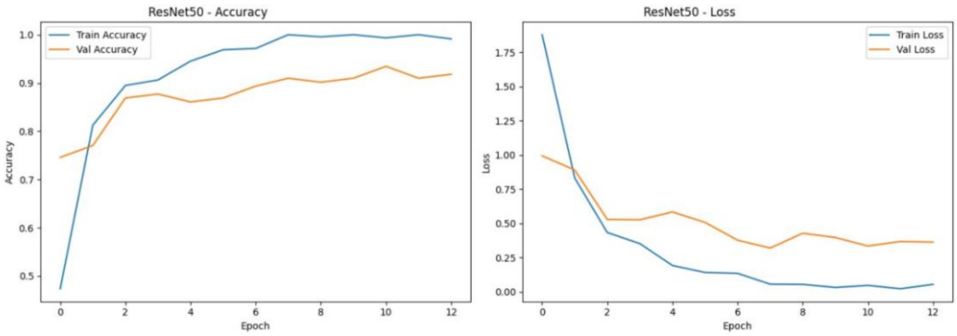

Figure 8. Results Accuracy ResNet50

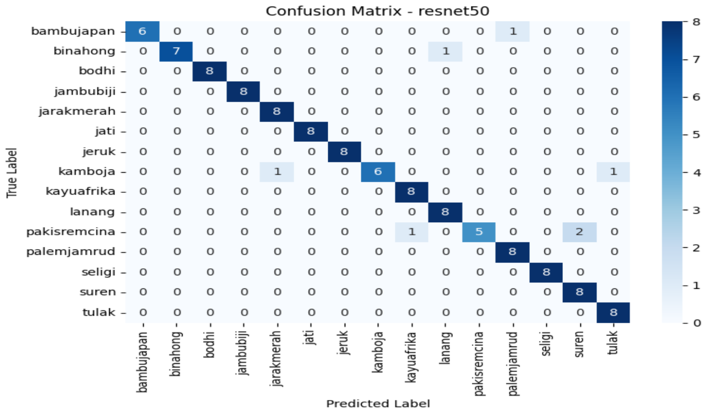

Figure 9. Validation Results Confusion Matrix of ResNet50

Table 4 presents the performance evaluation of the ResNet50 model in ecoprint leaf classification. The model achieved an overall accuracy of 94%, with consistent macro and weighted averages of 0.94–0.95, indicating accurate and balanced predictions across most leaf classes.

Table 4. Results Accuracy Matrix ResNet50

Class	*Precision*	*Recall*	*F1-score*
bambujapan	1.00	0.86	0.92
binahong	1.00	0.88	0.93
bodhi	1.00	1.00	1.00
jambubiji	1.00	1.00	1.00
jarakmerah	0.89	1.00	0.94
jati	1.00	1.00	1.00
jeruk	1.00	1.00	1.00
kamboja	1.00	0.75	0.86
kayuafrika	0.89	1.00	0.94
lanang	0.89	1.00	0.94
pakisremcina	1.00	0.62	0.77
palemjamrud	0.89	1.00	0.94
seligi	1.00	1.00	1.00
suren	0.80	1.00	0.89
tulak	0.89	1.00	0.94
Accuracy			0.94
Macro avg	0.95	0.94	0.94
Weighted avg	0.95	0.94	0.94

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At the class level, performance was generally strong. Leaves such as bodhi, jambubiji, jati, jeruk, seligi, and suren reached perfect scores (1.00) in Precision, Recall, and F1-Score, showing the model's ability to correctly identify their unique characteristics. Classes like binahong, kayu afrika, palem jamrud, and tulak also achieved high scores (F1-Score 0.93–0.94). In contrast, kamboja (0.86) and pakis remcina (0.77) recorded lower performance, likely due to visual or textural similarities with other leaf types, which increased misclassification rates.

3.3. Analysis

The results of the comparative analysis from the summary of the best validation accuracy of the two popular CNN models, MobileNetV2 and ResNet50, were conducted with and without fine-tuning. The results can be seen in Table 5.

