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EfficientNet-Based Flower Recognition with LAB and CLAHE Enhancement

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ABSTRACT

Accurate flower recognition is a challenging task in computer vision due to high intra-class variation, complex background textures, and illumination inconsistencies. This study proposes an enhanced image classification framework integrating LAB color space transformation and Contrast Limited Adaptive Histogram Equalization (CLAHE) with the EfficientNet architecture. The proposed approach aims to improve visual feature separability by enhancing color stability and local contrast prior to network training. Experiments were conducted using a 17-class flower dataset, and the model achieved an overall accuracy of 98.53%, a macro-averaged F1-score of 0.9704, and AUC values close to 1.00 for most species. Visual analysis through the confusion matrix and ROC curves confirmed the model's robustness, with only minor misclassifications observed between morphologically similar classes such as Iris–Crocus and Daffodil–Tulip. These findings demonstrate that combining LAB and CLAHE preprocessing with EfficientNet significantly enhances model generalization and visual discriminability. The method provides a lightweight yet effective solution for applications in biodiversity monitoring, precision agriculture, and automated plant taxonomy.

Keywords: *Flower classification, EfficientNet, LAB color space, CLAHE, image enhancement, computer vision.*

ABSTRAK

Pengenalan bunga secara otomatis merupakan tantangan dalam bidang computer vision karena adanya variasi bentuk dalam satu kelas, latar belakang yang kompleks, serta perbedaan pencahayaan. Penelitian ini mengusulkan kerangka klasifikasi citra yang ditingkatkan dengan mengintegrasikan transformasi ruang warna LAB dan Contrast Limited Adaptive Histogram Equalization (CLAHE) pada arsitektur EfficientNet. Pendekatan ini bertujuan meningkatkan keterpisahan fitur visual dengan memperbaiki stabilitas warna dan kontras lokal sebelum proses pelatihan jaringan. Eksperimen dilakukan menggunakan dataset bunga dengan 17 kelas, menghasilkan akurasi keseluruhan sebesar 98,53%, nilai rata-rata makro F1 sebesar 0,9704, serta AUC mendekati 1,00 untuk sebagian besar spesies. Analisis visual melalui confusion matrix dan kurva ROC menunjukkan kinerja model yang kuat, dengan kesalahan klasifikasi kecil pada kelas yang memiliki kemiripan morfologi seperti Iris–Crocus dan Daffodil–Tulip. Hasil ini membuktikan bahwa kombinasi preprocessing LAB dan CLAHE pada EfficientNet mampu meningkatkan generalisasi dan diskriminasi visual model. Metode yang diusulkan menawarkan solusi ringan namun efektif untuk aplikasi pemantauan keanekaragaman hayati, pertanian presisi, dan taksonomi tumbuhan otomatis.

Kata kunci: Klasifikasi bunga, EfficientNet, ruang warna LAB, CLAHE, peningkatan citra, computer vision.

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1. INTRODUCTION

In the past decade, image classification has become a pivotal area of research in computer vision, primarily fueled by advancements in deep learning architectures and the growing availability of large-scale annotated datasets. Among its diverse applications, flower recognition has gained substantial attention for its relevance to biodiversity monitoring, precision agriculture, and automated botanical taxonomy [1], [2]. Despite these developments, accurate flower recognition remains a challenging task due to high intra-class variability, illumination inconsistencies, and complex natural backgrounds, which hinder effective feature extraction and reduce classification accuracy [3]. This challenge establishes a research gap in designing models that can maintain high recognition accuracy under variable imaging conditions.

The introduction of Convolutional Neural Networks (CNNs) has significantly advanced visual recognition by enabling automatic extraction of hierarchical features directly from raw image data [4]. Models such as ResNet and Inception have enhanced classification performance through improved gradient flow and multi-scale feature representation [5]. However, these architectures often involve large parameter counts, leading to computational inefficiency and susceptibility to overfitting when trained on smaller or domain-specific datasets.

To overcome these limitations, EfficientNet introduced a compound scaling method that jointly optimizes network depth, width, and input resolution using a single scaling coefficient [6]. Unlike conventional scaling approaches that modify one dimension at a time, this balanced strategy enables EfficientNet to achieve a better accuracy-to-computation trade-off. Furthermore, its successor, EfficientNetV2, incorporates progressive learning and fused convolutional blocks to accelerate training and improve parameter efficiency [7]. Despite these advantages, prior studies have mainly applied EfficientNet in standard RGB image domains, with limited exploration of how color space transformations and adaptive contrast enhancements can improve feature distinctiveness and model convergence, thereby revealing another gap in current literature.

