JOIN (Jurnal Online Informatika)
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 11 Number 1 | June 2026: 1-13
DOI: 10.15575/join.v11i1.1654

Comparison of MobilenetV2 and NASNetMobile for Lavender Flower Analysis using Convolutional Neural Network

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Article Info

Article history:

Received May 20, 2025
Revised July 19, 2025
Accepted July 27, 2025
Published April 25, 2026

Keywords:

Comparison
CNN
Lavender Flower
MobileNetV2
NASNetMobile

ABSTRACT

The identification of lavender flower varieties is a critical challenge in botany and agriculture, primarily due to the high morphological similarity among different varieties and the influence of environmental conditions on their appearance. Traditional methods of identifying lavender varieties, which often rely on manual observation, face significant limitations. These methods are time-consuming, prone to subjective error, and may not account for subtle environmental variations that affect flower morphology. The specific goal of this research is to develop an automated classification model using Deep Learning techniques, specifically Convolutional Neural Networks (CNN), to improve the accuracy and efficiency of lavender variety identification. The study leverages a dataset from Kaggle, which contains images of three lavender varieties—Lavandula angustifolia, Lavandula viridis, and Lavandula multifida. By applying data augmentation techniques to address dataset variability, the research compares two advanced CNN architectures, MobileNetV2 and NASNetMobile, for their classification performance. The key contribution of this work is demonstrating that NASNetMobile achieves superior performance, with 91.87% accuracy and a lower loss value, compared to MobileNetV2, which reaches 81.67% accuracy. This study highlights the novelty of using CNN models for lavender classification, offering a significant advancement over traditional methods by enhancing the identification process's accuracy and reducing reliance on manual and inefficient approaches. The findings have broad implications for botanical research, agricultural practices, and plant conservation efforts, showing that CNNs can significantly improve the efficiency of plant species identification.

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1. INTRODUCTION

The application of artificial intelligence (AI) in the fields of agriculture and plantations has become increasingly widespread, particularly in tasks such as plant species classification[1], [2], [3]. Advances in deep learning techniques, especially the Convolutional Neural Network (CNN), have significantly enhanced the potential to improve the efficiency and accuracy of plant classification through visual image analysis[4]. One notable application of this technology is in the identification and classification of flowers, such as lavender, which hold substantial economic value in both the agricultural sector and the perfume industry.

Lavender is a type of plant with high economic value, widely used in the perfume, pharmaceutical, and cosmetic industries. In many countries, lavender has also been extensively utilized as a complementary therapy to help manage conditions associated with pain and inflammation[5]. Lavender is one of the most widely used essential oils in aromatherapy[6]. The diversity of lavender varieties plays a crucial role in determining the quality and therapeutic benefits of the plant. However, many varieties, such as Lavandula angustifolia, Lavandula viridis, and Lavandula multifida,exhibit highly similar morphological characteristics, making them difficult to distinguish visually. In fact, the flowers and leaves of many lavender species are nearly identical in appearance, which often renders classification based solely on physical traits insufficient, both in commercial cultivation and scientific research contexts[7].

Traditional plant identification methods, which rely heavily on manual inspection and expert knowledge, are often time consuming, labor intensive, and prone to human error particularly when dealing with subtle variations among species or cultivars[8]. These limitations highlight the urgent need for more reliable and automated systems for plant classification[9]. In the fields of agricultural monitoring and disease detection, the application of computer vision and machine learning techniques has gained significant momentum[10].

However, a gap exists between traditional methods and the datasets used for modern lavender classification. Traditional methods struggle with the variability in lavender morphology due to environmental factors and subtle genetic differences, which cannot be easily captured by manual inspection. In contrast, the datasets used in deep learning-based approaches often consist of high-resolution images collected under controlled conditions, which may not fully represent the variability encountered in real-world agricultural environments. These datasets typically feature images in standard formats (e.g., JPG, PNG) with consistent lighting, background, and image size, which do not reflect the complexity of natural environments where lavender grows. This discrepancy highlights the need for datasets that can better mimic real-world conditions, allowing machine learning models to generalize across diverse environmental conditions and lavender varieties.

With the advancement of Artificial Intelligence (AI), particularly in the field of image processing, the application of Convolutional Neural Network (CNN) has shown promising results for visual object classification tasks [11], [12], [13]. CNN, a class of deep learning models known for their outstanding performance in image recognition and classification tasks[14], [15], have emerged as powerful tools for automating plant identification and disease diagnosis[16], [17]. Their ability to automatically learn complex features from raw image data without the need for manual feature extraction makes them especially well suited to address the complexities associated with plant phenotyping. Previous studies on plant and flower classification have revealed a wide range of methodologies, with a growing emphasis on deep learning techniques to overcome the limitations of traditional feature extraction methods[18]. The implementation of deep learning particularly CNN has revolutionized image processing and computer vision, proving highly effective in object classification by eliminating the need for manual feature engineering[19].