Table 5. Comparison Results

Model	Not *Fine-Tune*	with *Fine-Tune*
MobileNetV2	92.44%	94.12%
ResNet50	93.28%	94.96%

Referring to Table 5, in general, both models performed optimally when fine-tuning was applied to the dataset. In MobileNetV2, the accuracy increased from 92.44% (without fine-tuning) at the 8th epoch to 94.12% at the 3rd epoch after fine-tuning. Meanwhile, ResNet50 showed an improvement from 93.28% at the 5th epoch to 94.96% at the 1st epoch. Fine-tuning plays a crucial role in adjusting the weights of the pre-trained model to match the specific characteristics of the dataset, which consists of leaf images with unique ecoprint textures.

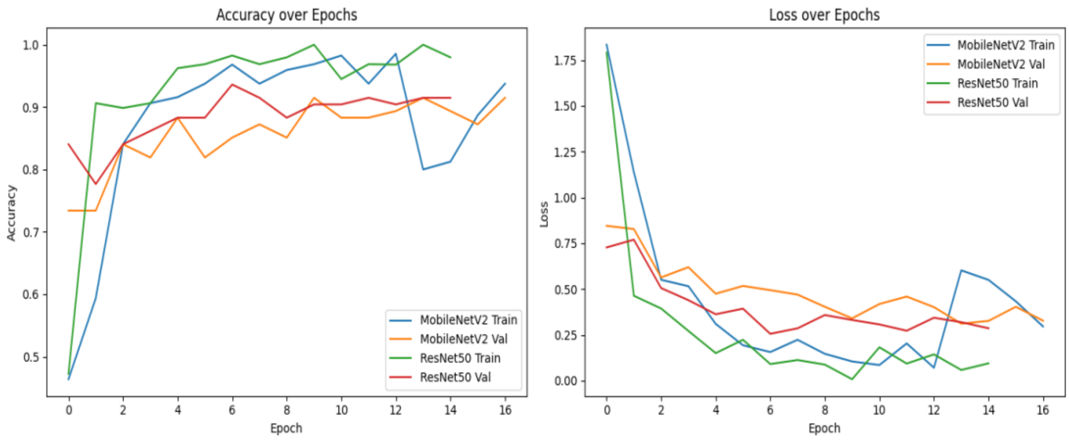

Figure 10. Comparison MobileNetV2 and ResNet50

The graph results in Figure 10 show a comparison of the classification accuracy between MobileNetV2 and ResNet50.

This improvement indicates that fine-tuning not only enhances accuracy but also accelerates the model's convergence process. These changes may be attributed to the fine-tuning process itself, the limited amount of training data, or the use of an appropriate learning rate.

Based on the evaluation using the confusion matrix, the application of fine-tuning on the MobileNetV2 and ResNet50 architectures has proven to improve the model's accuracy in classifying ecoprint leaves. The comparative evaluation results can be seen in Table 6.

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Table 6. Comparison Evaluation confusion matrix

	Accuracy	Precision	Recall	F1-score
MobileNetV2	0.92	0.93	0.92	0.92
ResNet50	0.94	0.95	0.94	0.94

This table presents a performance comparison between two CNN models based on transfer learning, namely MobileNetV2 and ResNet50, using evaluation metrics derived from the confusion matrix. ResNet50 classified slightly more data correctly than MobileNetV2, it also performed better in minimizing false positives, meaning it was more accurate in predicting leaves that are truly suitable for ecoprint. Additionally, ResNet50 was more effective in capturing all truly suitable leaves, resulting in fewer false negatives, and it demonstrated better overall balance and accuracy.

4. DISCUSSIONS

This further reinforces the evidence that transfer learning can be effectively utilized both with and without fine-tuning, by leveraging CNN architectures such as MobileNetV2 and ResNet50 to identify appropriate leaf types for ecoprint. The addition of fine-tuning in the training of MobileNetV2 resulted in higher accuracy and faster convergence, achieving high performance as early as the 3rd epoch. Meanwhile, in the training of ResNet50, the application of fine-tuning from the first epoch directly yielded a higher accuracy of 94.96%. The model demonstrated high sensitivity to parameter updates when trained on specific data and improved adaptability to the unique characteristics of leaf images used in ecoprint techniques, as the parameters were re-optimized using a new dataset. Despite the accuracy improvement being only 1.68% with fine-tuning. Furthermore, the evaluation results from the confusion matrix test using four key metrics Accuracy, Precision, Recall, and F1-score. Indicated that ResNet50 performed better in classification tasks than MobileNetV2, with a 2% advantage in both accuracy and consistency of correct classification.