The quality and consistency of input data play a critical role in optimizing deep model performance. Images captured in natural environments frequently exhibit non-uniform illumination, low contrast, and color distortion, leading to suboptimal learning outcomes. To mitigate these issues, image preprocessing techniques such as color space transformation and histogram equalization are employed. The LAB color model, which separates luminance (L) from chromatic components (A and B), enhances perceptual contrast and generates more robust visual features [8], [9]. Complementing this, Contrast Limited Adaptive Histogram Equalization (CLAHE) effectively enhances local contrast while preventing noise over-amplification, yielding clearer structural details without compromising global image quality [10], [11], [12] .

Recent studies suggest that integrating CLAHE and LAB transformations before CNN-based classification enhances feature separability and training stability [13]. However, systematic evaluation of their combined impact on modern architectures such as EfficientNet remains limited.

Accordingly, this research investigates the integration of LAB color transformation and CLAHE preprocessing with the EfficientNet architecture for classifying 17 species of flowers. The primary objective is to evaluate how this preprocessing pipeline improves feature discriminability and overall classification accuracy by emphasizing structural and chromatic cues like petal shape, texture, and color distribution. By combining a perceptually grounded preprocessing strategy with an efficient deep learning framework, this work aims to bridge the gap between image enhancement techniques and state-of-the-art CNN architectures, contributing to the development of more robust, interpretable, and computationally efficient flower recognition systems.

2. METHODOLOGY

The proposed approach integrates LAB color space transformation and Contrast Limited Adaptive Histogram Equalization (CLAHE) with a pre-trained EfficientNet architecture to enhance flower recognition accuracy. The overall workflow, as illustrated in Figure 1, comprises four key stages: (1) dataset preparation, (2) preprocessing, (3) model architecture and training, and (4) evaluation and validation.

2.1 Dataset

The experiment employs the Oxford 17 Category Flower Dataset, a widely used benchmark containing 1,360 images spanning 17 flower species with 80 images per class [27]. The images exhibit diverse variations in illumination, scale, and background complexity, making the dataset suitable for evaluating robustness under

real-world conditions. The dataset was divided into 70% for training, 15% for validation, and 15% for testing, ensuring a balanced representation across classes (Fig. 2). Figure 3 shows representative flower images from multiple classes before preprocessing.