The classification of lavender plants in remote sensing is crucial for accurate plant identification in precision agriculture. Previous studies have traditionally used satellite or aircraft imagery, but UAVs offer a faster, cost-effective alternative with high-resolution images. Challenges exist in distinguishing mature and young lavender due to their similar morphology. Research developed a deep learning-based method using a hybrid approach with DSC and SENet, improving accuracy without increasing computational complexity. These findings could be applied in precision agriculture and automated crop monitoring[20].

Building on these developments, this study aims to compare the performance of two lightweight CNN architectures MobileNetV2[21] and NASNetMobile[2], in the classification of lavender flower images. The primary objective is to evaluate and benchmark both models in terms of accuracy, precision, recall, and computational efficiency when applied to the task of lavender flower classification. MobileNetV2 and NASNetMobile were chosen due to their lightweight architecture, which makes them well-suited for environments with limited computational resources, such as mobile and edge computing platforms. Compared to heavier models like ResNet and Inception, these architectures offer significant advantages in terms of computational efficiency without compromising classification accuracy, especially for real-time applications. The MobileNetV2 model is known for its depthwise separable convolutions, which reduce computational load while maintaining performance, while NASNetMobile is optimized through neural architecture search, making it highly efficient for mobile applications.

The expected benefit of this study is to support the development of automated, accurate, and lightweight systems for plant species recognition, which can be utilized in commercial agriculture, aromatherapy product quality control, and scientific research where morphological similarities among plant varieties present significant challenges. The main contribution of this research is the demonstration that lightweight CNN architectures, specifically MobileNetV2 and NASNetMobile, can effectively handle the complexities of lavender flower classification, offering significant improvements in both accuracy and computational efficiency compared to traditional methods. This study also provides a comparative analysis of these models in the context of real-world applications, helping to guide future advancements in automated plant identification systems, particularly in environments with limited computational resources.

2. METHOD

This study adopts a quantitative experimental approach to develop and evaluate a CNN-based classification model for lavender flower varieties. The use of a quantitative experimental approach is essential as it allows for the systematic evaluation of model performance through measurable metrics such as accuracy, precision, and recall. By quantifying the effectiveness of the CNN-based model, we can objectively compare different architectures and optimize the system for better classification results. The CNN model is designed to recognize and distinguish between different lavender varieties using collected digital images. The experimental design of this study is illustrated in Figure 1. Figure 1 illustrates the flowchart of the image classification process using deep learning**.** The process begins with the "Start" stage, followed by inputting a dataset consisting of a collection of images. The dataset then undergoes preprocessing to prepare the images in a suitable format for training. After that, image augmentation is performed to increase data variability and prevent overfitting. The processed dataset is subsequently labeled and split into three main parts: training data, validation data, and testing data.

Next, the user can choose between creating a custom convolutional neural network (CNN) architecture using layers such as Conv2D, MaxPool2D, Dropout, Flatten, Dense, and Softmax or importing a pre-existing deep learning architecture such as MobileNetV2 or NASNetMobile. Once the model is built and trained with the data, it will generate prediction results for the given images. The process concludes at the "Finish" stage once the prediction results are obtained. This diagram represents the general workflow of an image classification project based on deep learning.

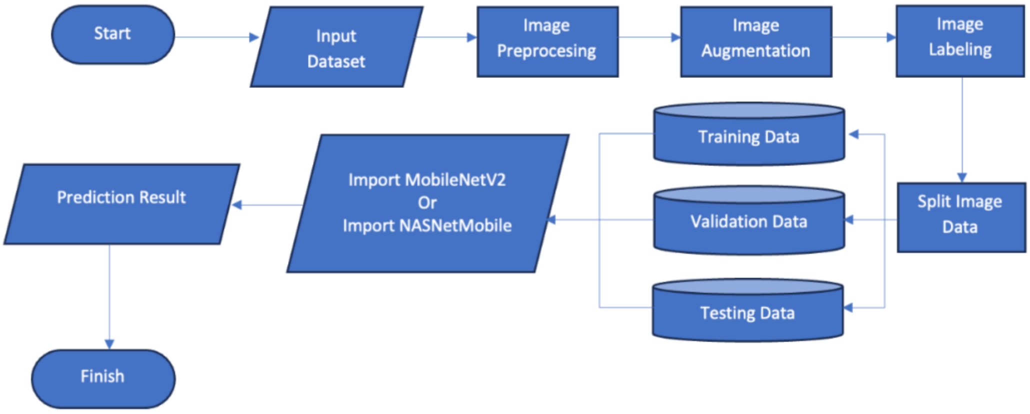


Figure 1. Experiment Design

2.1. *Start and Input Dataset*

The process begins with initializing the workflow for image classification. The dataset used in this study was obtained from Kaggle, focusing on three varieties of lavender: Lavandula Angustifolia, Lavandula Viridis, and Lavandula Multifida. The dataset consists of 2,400 images evenly divided into three classes, namely Lavandula angustifolia (637 images), Lavandula viridis (644 images), and Lavandula multifida (639 images). The data is split in an 80:20 ratio, with 1,920 images used for training and 480 images for validation. The images are of high quality with sufficient resolution, allowing for optimal capture of the flowers' visual details. The dataset is organized in a directory structure based on variety classes, facilitating automatic labeling in subsequent stages. Efforts were made to ensure that each class contains a balanced number of images to prevent bias in the model. This systematic dataset preparation is expected to enhance the model's performance and accuracy in automatically identifying different lavender flower varieties.

