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Research Article

Classification Of Bougainvillea Flower Varieties Using Variant Of CNN: Resnet50

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Abstract:

Bougainvillea is a tropical ornamental plant renowned for its vibrant colors and variety of cultivars, yet classifying its species remains challenging due to morphological similarities. This study aims to develop an automated classification system using the ResNet50 deep learning architecture to identify Bougainvillea flower varieties based on visual imagery. The dataset consists of 700 images from seven distinct classes, captured under natural lighting using a smartphone camera. The research process includes image preprocessing (resizing to 224x224 pixels), geometric data augmentation to increase dataset diversity, and evaluation using K-Fold Cross Validation to ensure robust model assessment. The model was trained using transfer learning, and its performance was compared between augmented and non-augmented datasets through evaluation metrics such as accuracy, precision, recall, and F1-score. The results show that augmentation significantly improved the model's performance, achieving an average accuracy of 99.67% on augmented data compared to 93.39% on non-augmented data. The augmented model also exhibited greater consistency across all folds, with several achieving perfect scores. These findings highlight that combining ResNet50 with transfer learning and image augmentation produces a highly accurate and reliable Bougainvillea classification system. This research contributes to the field of AI-based plant phenotyping and lays the groundwork for future applications in horticulture, biodiversity conservation, and education. Further development is recommended to explore larger and more diverse datasets, investigate advanced architectures such as EfficientNet or Vision Transformers, and build real-time mobile-based classification tools for practical field usage.

Keywords: Bougainvillea Classification; ResNet50; image augmentation; deep learning; transfer learning; K-Fold Cross Validation.

1. Introduction

Bougainvillea spp. is a popular tropical ornamental plant cultivated in many countries for its vibrant aesthetics, striking color variations, and high adaptability to diverse environmental conditions. The visual appeal and diversity of Bougainvillea varieties have made it a valuable commodity in the horticultural and landscape architecture industries. However, classifying and identifying Bougainvillea varieties poses a challenge due to morphological similarities among species and hybrids. In this context, automated recognition based on visual imagery emerges as a promising approach to streamline the plant classification process efficiently and accurately. Advances in image processing and artificial intelligence, particularly in the field of computer vision, have enabled the automation of ornamental plant classification using visual features from images [1], [2], [3], [4], [5].

Manual classification of plants like Bougainvillea requires botanical expertise and meticulous attention to detail, which are not always accessible to the general public or applicable at an industrial scale. This challenge can hinder identification processes, especially when handling large-scale data, such as in digital plant catalogs or ornamental plant trading platforms. The use of image recognition technology powered by deep learning has proven effective in recognizing complex objects in various domains [6], [7], [8].

This study aims to implement the ResNet50 model to perform automated classification of Bougainvillea flower images. ResNet50 was selected due to its ability to overcome accuracy degradation in deep CNN architectures through residual learning, and its strong performance in various image classification tasks [9], [10], [11]. This study seeks to answer the following key research question: How effective is the ResNet50 model in classifying Bougainvillea varieties based on visual imagery? [12], [13], [14].

This research focuses on the classification of Bougainvillea using images under natural lighting conditions, based on a limited dataset collected through field documentation. The main emphasis is on applying and evaluating the ResNet50 model using transfer learning. This study does not explore classification based on genetic or non-visual features, and classification accuracy may be influenced by image quality or class diversity in the dataset [15], [16].

This study provides empirical contributions to the classification of tropical ornamental plants using deep learning, particularly through the application of the ResNet50 architecture for Bougainvillea flowers—an area that remains underexplored. The developed model is expected to serve as an initial prototype for AI-based plant classification applications, supporting the digitization of flora identification systems in education, agribusiness, and biodiversity conservation. The dataset consists of 700 images across 7 classes: Bougainvillea Gold Rush, Bougainvillea Bambino Baby Allison, Bougainvillea Baby Victoria, Bougainvillea Afterglow, Bougainvillea Baby Laurent, Bougainvillea Ice Coconut, and Bougainvillea Bambino Majik, with 100 images per class. Additionally, classification experiments will be conducted to compare the performance of the ResNet model with and without image augmentation.