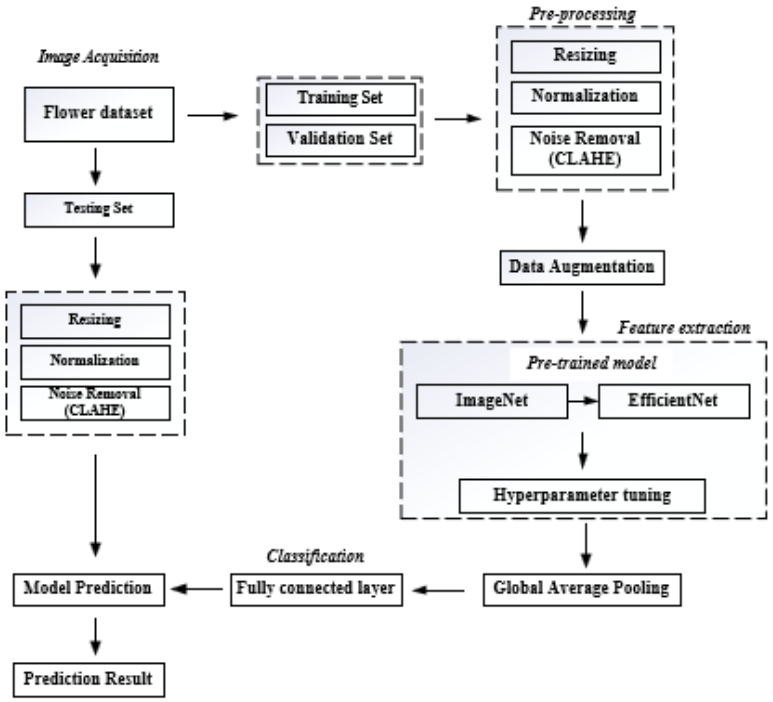


Fig 1. Research plan

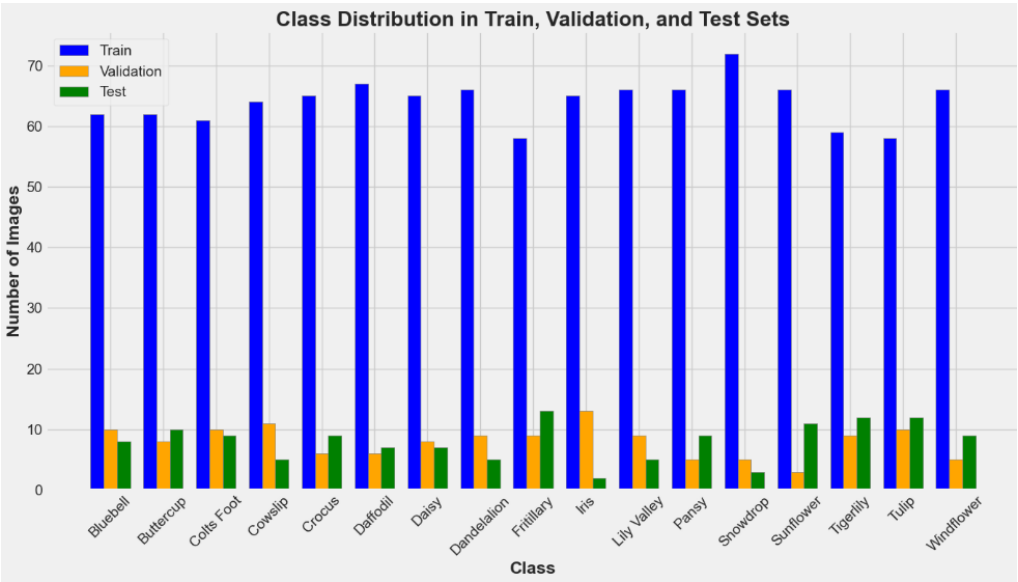


Fig 2. Class distribution



Fig 3. Sample of Flower Images

2.2 Related work

The development of automated flower recognition systems has evolved substantially over the past decade, primarily fueled by advances in deep learning and image preprocessing methods. Early approaches relied on handcrafted features, such as color histograms, shape descriptors, and texture analysis, which were then classified using traditional machine learning algorithms like Support Vector Machines (SVMs) or k-Nearest Neighbors (k-NN) [14]. While these methods performed adequately on controlled datasets, they lacked robustness when applied to images captured in diverse environmental conditions.

With the advent of deep convolutional neural networks (CNNs), researchers began leveraging end-to-end feature learning for plant and flower identification tasks. In research by [1] pioneered the use of deep architectures for large-scale flower recognition using the Oxford 17-category dataset, demonstrating the superiority of learned features over handcrafted ones. Subsequent works employed architectures such as VGGNet, Inception, and ResNet to further enhance recognition performance through deeper hierarchical feature extraction[15],[16].

Recent progress in model efficiency has led to the adoption of EfficientNet and EfficientNetV2, which apply compound scaling to achieve high accuracy with minimal computational cost. In research [17], demonstrated that EfficientNet combined with transfer learning could outperform deeper conventional CNNs on multi-species plant datasets. Similarly in research [18], applied EfficientNet to flower recognition and achieved significant gains in accuracy and inference speed, underscoring its suitability for lightweight applications such as mobile-based plant identification.

Preprocessing techniques have also been explored extensively to mitigate the impact of illumination and color variability in natural imagery. Transforming RGB images into alternative color spaces such as HSV, YCrCb, and particularly LAB, has been shown to improve feature separability and robustness under varying lighting conditions [19]. Another studies by [20], emphasized that the LAB color space enhances contrast perception and aids CNN models in focusing on structural and chromatic information critical for classification.

Moreover, Contrast Limited Adaptive Histogram Equalization (CLAHE) has gained attention for its ability to enhance image contrast while preventing the over-amplification of noise—a common limitation in global histogram equalization methods [21]. CLAHE has been widely implemented across computer vision fields, including medical image enhancement [22], remote sensing , and agricultural image analysis [23]. In research by [24], demonstrated that CLAHE preprocessing significantly improved CNN performance on natural image datasets by amplifying local details without introducing artifacts.