Figure 2. Dataset Sample Lavandula Angustifolia (a, b), Lavandula Multifida (c, d), Lavandula Viridis (e, f)

Figure 2 shows sample images from the dataset, consisting of Lavandula Angustifolia (a, b), Lavandula Multifida (c, d), and Lavandula Viridis (e, f), with each class containing 800 images. All images are stored in common formats such as JPG or PNG and will undergo further processing during the image preprocessing stage to adjust their size and standardize the input format for the model. The total number of images in the dataset is 2,400. These images were captured from various angles and under different lighting conditions to ensure data diversity, which can help improve the model's generalization when applied to real-world data.

Table 1 shows information about the lavender flower dataset used in this study. The table consists of three lavender varieties: Lavandula Angustifolia, Lavandula Multifida, and Lavandula Viridis. Each variety contains 800 images with dimensions of 224x224 pixels, which is a standard input size for many modern convolutional neural network (CNN) architectures. The balanced number of images across all classes is intended to ensure an even data distribution, allowing the model to learn fairly without being biased toward any specific class. The information in this table provides a concise yet clear overview of the dataset composition used during the training and testing phases of the classification model.

Table 1. Lavender Datasets Information

No	Lavender Type	Dimensions	Quantity
1	Lavandula Angustifolia	224x224	800
2	Lavandula Multifida	224x224	800
3	Lavandula Viridis	224x224	800

2.2. *Image Preprocesing*

In the preprocessing stage, image quality enhancement was performed to remove noise and irrelevant components. This process included resizing the images to 224x224 pixels, using a batch size of 16, and splitting the dataset into training and validation sets with an 80:20 ratio. To maintain consistency and facilitate reproducibility of the results, all experiments were conducted using a fixed random seed. In addition to resizing and splitting, normalization techniques were applied to scale pixel values to a range of 0 to 1, which helps accelerate model convergence during training. Furthermore, image data generators were utilized to streamline the preprocessing pipeline by automatically applying these transformations in real time during model training. These preprocessing steps are crucial for ensuring the input data is standardized, which contributes significantly to the stability and performance of the deep learning model.

2.3. Image Augmentation

The image augmentation stage aims to expand and enrich the variety of image data used in training the Convolutional Neural Network (CNN) model, making the model more robust and capable of better generalization. This process begins with normalization using Rescaling(1./255), which converts pixel values from the range of 0–255 to 0–1 to ensure learning stability. Subsequently, various augmentation techniques are applied through random transformations, including random flipping to simulate objects oriented to the left or right, random rotation up to 10% to account for viewpoint variations, random zoom to simulate changes in object scale, and random translation both horizontally and vertically to introduce positional shifts of the object within the image.

2.4. Image Labelling

The image labeling stage involves assigning labels or identifiers to each image in the dataset according to the class or category it represents. These labels serve as references for the model during training to learn the relationship between the image and its corresponding class. In the context of plant classification, such as lavender flowers, each image is labeled based on its respective variety folder, for example, the Lavandula Angustifolia folder, Lavandula Viridis folder, and Lavandula Multifida folder. To address any imbalance in label distribution, automatic class weight computation is applied using the compute_class_weight function. Model evaluation is performed using several metrics, including accuracy, loss, confusion matrix, and a classification report that includes precision, recall, and F1-score for each class.

Labeling not only plays a vital role in supervised learning but also significantly impacts model performance. Accurate and consistent labels ensure that the model learns the correct patterns associated with each class. Any mislabeling or inconsistency during this stage can lead to poor model predictions and reduced reliability. Therefore, careful organization of the dataset and validation of labels are crucial to ensure a successful classification outcome.

2.5. Split Image Data

In the Image Data Split stage, the image dataset is divided into several parts used for different purposes in model training, namely into training data and validation (or testing) data. The training data is used to train the model to recognize patterns in the images, while the validation data serves to evaluate the model's performance on data that it has not been directly trained on, thereby measuring the model's generalization ability. This division is typically done using a standard proportion of 80% for training and 20% for validation. By performing a random and consistent data split, the training process becomes more reliable and reproducible. This strategy is important to prevent overfitting and to ensure that the model does not simply "memorize" the data but truly learns from relevant features.

This approach also facilitates the tuning of hyperparameters and model selection by providing a separate dataset that reflects unseen data. Without proper data splitting, it would be difficult to assess whether improvements in model accuracy are due to actual learning or merely overfitting to the training set. Additionally, sometimes a third dataset, called the test set, is used to provide a final unbiased evaluation after model training and validation are complete. Overall, careful management of data splitting is a fundamental step toward building robust and effective machine learning models.