The performance in this research method, although using the same ResNet50 method, consistently achieved higher accuracy compared to the results reported by Abdul (2021), which showed an accuracy of 78%, even though both evaluations used the confusion matrix for leaf classification. In this study, the addition of fine-tuning in the training process helped reduce overfitting during retraining, as the model was more general at the beginning and more specific at the end [7].

Specifically, although both employed transfer learning, a study by Muslikh, Setiadi, and Ojugo (2023) demonstrated that the Xception model was effective in recognizing rice diseases through leaf images, outperforming other CNN architectures such as VGG16, MobileNetV2, and EfficientNetV2 in rice disease detection [20].

Similarly, the study by Chusna and Khumaidi (2024), with orchid flowers as the object, the study applied the same method using CNN attributes and transfer learning, and also evaluated it using a confusion matrix. Although the results showed that ResNet-50 performed lower compared to VGG-16, this highlights the potential of transfer learning in classification, advancing research on ornamental plants and the salability of orchid flowers [18].

Another study by Saifullah et al. (2023), although using a different object, namely chicken eggs, this study applied the same method based on transfer learning with CNN attributes and also utilized a confusion matrix for evaluation. The evaluation results showed that InceptionNet outperformed the other models in detecting fertile and non-fertile eggs [22].

This study also highlights the potential of transfer learning-based CNNs to be more extensively applied in plant recognition tasks, particularly in leaf classification.

5. CONCLUSION

This study successfully implemented an image classification method using a transfer learning approach to identify leaf types that are suitable for use in the ecoprint steaming technique. The classification process was carried out through several stages: pre-processing, model training, and performance evaluation. These results emphasize that fine-tuning is a crucial strategy in transfer learning, especially when the target dataset differs significantly from the pre-training data.

The two CNN architectures used MobileNetV2 and ResNet50 demonstrated satisfactory classification performance. MobileNetV2 excels in terms of efficiency and speed, making it ideal for deployment on resource-constrained devices. It achieved a highest training accuracy of 94.12%, with an evaluation result matrik accuracy indicating 0.92 suitability for ecoprint. On the other hand, ResNet50 produced more accurate results, reaching 94.96% training accuracy and evaluation result matrik 0.94 suitability for ecoprint based on the evaluation. In conclusion, ResNet50 slightly outperforms MobileNetV2 in terms of accuracy, due to its deeper and more complex architecture, making it more capable of automatically identifying various types of leaves.

Based on the evaluation results, both models demonstrate significant potential in supporting the digital identification of leaf types, particularly in the context of ecoprint production where precise leaf selection is crucial. The transfer learning approach has proven effective in adapting pre-trained models to limited local datasets. If computational resources are sufficient, ResNet50 is more recommended as it can deliver more optimal classification results. Nevertheless, architectures such as MobileNetV2 remain a relevant alternative for resource-constrained devices, such as mobile applications. Looking ahead, it is suggested that future research expand the dataset to include a broader and more diverse range of leaf species—not only tens or hundreds, but potentially thousands—as experimental material, and explore mobile-based implementations for practical real-world applications.

REFERENCES

[1] R. Chusna Tsani, "Teknik Iron Blanket Pada Ecoprint Menggunakan Pewarna Alam," *BAJU Journal of Fashion & Textile Design Unesa*, vol. 5, no. 1, pp. 110–116, Oct. 2024, doi: 10.26740/baju.v5n1.p110-116.

[2] A. Cahyana and A. Afrizal, "Optimasi Produksi Ecoprint Fabric Dengan Teknik Rotary Printing," *Acintya Jurnal Penelitian Seni Budaya*, vol. 13, no. 2, pp. 109–118, 2022, doi: 10.33153/acy.v13i2.4049.

[3] Purwosiwi Pandansari, Rina Purwanti, and Dessy Ayu Alfianti, "Analysis of Steaming Ecoprint Techniques on Various Fabrics," *Formosa Journal of Social Sciences*, vol. 1, no. 4, pp. 411–424, Dec. 2022, doi: 10.55927/fjss.v1i4.2049.

[4] A. Sudrajat, R. D. Apnena, A. H. Rahayu, and M. Iqtait, "Multi-Class Mangrove Classification Using Transfer Learning with MobileNet-V3 on Multi-Organ Images," *Jurnal Teknik Informatika,* vol. 6, no. 3, pp. 1631–1642, 2025, doi: 10.52436/1.jutif.2025.6.3.4683.