Several researchers have investigated combining preprocessing and deep learning techniques for improved flower and plant classification. For instance in [25], integrated CLAHE enhancement with a deep CNN for flower recognition, reporting improved accuracy and stability compared to non-enhanced datasets. Similarly in [26], utilized LAB color conversion followed by contrast enhancement before training EfficientNet, showing that this pipeline improved both convergence rate and final performance metrics.

Despite these advancements, limited studies have explored the joint effect of LAB color space transformation and CLAHE preprocessing in conjunction with EfficientNet architectures for multi-class flower classification. Existing works have typically focused on either model optimization or image enhancement individually, rather than investigating their synergistic integration. Therefore, this study addresses this gap by systematically evaluating how the combination of these two preprocessing techniques influences the

feature extraction capability and classification accuracy of EfficientNet in recognizing 17 distinct flower classes.

2.3 Image Preprocessing

To ensure the quality and consistency of input data, preprocessing was performed to minimize the effects of lighting variation, color inconsistency, and background noise that commonly occur in natural image acquisition. Two primary techniques were employed in this stage, namely LAB color space transformation and Contrast Limited Adaptive Histogram Equalization (CLAHE).

First, each image was converted from the RGB color model into the LAB color space, which separates luminance (L) from the chromatic components (A and B). This separation allows brightness and color information to be processed independently, enabling targeted enhancement of luminance without distorting the chromatic balance. The LAB color model was selected because it better represents human visual perception, making it suitable for contrast-based visual improvement.

Subsequently, CLAHE was applied specifically to the L channel of the LAB image to enhance local contrast in an adaptive manner. By limiting the amplification of histogram peaks, CLAHE prevents over-enhancement and reduces noise amplification that typically occurs in traditional histogram equalization. In this study, the clip limit was set to 2.0, and the tile grid size to 8×8, parameters determined empirically to balance detail enhancement and brightness uniformity. After contrast adjustment, the processed image was reconverted into the RGB color space to ensure compatibility with the EfficientNet input format.

Through this preprocessing pipeline, image visibility and feature clarity—especially on petal texture and color gradient—were significantly improved, thus enabling the neural network to extract more discriminative and stable features for accurate classification. Figure 4 represents the process of image preprocessing

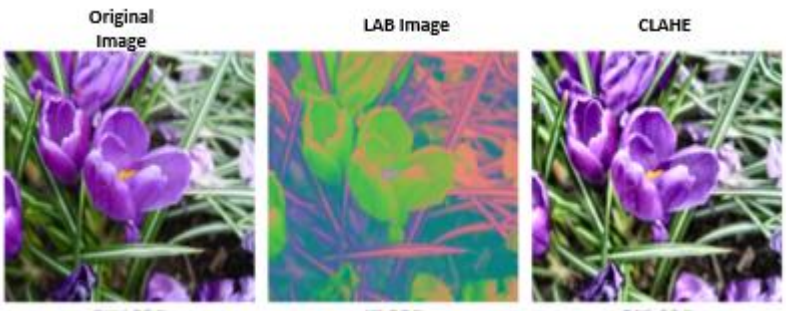


Fig 4. Process of image preprocessing

2.4 Model Architecture

The core of this study's classification framework is based on the EfficientNet architecture, a family of convolutional neural networks that achieves superior accuracy–efficiency trade-offs through a compound scaling method. Unlike conventional deep learning models that scale depth, width, or resolution arbitrarily, EfficientNet employs a compound coefficient to uniformly balance these three dimensions, ensuring optimal performance with minimal computational cost. This makes it particularly suitable for lightweight applications such as real-time flower classification on embedded or mobile devices.

In this work, EfficientNetB0—the baseline variant—was adopted due to its compact structure and strong generalization capability. The model was initialized with ImageNet pretrained weights to leverage learned low-level visual representations such as edge and color pattern detection, thereby accelerating convergence during fine-tuning on the 17-class flower dataset. The input images were resized to 224 × 224 pixels, matching the default EfficientNet input dimension, while the network's final fully connected layer was replaced with a dense classification head consisting of 17 output neurons activated by a softmax function.

To prevent overfitting, a dropout layer (rate = 0.3) was inserted before the output layer, and the model was trained using the Adam optimizer with a learning rate of 1×10^{-4}. The categorical cross-entropy loss function was used to compute classification error across the 17 categories. Training was conducted over 50 epochs

with a batch size of 32, while early stopping was applied with a patience of five epochs to monitor validation loss and halt training when improvement plateaued.