In this study, evaluation was conducted using the validation dataset, which was previously separated as 20% of the total data. The evaluation methods included calculating accuracy, loss, confusion matrix, and a classification report covering precision, recall, and F1-score metrics for each class. The use of the confusion matrix helps visualize classification errors between classes, while the classification report provides detailed information on the model’s performance in recognizing each class. In addition to numerical evaluation metrics, visualizations of the evaluation results, such as accuracy and loss graphs, are also used to monitor the model training process from start to finish. This aims to ensure that the model does not experience overfitting or underfitting.

At this stage, the performance of two architectures, MobileNetV2 and NASNetMobile, is compared based on validation accuracy results and the prediction distribution in the confusion matrix. This evaluation provides insight into how well the models can generalize to new data and helps determine which model is most optimal for the image classification task.

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

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

$$F1 = 2\,x\,\frac{PR\ x\ Recall}{PR + Recall} \tag*{3}$$

The accuracy calculation in equation (1) is the ratio of correct predictions, which is the sum of True Positives (TP) and True Negatives (TN), to the total number of predictions made, including True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Meanwhile, recall in equation (2) evaluates the model's ability to detect all actual positive cases by comparing True Positives (TP) to the total actual positive cases (TP + FN). The F1 Score in equation (3) is a combined metric that balances precision and recall, calculated by multiplying 2 by the product of precision and recall, then dividing by their sum.

2.6. MobileNetV2 and NASNetMobile

The next step involves configuring the models and running the architectures of MobileNetV2 and NASNetMobile, after the image data splitting stage. These two models are widely used convolutional neural networks designed for efficient performance on mobile and embedded devices. MobileNetV2 is known for its lightweight design and use of inverted residuals, which help maintain accuracy while reducing computational cost. NASNetMobile, on the other hand, is a neural architecture search-based model optimized to balance accuracy and efficiency. Implementing both architectures allows for a comparative evaluation of their effectiveness on the given image dataset.. These two models are widely used convolutional neural networks designed for efficient performance on mobile and embedded devices. MobileNetV2 is known for its lightweight design and use of inverted residuals, which help maintain accuracy while reducing computational cost. NASNetMobile, on the other hand, is a neural architecture search-based model optimized to balance accuracy and efficiency. Implementing both architectures allows for a comparative evaluation of their effectiveness on the given image dataset.

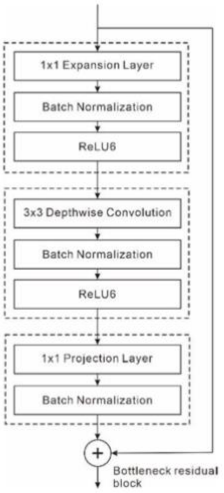


Figure 3. MobileNetV2 Convolution Block [14]

The MobileNet V2 model, in Figure 4, replaces conventional convolutions with depthwise separable convolutions to reduce computational complexity and model size. Unlike MobileNet V1, MobileNet V2 uses convolutional blocks equipped with residual connections, as in Figure 3. In the initial stage, a 1×1 convolution is applied to expand the number of channels in the data, producing an output with more channels than the input. Then, an efficient depthwise convolution is performed to extract features and apply a non-linear activation using ReLU6. Next, a 1×1 convolution serves to reduce the data dimensionality into a lower-dimensional tensor through a bottleneck mechanism, which is the opposite approach compared to MobileNet V1. Enhancements in the MobileNet V2 architecture also include the use of standard 1×1 convolutions, a global average pooling layer, and a final classification layer.

This innovative architecture enables MobileNet V2 to achieve a strong balance between accuracy and efficiency, making it particularly suitable for deployment on devices with limited computational resources, such as smartphones and embedded systems. The residual connections help preserve information flow and improve gradient propagation during training, which enhances the model's ability to learn complex features without a significant increase in computational cost. As a result, MobileNet V2 has become a popular choice for various computer vision tasks where both speed and accuracy are critical.

Next is the NASNetMobile model, which is a neural network architecture developed by Google in 2017 using a reinforcement learning approach through the Neural Architecture Search (NAS) framework. Figure 5 illustrates the workflow of the NASNetMobile architecture, consisting of two main stages: Encoder and Decoder. The Encoder stage involves convolution and reduction cells, while the Decoder performs upsampling and 1×1 convolution operations. After passing through these two stages, the data is processed through a flatten layer and a dense layer to produce the final output, which is the accuracy value of the NASNetMobile architecture [2].