2. Method:

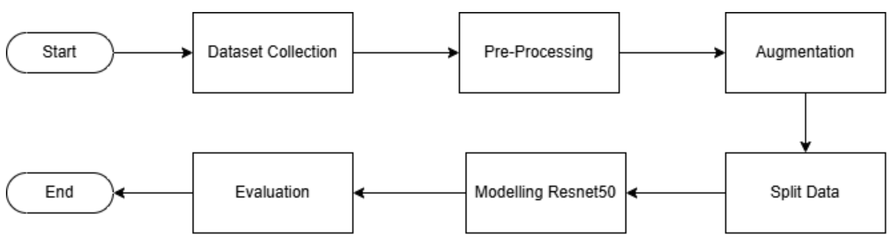

Figure 1. Research Flow

Figure 1 illustrates the research flow for classifying Bougainvillea flowers using the ResNet50 model. The process begins with dataset collection, consisting of 700 images—100 images for each of the 7 Bougainvillea classes. This is followed by a pre-processing stage, including resizing and normalization to ensure uniform data format. Image augmentation is then applied to artificially increase data diversity, enhancing the model’s robustness against variations in the input. The processed data is subsequently split into training and testing sets. The ResNet50 model is then trained using transfer learning. Finally, the model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the classification results.

Data Collection

The primary data used in this study was collected from a plantation owned by Mrs. Ni Wayan Eviari. The images were captured using an iPhone X smartphone camera and focused on fully bloomed Bougainvillea flowers. Photos were taken from various angles, including front, back, and side views. The image collection process was assisted directly by cocoa farmers working on the plantation. The collected dataset consists of Bougainvillea flower images, totaling 700 original images, which were categorized into 7 classes: Bougainvillea Gold Rush, Bougainvillea Bambino Baby Allison, Bougainvillea Baby Victoria, Bougainvillea Afterglow, Bougainvillea Baby Laurent, Bougainvillea Ice Coconut, and Bougainvillea Bambino Majik.

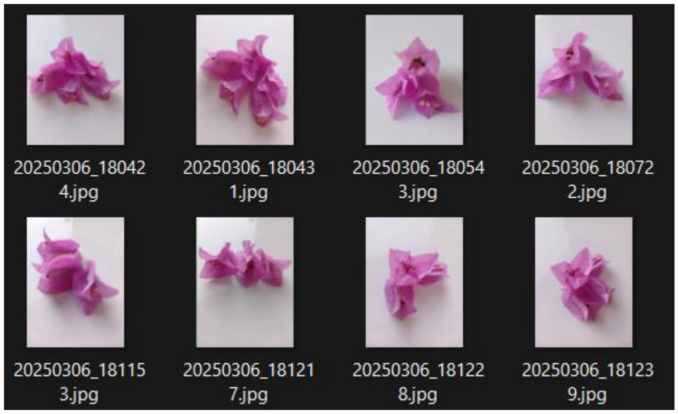

Figure 2. Sample Dataset of one of the classes

Pre-processing

Pre-processing is the initial stage in image data handling aimed at preparing raw images before further analysis. The main objectives of this stage are to align the data with the model's requirements, reduce noise, standardize the scale, and ensure uniform image dimensions. In this study, the applied pre-processing technique is resizing, where all images are resized to 224×224 pixels. Using consistent dimensions enhances the accuracy of transfer learning, ensures uniformity of input data, and reduces computational load while preserving essential image information.

Augmentation

Data augmentation is a technique used in deep learning model training to increase the quantity and diversity of training data by modifying original images through transformations such as rotation, flipping, random cropping, lighting adjustments, and color scheme alterations, without changing their class labels. The primary goal is to expand the data distribution to reduce overfitting and enhance the model's generalization capability to new data, especially when the training dataset is limited [17]. In specific applications like image captioning, augmentation has been shown to enrich visual variation and significantly improve model accuracy [18]. Moreover, newer approaches such as Advanced Random Mix Augmentation offer unique combinations of transformations for each image, creating more complex and realistic datasets that substantially boost classification performance [19]. In this study, the augmentation method used is geometric transformation, which introduces variations in object positioning through techniques such as rotation, flipping, zooming, and translation. This approach provides positional diversity in the dataset, enabling the model to better handle differences in perspective, size, or object orientation in real-world data. From the original 700 images, the dataset was expanded to 4,900 images after augmentation.