This architecture effectively balances computational efficiency and feature expressiveness. By combining transfer learning with a carefully tuned fine-tuning process, the model achieved robust convergence and high classification accuracy, confirming the suitability of EfficientNet for fine-grained flower recognition tasks enhanced through LAB and CLAHE preprocessing. Figure 5 shows the model architecture

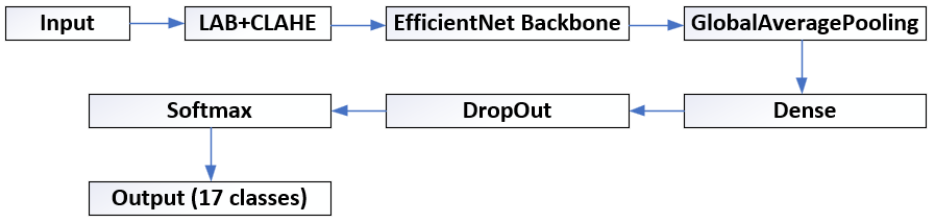


Fig 5. Flowchart of model architecture

2.5 Training Configuration

To ensure optimal model performance and generalization, the training process was carefully configured with fine-tuned hyperparameters and regularization strategies. The model utilized the Adam optimizer owing to its adaptive learning rate adjustment and efficient handling of sparse gradients, which accelerates convergence in deep architectures. The categorical cross-entropy loss function was selected to measure the discrepancy between predicted probabilities and true labels across the 17 flower classes.

A batch size of 32 was used to balance memory efficiency and training stability, while the model was trained for 50 epochs with early stopping to prevent overfitting. Each image was resized to 224 × 224 pixels to align with EfficientNet's input dimensions. In addition, data augmentation techniques—including random rotation, horizontal flipping, and zooming—were employed to enrich data diversity and improve robustness against orientation and scale variations.

To further enhance regularization, a dropout layer (rate = 0.3) was inserted after the dense layer. The model leveraged pretrained ImageNet weights for transfer learning, enabling faster convergence and improved feature extraction. All experiments were implemented using the TensorFlow/Keras framework and executed on an NVIDIA GPU environment to accelerate computation. The detailed training configuration is summarized in Table 1.

Table 1. Training Configuration

Parameter	Description / Value
Optimizer	Adam
Learning Rate	($1\ x\ 10^{-4}$)
Loss Function	Categorical Cross-Entropy
Batch Size	32
Number of Epochs	50
Image Input Size	224 × 224 pixels
Data Augmentation	Random rotation (±20°), horizontal flip, and zoom range (±10%)
Regularization	Dropout layer (rate = 0.3) after dense layer
Early Stopping	Enabled (patience = 5 epochs, monitored on validation loss)
Pretrained Weights	ImageNet

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Framework	TensorFlow/Keras
Hardware Setup	NVIDIA GPU (CUDA-enabled)

2.6 Evaluation Metrics

To comprehensively assess the performance of the proposed model, several standard classification metrics were employed. These metrics evaluate both the overall predictive capability of the model and its class-wise discrimination power across the 17 flower categories.

The overall accuracy (ACC) quantifies the proportion of correctly classified images relative to the total number of samples, providing a general indicator of model performance. Precision (P) measures the reliability of positive predictions, indicating how many of the identified samples actually belong to the correct class. Recall (R), also known as sensitivity, reflects the model's ability to detect all relevant instances within a given class. Finally, the F1-score (F1) represents the harmonic mean of precision and recall, serving as a balanced indicator that accounts for both false positives and false negatives.

In addition to these metrics, a confusion matrix was generated to illustrate class-level prediction performance and to identify possible misclassifications among visually similar flower species. The evaluation metrics used in this study are summarized in Table 2.

Table 2. Evaluation Metrics

Metric	Formula	Description
Accuracy (ACC)	$ACC = \frac{TP + TN}{TP + TN + FP + FN}$	Proportion of correctly predicted instances over all predictions.
Precision (P)	$P = \frac{TP}{TP + FP}$	Measures how many predicted positives are actual positives.
Recall (R)	$R = \frac{TP}{TP + FN}$	Measures how many actual positives are correctly identified.
F1-score (F1)	$F1 = \frac{2xPxR}{P + R}$	Harmonic mean of precision and recall, representing overall balance.