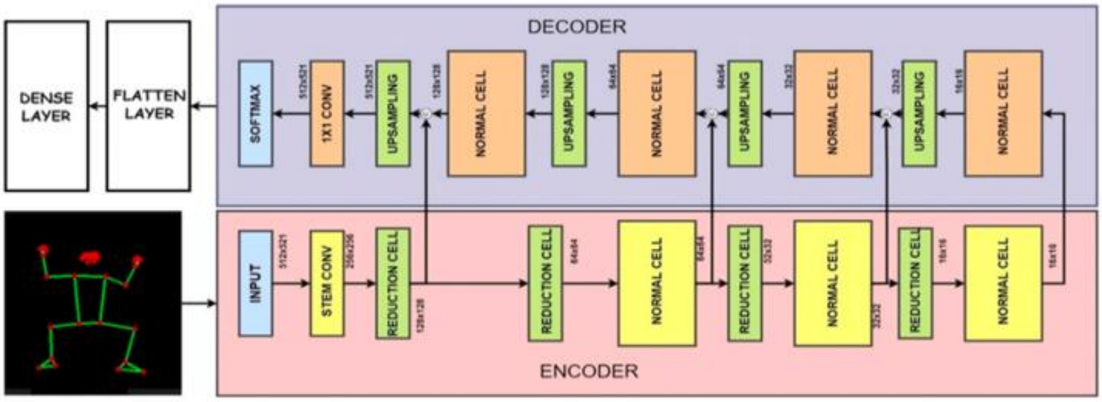


Figure 4. MobileNetV2 Convolution

NASNetMobile has fewer parameters compared to NASNet Large. This architecture was discovered through an optimal design search within a search space known as the NASNet search space and was then applied to larger datasets. NASNetMobile consists of two types of convolutional cells: Normal Cells, which maintain the feature map size, and Reduction Cells, which reduce the height and width of the feature map by half [22]. This architecture allows NASNetMobile to achieve high accuracy while maintaining computational efficiency, making it suitable for mobile and embedded applications. By automating the design process with reinforcement learning, NASNet is able to explore a vast space of possible architectures and identify configurations that outperform manually designed models. The use of Normal and Reduction Cells provides flexibility in controlling feature map sizes throughout the network, enabling effective feature extraction and dimensionality reduction. Consequently, NASNetMobile is widely adopted in image recognition tasks where a balance between performance and resource usage is critical.

2.7. Prediction Result

The Prediction Result stage occurs after the model has been trained on the dataset and is ready to make predictions on new, unseen data. During this phase, the trained model processes the input images and generates predicted outputs, typically in the form of class labels or probabilities. The model assigns a probability to each class (e.g., different lavender varieties) based on the features it has learned from the training data. The class with the highest probability is selected as the predicted label. These predictions are then compared to the ground truth (actual labels) in the test dataset to evaluate the model's performance, using metrics such as accuracy, precision, and recall. The Prediction Result stage marks the final step where the model's ability to correctly classify new images is assessed.

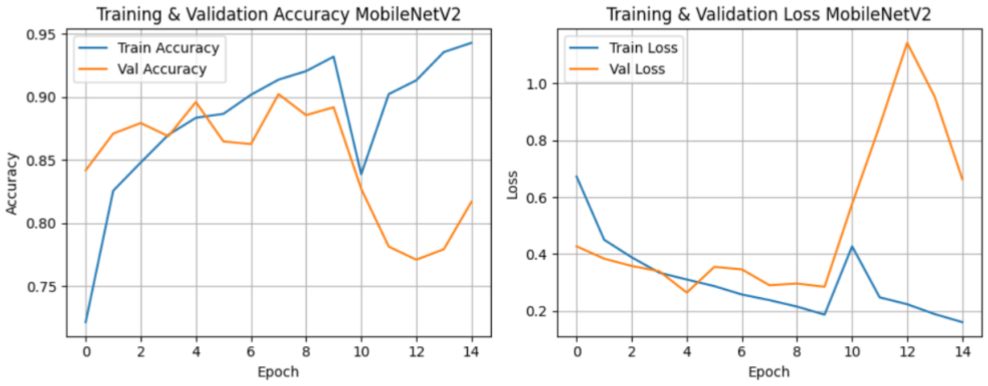
3. RESULT AND DISCUSSION

After completing the model training and testing stages and obtaining the results from each scenario, the next step is to visualize the data and perform an analysis to evaluate which architecture delivers the best performance in classifying the data.

3.1. Analysis of MobileNetV2 Results

The training results using the MobileNetV2 architecture are presented through training and validation accuracy graphs, training and validation loss graphs, and a confusion matrix. Figure 5 shows the Training & Validation Accuracy and Training & Validation Loss graphs for the MobileNetV2 model, from which it can be concluded that the model demonstrates good learning capability. The training accuracy consistently improves throughout the training process, reaching a value close to 0.95 by the 14th epoch, indicating that the model effectively learns patterns from the training data. The training of the MobileNetV2 model utilized several key hyperparameters to optimize its performance. The Adam optimizer was employed with an initial learning rate of 0.001, chosen to strike a balance between training speed and model accuracy. This learning rate was crucial in ensuring that the model could converge effectively while minimizing errors. The model was trained for 14 epochs, which was determined to be an appropriate number of iterations to achieve optimal performance without overfitting the data. Additionally, a batch size of 32 was used to ensure efficient learning while preventing excessive memory usage, allowing for smooth and effective model training. These hyperparameters contributed to the model's overall performance and efficiency in the classification task.