K-fold Cross Validation

K-Fold Cross Validation is a widely used validation method in training and evaluating machine learning models, including deep learning, to address overfitting issues and ensure good model generalization. This technique splits the dataset into k parts (folds), where training is performed on k–1 parts while the remaining part is used for testing. This process is repeated k times so that each fold serves as the test set once, and the average of all evaluation results is used as the estimated performance of the model. The main advantage of this method lies in its efficiency in data utilization especially valuable when dealing with limited datasets as all data are used for both training and testing [20]. Additionally, k-fold provides a more stable estimate of model performance compared to a single data split [21]. This method is also applied in reinforcement learning and deep learning to assess task difficulty in automated curriculum learning scenarios [22]. When applied appropriately, K-Fold Cross Validation not only improves model accuracy but also assists in selecting the most suitable model for the given problem and available data.

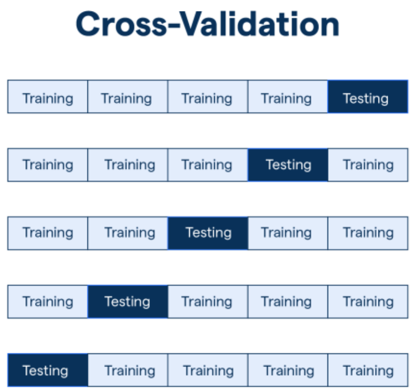

Figure 3. K-Fold Cross Validation

ResNet50

ResNet50 is one of the most well-known convolutional neural network architectures in deep learning, recognized for its efficiency in handling large-scale image classification tasks. This architecture consists of 50 layers and was introduced to address the vanishing gradient problem commonly encountered in very deep networks. The key strength of ResNet50 lies in its use of residual blocks or shortcut connections, which allow information to flow more directly from earlier to later layers without degradation, thereby accelerating training convergence and improving accuracy [23]. In various studies, ResNet50 has demonstrated outstanding performance in image classification tasks such as fresh and rotten fruit recognition, plant disease detection, and artwork classification [24], [25]. This architecture is also highly suitable for transfer learning, as its pretrained weights on large datasets like ImageNet can be reused for new classification tasks, saving both time and computational resources [26]. With its combination of depth, efficiency, and generalization capability, ResNet50 remains a popular choice in modern computer vision applications.

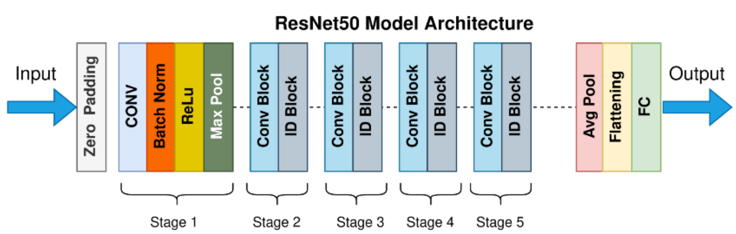

Figure 4. Resnet50 Architecture

Evaluation

The confusion matrix is a crucial evaluation tool in machine learning and deep learning used to assess the performance of classification models. It presents the model's prediction results in a table format, showing the number of correct and incorrect predictions for each class, categorized into four main outcomes: true positive (TP), false positive (FP), true negative (TN), and false negative (FN) [27]. From this matrix, various performance metrics such as accuracy, precision, recall, and F1-score can be derived, providing a comprehensive understanding of how well the model recognizes both correct and incorrect patterns. The use of a confusion matrix not only supports the evaluation of a single model but can also be extended to compare the performance of multiple models through approaches such as the relative confusion matrix, which visualizes prediction differences in a more informative manner [28], [29], [30], [31].

3. Results and Discussion

Results

The training of the ResNet50 model was conducted by testing several hyperparameters, including learning rates of 0.0001 and 0.00001, as well as using both the Adam and SGD optimizers. These configurations were evaluated using the grid search method to identify the best-performing combination. Additionally, the model was trained under two different scenarios: with data augmentation and without data augmentation. The table below presents the training results of the ResNet50 model using the best hyperparameter settings.