[5] J. I. Komputer, T. Informasi, T. Jcositte, S. Winiarti, and I. Faisal, "Particle Swarm Optimization Algorithm for Hyperparameter Convolutional Neural Network and Transfer Learning VGG16 Model," *Journal of Computer Science, Information Technology and Telecommunication Engineering*, vol. 5, no. 1, pp. 474–480, 2024, doi: 10.30596/jcositte.v5i1.16680.

[6] G. Eka Okta Putra, K. Q. Fredlina, and I. N. Yudi Anggara Wijaya, "Implementasi Transfer Learning Menggunakan Convolutional Neural Network Dalam Klasifikasi Penyu," *Jurnal Mahasiswa Teknik Informatika*, vol. 8, no. 1, pp. 1077–1082, 2024, doi: 10.36040/jati.v8i1.8929.

[7] Abdul Jalil Rozaqi, A. Sunyoto, and M. R. Arief, "Implementation of Transfer Learning in the Convolutional Neural Network Algorithm for Identification of Potato Leaf Disease," *Procedia of Engineering and Life Science*, vol. 1, no. 1, Apr. 2021, doi: 10.21070/pels.v1i1.820.

[8] A. E. Wijaya, W. Swastika, and O. H. Kelana, "Implementasi Transfer Learning Pada Convolutional Neural Network Untuk Diagnosis Covid-19 Dan Pneumonia Pada Citra X-Ray," *Sainsbertek Jurnal Ilmiah Sains & Teknologi*, vol. 2, no. 1, pp. 10–15, Sep. 2021, doi:

Vol. 6, No. 5, October 2025, Page. 3251-3264
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.5.5266