The validation accuracy also shows a positive trend during the initial epochs, reflecting the model's ability to generalize to new data. Although fluctuations in validation accuracy and loss occur in the later epochs, this suggests opportunities for further improvement through parameter optimization and additional regularization techniques. Overall, these results indicate that the MobileNetV2 architecture holds strong potential for high-accuracy classification tasks with efficient training time.



(a) (b)

Figure 5. Training Validation Accuracy(a) and Loss (b) MobileNetV2

Based on the model evaluation results, a final accuracy of 81.67% was obtained with a loss value of 0.6631. This accuracy indicates that the model has a good ability to classify the data overall. Meanwhile, the relatively low loss value suggests that the model's prediction errors during evaluation are within an acceptable range. Meanwhile, Figure 6 illustrates the confusion matrix results for the MobileNetV2 model, showing good performance in classifying three types of lavender plants: lavandula angustifolia, lavandula multifida, and lavandula viridis. The model classifies lavandula angustifolia very accurately, with 157 correct predictions out of the total test data. Similarly, for lavandula multifida, the model produces 136 correct predictions, with relatively few errors. For lavandula viridis, although there are some misclassifications, the model still correctly recognizes 104 images.

Overall, these results reflect a positive performance from the MobileNetV2 model, which is able to correctly identify the majority of images for all three plant classes, demonstrating that the model is effective and has potential for application in image-based plant species classification. These results highlight the model's robustness in handling variations within each class, such as differences in lighting, angle, and background conditions in the images. However, the presence of some misclassifications suggests there is still room for improvement, possibly through techniques such as data augmentation, fine-tuning hyperparameters, or incorporating additional training data. Future work could also explore combining MobileNetV2 with other architectures or leveraging ensemble methods to further enhance classification accuracy and reliability.

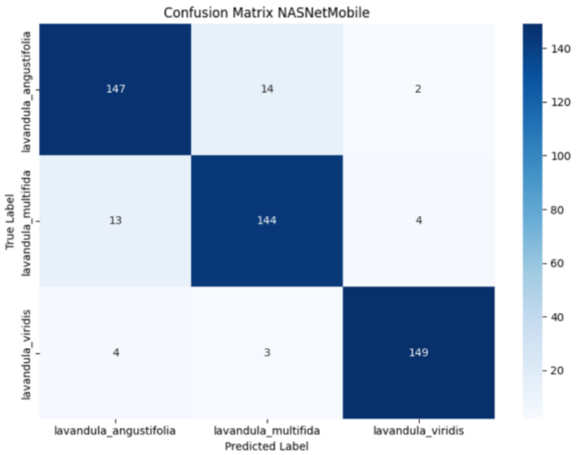
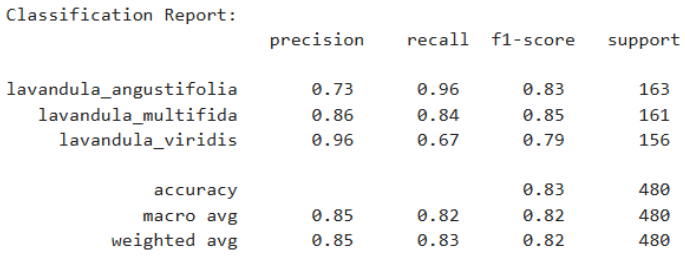


Figure 6. Confusion Matrix Result of MobileNetV2 Model

Based on the classification report shown in Figure 7, the MobileNetV2 model demonstrates fairly good performance in classifying three types of lavender plants. The model achieved an overall accuracy of 83%, which is a strong indication that the majority of its predictions are correct. The highest precision value of 0.96 was observed in the lavandula_viridis class, indicating that predictions for this class are rarely incorrect. Meanwhile, Lavandula angustifolia has the highest recall at 0.96, meaning that almost all data from this class were correctly recognized by the model. The average macro and weighted average values for precision, recall, and F1-score are all above 0.82, indicating consistent and balanced performance across all classes. Overall, these results show that MobileNetV2 is quite reliable and accurate for the task of lavender plant image classification.