Table 1. Evaluation Results of Restnet50 Data Model

Model	Learning Rate	Optimizer	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)
Resnet50 Without Augmentation	**0.0001**	**adam**	**89.29%**	**89.27%**	**89.29%**	**89.16%**
	0.0001	sgd	85.71%	88.38%	85.71%	85.79%
	0.00001	adam	28.57%	23.84%	28.57%	24.29%
	0.00001	sgd	16.43%	13.69%	16.43%	12.46%
Resnet50 With Augmentation	**0.0001**	**adam**	**99.69%**	**99.70%**	**99.69%**	**99.69%**
	0.0001	sgd	98.67%	98.69%	98.67%	98.67%
	1.00E-05	adam	76.63%	76.55%	76.63%	76.41%
	1.00E-05	sgd	70.00%	69.75%	70.00%	69.47%

Table 2. Evaluation Fold Validation of Restnet50 Without Augmentation Data Model

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	92.86%	93.51%	92.86%	92.81%
2	89.29%	91.67%	89.29%	89.32%
3	92.86%	94.06%	92.86%	92.98%
4	87.50%	89.36%	87.50%	87.71%
5	96.43%	96.63%	96.43%	96.42%
6	94.64%	95.56%	94.64%	94.58%
7	92.86%	93.97%	92.86%	92.79%
8	96.43%	96.63%	96.43%	96.42%
9	98.21%	98.41%	98.21%	98.21%
10	92.86%	93.77%	92.86%	92.93%
Rata-rata	**93.39%**	**94.02%**	**93.39%**	**93.42%**

Table 3. Evaluation Fold Validation of Restnet50 With Augmentation Data Model

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	99.74%	99.75%	99.74%	99.74%
2	100.00%	100.00%	100.00%	100.00%
3	100.00%	100.00%	100.00%	100.00%
4	99.49%	99.51%	99.49%	99.49%
5	100.00%	100.00%	100.00%	100.00%
6	99.49%	99.51%	99.49%	99.49%
7	99.74%	99.75%	99.74%	99.74%
8	99.74%	99.75%	99.74%	99.74%
9	99.49%	99.50%	99.49%	99.49%

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
10	100.00%	100.00%	100.00%	100.00%
Rata-rata	**99.67%**	**99.68%**	**99.67%**	**99.67%**

Table 1 compares the performance of the ResNet50 model with and without data augmentation, revealing a substantial improvement when augmentation is applied. Without augmentation, the best accuracy reached only 89.29% using the Adam optimizer with a learning rate of 0.0001, whereas the same configuration with augmentation achieved 99.69% accuracy along with equally high precision, recall, and F1-score. This indicates that data augmentation significantly enhances the model's generalization ability in recognizing diverse Bougainvillea flower variations. **Tables 2** and **3** further support this conclusion through 10-Fold Cross Validation. The model without augmentation achieved an average accuracy of 93.39% and F1-score of 93.42%, while the augmented model reached an average of 99.67% for both metrics. All performance indicators for the augmented model remained consistently high across all folds, with several folds achieving perfect scores (100%), indicating that augmentation improves not only accuracy but also model stability and robustness.

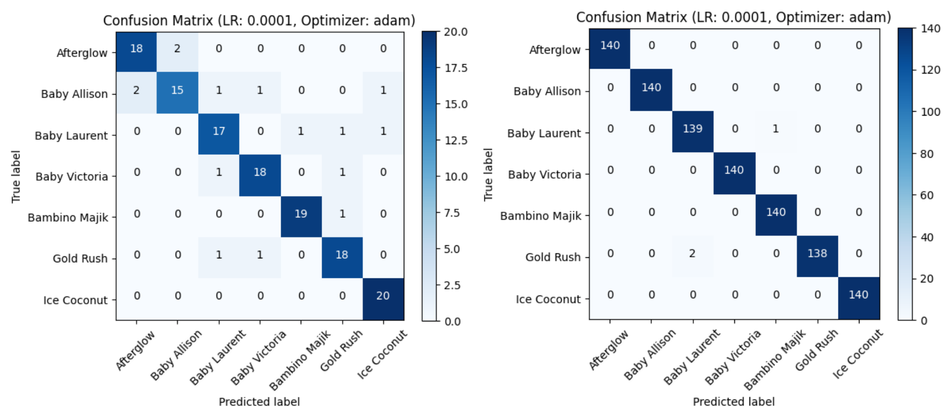

Figure 5. Confusion Matrix Result Without Augmentation Data and With Augmentation Data