10.33479/sb.v2i1.125.
[9] A. Muis, S. Sunardi, and A. Yudhana, "CNN-based Approach for Enhancing Brain Tumor Image Classification Accuracy," *International Journal of Engineering*, vol. 37, no. 5, pp. 984–996, 2024, doi: 10.5829/IJE.2024.37.05B.15.
[10] M. A. Hasan, Y. Riyanto, and D. Riana, "Grape leaf image disease classification using CNN-VGG16 model," *Jurnal Teknologi dan Sistem Komputer*, vol. 9, no. 4, pp. 218–223, Oct. 2021, doi: 10.14710/jtsiskom.2021.14013.
[11] F. Mashuri and U. Enri, "Implementasi Transfer Learning Dalam Mendeteksi Penyakit Pada Daun Gandum," *Jurnal NUANSA Informatika*, vol. 16, no. 1, pp. 66–77, Jan. 2022, doi: 10.25134/nuansa.v16i1.4702.
[12] Fauzan Muhammad, Aniati Murni Arimurthy, and Dina Chahyati, "Transfer learning pada Network VGG16 dan ResNet50," *Indonesia Journal of Computer Science*, vol. 12, no. 1, pp. 361–374, Feb. 2023, doi: 10.33022/ijcs.v12i1.3130.
[13] M. R. Maulidi, F. Indriani, A. Farmadi, I. Budiman, and D. Kartini, "Optimizing South Kalimantan Food Image Classification Through CNN Fine-Tuning," *Jurnal Ilmiah Tek. Elektro Komputer dan Informmatik*, vol. 10, no. 4, pp. 897–913, 2024, doi: 10.26555/jiteki.v10i4.30325.
[14] M. G. Somoal and A. R. Dzikrillah, "Komparasi MobileNETV2 dengan Kustomisasi Transfer Learning dan Hyperparameter untuk Identifikasi Tumor Otak," *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 12, no. 1, pp. 229–240, Feb. 2025, doi: 10.25126/jtiik.2025129582.
[15] M. Khoiruddin and S. Tena, "Fruit and Vegetable Classification using Convolutional Neural Network with MobileNetV2," *Journal of Applied and Research Computer Science and Information Systems*, vol. 2, no. 2, pp. 203–210, 2024, doi: 10.61098/jarcis.v2i2.197.
[16] R. K. Shukla and A. K. Tiwari, "Masked Face Recognition Using MobileNet V2 with Transfer Learning," *Computer Systems Science & Engineering*, vol. 45, no. 1, pp. 293–309, 2023, doi: 10.32604/csse.2023.027986.
[17] Buyut Khoirul Umri and V. Delica, "Penerapan transfer learning pada convolutional neural networks dalam deteksi covid-19.," *JNANALOKA*, pp. 9–17, Sep. 2021, doi: 10.36802/jnanaloka.2021.v2-no2-53-61.
[18] N. L. Chusna and A. Khumaidi, "Comparison of Convolutional Neural Network Models for Feasibility of Selling Orchids," *Ilkom Jurnal Ilmiah*, vol. 16, no. 3, pp. 296–304, Dec. 2024, doi: 10.33096/ilkom.v16i3.2006.296-304.
[19] V. K. Isuyama and B. D. C. Albertini, "Comparison of Convolutional Neural Network Models for Mobile Devices," in *Anais do XX Workshop em Desempenho de Sistemas Computacionais e de Comunicação (WPerformance 2021)*, Sociedade Brasileira de Computação - SBC, Jul. 2021, pp. 73–83. doi: 10.5753/wperformance.2021.15724.
[20] A. R. Muslikh, D. R. I. M. Setiadi, and A. A. Ojugo, "Rice Disease Recognition Using Transfer Learning Xception Convolutional Neural Network," *Jurnal Teknik Informatika*, vol. 4, no. 6, pp. 1535–1540, 2023, doi: 10.52436/1.jutif.2023.4.6.1529.
[21] E. I. Haksoro and A. Setiawan, "Pengenalan Jamur Yang Dapat Dikonsumsi Menggunakan Metode Transfer Learning Pada Convolutional Neural Network," *Jurnal ELTIKOM*, vol. 5, no. 2, pp. 81–91, 2021, doi: 10.31961/eltikom.v5i2.428.
[22] S. Saifullah *et al.*, "Nondestructive Chicken Egg Fertility Detection Using CNN-Transfer Learning Algorithms," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, vol. 9, no. 3, pp. 854–871, Sep. 2023, doi: 10.26555/jiteki.v9i3.26722.
[23] S. Aras, A. Setyanto, and Rismayani, "Deep Learning Untuk Klasifikasi Motif Batik Papua Menggunakan EfficientNet dan Trasnfer Learning," *Insect (Informatics Security Jurnal Teknik Informatika*, vol. 8, no. 1, pp. 11–20, 2022, doi: 10.33506/insect.v8i1.1865.
[24] Y. I. Sulistya, E. T. Br Bangun, and D. A. Tyas, "CNN Ensemble Learning Method for Transfer learning: A Review," *Ilkom Jurnal Ilmmiah*, vol. 15, no. 1, pp. 45–63, Apr. 2023, doi: 10.33096/ilkom.v15i1.1541.45-63.
[25] N. W. Kencana, R. Umar, and Murinto, "Implementasi Transfer Learning Untuk Klasifikasi Jenis Ras Ayam Menggunakan Arsitektur MobileNetV2," *Jurnal Informatika Polinema*, vol. 11, no. 2, pp. 147–154, Feb. 2025, doi: 10.33795/jip.v11i2.6469.
[26] R. Faturrahman, Y. S. Haryani, and S. Hadiyoso, "Klasifikasi Jajanan Tradisional Indonesia

Vol. 6, No. 5, October 2025, Page. 3251-3264
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.5.5266

berbasis Deep Learning dan Metode Transfer Learning," *ELKOMIKA Jurnal Teknik Energi Elektrik, Teknik Telekomunikasi, & Teknik Elektronika.*, vol. 11, no. 4, p. 945, 2023, doi: 10.26760/elkomika.v11i4.945.

[27] A. Peryanto, A. Yudhana, and R. Umar, "Convolutional Neural Network and Support Vector Machine in Classification of Flower Images," *Khazanah Informatika. Jurnal Ilmu Komputer dan Informatika*, vol. 8, no. 1, pp. 1–7, 2022, doi: 10.23917/khif.v8i1.15531.

[28] Herman, M. Akbar, H. Nasir, Herdianti, H. Azis, and L. N. Hayati, "Comparative Performance of ResNet Architectures for Toraja Carving Image Classification with Data Augmentation," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 9, no. 4, pp. 737–744, Aug. 2025, doi: 10.29207/resti.v9i4.6181.

[29] B. A. Sadewa and Y. Yamasari, "Implementasi Deep Transfer Learning untuk Klasifikasi Nominal Uang Kertas Rupiah," *Journal of Informatics and Computer Science*, vol. 5, no. 04, pp. 543–551, 2024, doi: 10.26740/jinacs.v5n04.p543-551.