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Classification Report:
                        precision    recall  f1-score   support

lavandula_angustifolia       0.73      0.96      0.83       163
   lavandula_multifida       0.86      0.84      0.85       161
     lavandula_viridis       0.96      0.67      0.79       156

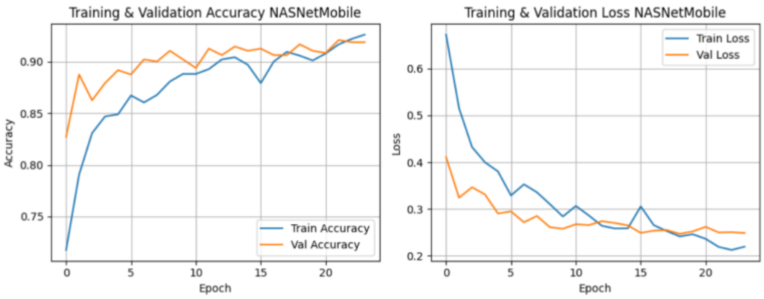
              accuracy                           0.83       480
             macro avg       0.85      0.82      0.82       480
          weighted avg       0.85      0.83      0.82       480
```

Figure 7. Classification Report Results MobileNetV2 Model

3.2. Analysis of NASNetMobile Results

The NASNetMobile model demonstrates competitive performance in the image classification task, particularly in distinguishing various types of lavender flowers. During the training process, the model was able to achieve a stable accuracy level with consistently decreasing loss values, indicating that the learning process proceeded well without significant signs of overfitting. The final evaluation results show that NASNetMobile is capable of capturing important features from each class quite accurately, as reflected by the relatively high validation accuracy. This suggests that the lightweight yet efficient architecture of NASNetMobile is well-suited for deployment on devices with limited resources without significantly sacrificing classification performance.

Figure 8 show the NASNetMobile model demonstrates excellent performance in the task of lavender image classification, achieving a validation accuracy of 91.87% and a low loss value of 24.88%. These results reflect the model's ability to accurately recognize patterns and visual features while maintaining a low prediction error rate. The high accuracy indicates that most of the validation data were correctly classified, while the low loss value suggests that the model's predictions are close to the true values. This performance signifies that NASNetMobile is an efficient and reliable architecture, making it well-suited for deployment in image-based classification systems such as plant species identification or other visual object recognition tasks.



(a) (b)

Figure 8. Training Validation Accuracy(a) and Loss (b) NASNetMobile

The confusion matrix results shown in Figure 9 for the NASNetMobile model demonstrate excellent and consistent classification performance in distinguishing the three types of lavender plants: lavandula_angustifolia, lavandula_multifida, and lavandula_viridis. The model correctly classified the majority of images, with accurate predictions numbering 147 for lavandula_angustifolia, 144 for lavandula_multifida, and 149 for lavandula_viridis. The number of misclassifications is very low for each class, indicating that the model has a low error rate and is capable of distinguishing the visual characteristics between plant types with high accuracy. The high number of correct predictions and minimal misclassifications reflect that NASNetMobile is a highly reliable and effective model for image classification tasks, particularly in botanical domains or image-based plant identification.

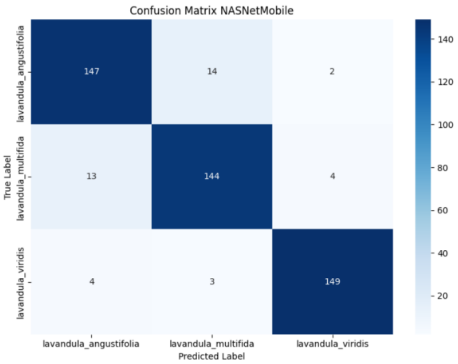
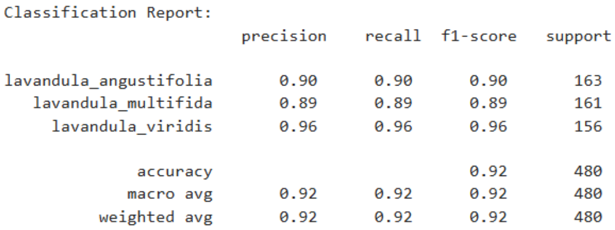


Figure 9. Confusion Matrix Result of NASNetMobile Model

Figure 10 shows the classification report for the NASNetMobile model, showing excellent classification performance across the three classes: lavandula angustifolia, lavandula multifida, and lavandula_viridis. All three classes have high and balanced precision, recall, and F1-score values, each ranging between 0.89 and 0.96. The highest precision and recall values of 0.96 were achieved by the lavandula_viridis class, indicating that the model is highly accurate and consistent in identifying this type.



```
Classification Report:
                        precision    recall  f1-score   support

lavandula_angustifolia       0.90      0.90      0.90       163
   lavandula_multifida       0.89      0.89      0.89       161
     lavandula_viridis       0.96      0.96      0.96       156

              accuracy                           0.92       480
             macro avg       0.92      0.92      0.92       480
          weighted avg       0.92      0.92      0.92       480
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Figure 10. Classification Report Results NASNetMobile Model

Based on the evaluation results, NASNetMobile outperforms MobileNetV2 in several key metrics. NASNetMobile achieves a higher overall accuracy of 91.87% compared to MobileNetV2's 81.67%, along with a significantly lower loss value, indicating more precise and reliable predictions. Both models demonstrate high precision, recall, and F1-score across all classes, but NASNetMobile maintains more balanced and consistently higher scores, with macro and weighted averages around 0.92 versus approximately 0.82 for MobileNetV2.