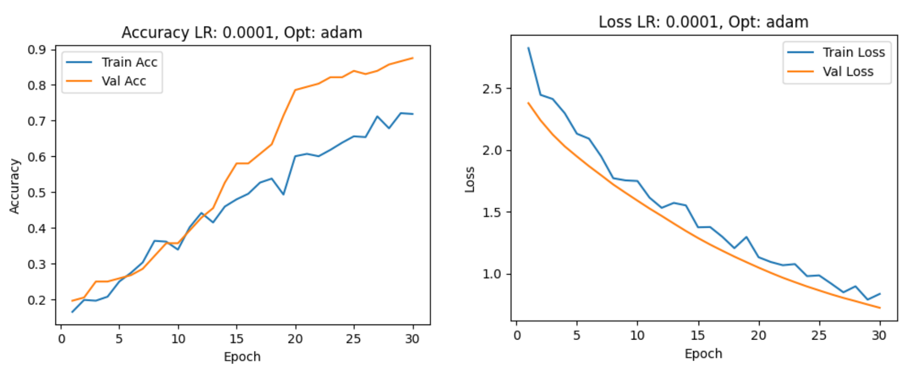

Figure 6. Accuracy and Loss Without Augmentation Data

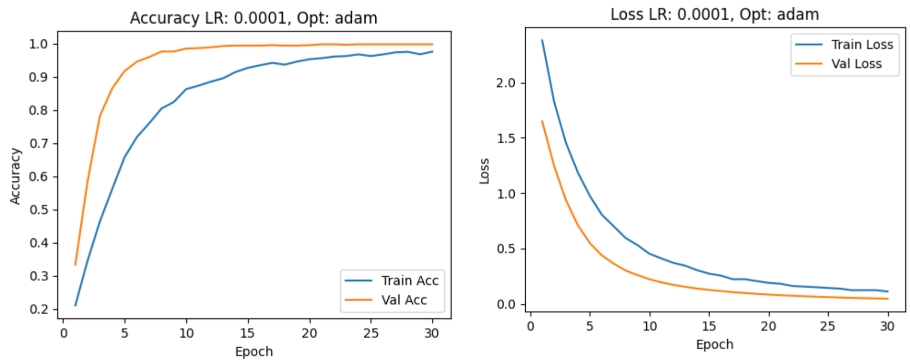

Figure 7. Accuracy and Loss with Augmentation Data

Discussion

The results of this study clearly demonstrate the effectiveness of combining the ResNet50 architecture with image augmentation techniques in improving the accuracy and robustness of Bougainvillea flower classification. Without augmentation, the model achieved decent performance; however, it struggled to generalize well to varied conditions. Geometric augmentation, including rotation, flipping, zooming, and translation, introduced diverse visual perspectives that enhanced the model's ability to recognize different classes with greater reliability. This was reflected in the substantial increase in evaluation metrics, with average accuracy improving from 93.39% to 99.67%. Additionally, the application of 10-Fold Cross Validation provided a comprehensive assessment of model stability, with consistently high results across all folds some reaching perfect scores. Hyperparameter tuning further confirmed that a learning rate of 0.0001 with the Adam optimizer was the most effective combination. These findings highlight that ResNet50, when optimized and combined with augmentation, is highly capable of performing complex classification tasks and holds strong potential for use in real-world agricultural and educational applications. For future research, it is recommended to expand the dataset with more diverse images captured under different lighting and background conditions, explore the use of other advanced architectures such as EfficientNet or Vision Transformers, and develop a real-time classification system deployable on mobile or embedded devices for field usage.

4. Conclusion

This study successfully implemented the ResNet50 architecture for the classification of Bougainvillea flower varieties using image data. The incorporation of geometric image augmentation significantly improved the model's accuracy and generalization ability, achieving an average performance of 99.67% across all key evaluation metrics. Moreover, K-Fold Cross Validation validated the robustness and consistency of the model. These results highlight the potential of deep learning-based image classification as an effective solution for ornamental plant identification and support future development of AI-powered tools in horticulture and environmental monitoring.

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