The superior performance of NASNetMobile can be attributed to its Neural Architecture Search (NAS) optimization, which allows the model to automatically design and select the most efficient architecture. Specifically, the use of Normal Cells and Reduction Cells in NASNetMobile provides a distinct advantage over MobileNetV2's use of inverted residuals. Normal Cells allow for better feature extraction by preserving spatial relationships in the data, while Reduction Cells downsample feature maps more effectively, enabling the network to capture more important features without losing critical information. These design choices improve the model's capacity to learn from complex data and contribute to its superior classification accuracy.

In terms of classification strength, MobileNetV2 performs best on Lavandula angustifolia with a recall of 0.96, while NASNetMobile excels in identifying Lavandula viridis, achieving both precision and recall at 0.96. Training stability is also notable for both models; MobileNetV2 shows steady accuracy improvements with minor fluctuations toward the end, whereas NASNetMobile maintains stable accuracy and steadily decreasing loss throughout training, as shown in Table 2.

Table 2. Results comparison between MobileNetV2 and NASNetMobile models

No	Metric	MobileNetV2	NASNetMobile
1	Accuracy (%)	81.67	91.87
2	Loss	0.6631	0.2488
3	Precision (range)	0.82 – 0.96	0.89 – 0.96
4	Recall (range)	0.82 – 0.96	0.89 – 0.96
5	F1-Score (range)	0.82 – 0.96	0.89 – 0.96
6	Macro Average (Precision, Recall, F1)	~0.82	0.92
7	Weighted Average (Precision, Recall, F1)	~0.82	0.92

Overall, while both models are efficient and suitable for deployment on resource-limited devices, NASNetMobile demonstrates superior performance and reliability, making it the preferred choice for precise and consistent lavender plant classification.

3.3. Discussion

This study compares the performance of MobileNetV2 and NASNetMobile in classifying lavender flower varieties. The results demonstrate that NASNetMobile outperforms MobileNetV2, achieving higher accuracy (91.87%) and lower loss (0.2488) compared to MobileNetV2 (81.67% accuracy and 0.6631 loss). NASNetMobile showed steady improvement throughout the training process, without the fluctuations observed in MobileNetV2, indicating better generalization to unseen data. The use of Neural Architecture Search (NAS) likely contributed to NASNetMobile's superior performance by optimizing the network's structure for this task.

Despite MobileNetV2's strong performance with a final accuracy of 81.67%, the model experienced some overfitting, as indicated by fluctuations in validation accuracy and loss. This suggests that while MobileNetV2 can perform well with sufficient training, NASNetMobile is more effective for consistent and reliable plant classification tasks. NASNetMobile demonstrated a higher precision and recall across all lavender varieties, making it the more reliable choice, especially for applications in real-time systems like mobile devices or drones.

The findings highlight the potential of lightweight CNN architectures for efficient plant species classification, particularly in resource-limited environments. While both models show promise, future work should focus on expanding the dataset, incorporating transfer learning, and exploring ensemble methods to further improve model performance. Expanding the dataset to include more lavender species and environmental variations could help enhance the models' ability to generalize and increase their applicability in real-world scenarios.

4. CONCLUSION

This study addresses the challenge of identifying lavender flower varieties, which is a significant issue in botany and agriculture due to the morphological similarities among varieties and the influence of environmental factors on their appearance. The research focuses on developing an automatic classification model using Convolutional Neural Networks (CNN), specifically MobileNetV2 and NASNetMobile architectures, to enhance classification accuracy and efficiency. The problem is critical, as traditional identification methods often rely on manual inspection, which is prone to errors and inefficiency.

The results of the study show that NASNetMobile outperformed MobileNetV2, achieving an accuracy of 91.87% with a lower loss value, compared to MobileNetV2's 81.67% accuracy and 0.6631 loss. These findings demonstrate the unique contribution of using lightweight CNN architectures to address the challenge of lavender flower classification, showcasing the potential of deep learning models in overcoming the limitations of traditional, manual methods. This research highlights how Deep Learning technology, particularly CNNs, can improve both the accuracy identifying lavender varieties, which could be a significant advancement in agricultural and botanical practices.

Future research should focus on refining the model by exploring advanced data augmentation techniques, hyperparameter fine-tuning, and incorporating transfer learning from larger, pre-trained models to improve accuracy and generalization. Additionally, applying these models to classify other plant species in broader contexts and integrating multi-source data could further enhance the robustness of the models. Such steps could extend the applicability of these models beyond lavender classification, helping researchers and farmers to classify a wide range of plant species more accurately and efficiently in real-world agricultural scenarios.

ACKNOWLEDGEMENTS

This research was supported/partially supported by LPPM Universitas Kuningan. We would like to thank our colleagues at Universitas Kuningan for their valuable insights and expertise, which greatly contributed to this study. We acknowledge that they may not necessarily agree with all of the interpretations or conclusions presented in this paper.

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