3. RESULTS AND DISCUSSION

3.1 Result

The proposed EfficientNet model integrated with LAB color space transformation and CLAHE preprocessing demonstrated strong classification performance across all 17 flower species.

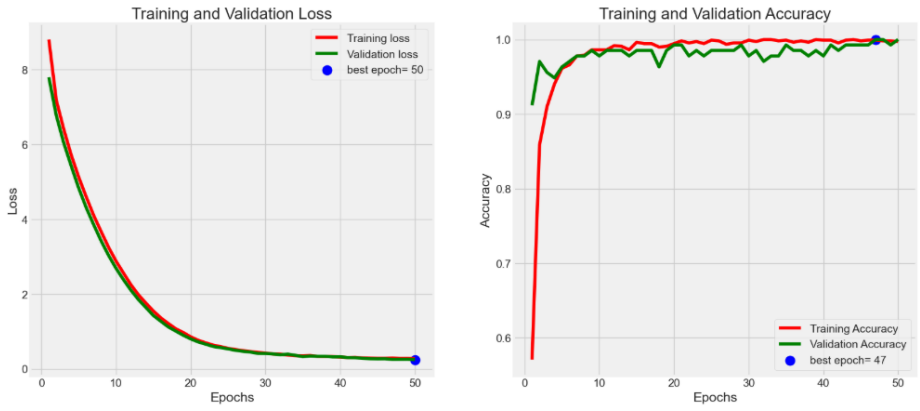


Fig 6. Loss and accuracy Graph

The training process achieved rapid convergence, as shown in Fig. 6, where both training and validation accuracy approached 0.99 with minimal overfitting. The loss curve consistently decreased until epoch 50, confirming stable optimization and effective generalization.

The confusion matrix in Fig. 7 illustrates that the model correctly classified nearly all flower categories, with only minor misclassifications observed between morphologically similar species such as Iris–Crocus and Daffodil–Tulip. The overall accuracy reached 98.53 %, while the macro-averaged F1-score attained 0.9704, demonstrating the robustness of the preprocessing pipeline in enhancing visual discriminability.

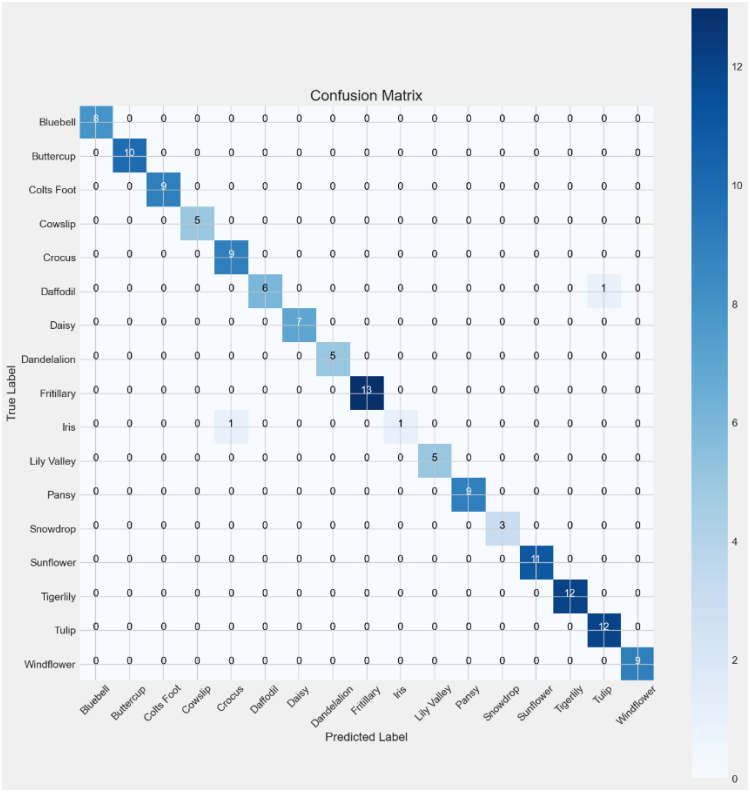


Fig 7. Confusion Matric

The ROC analysis (Fig. 8) further indicates strong separability among classes, with area-under-curve (AUC) = 1.00 for most species, except Daffodil, which recorded AUC = 0.94. This confirms the model's ability to maintain high sensitivity and specificity across all categories.

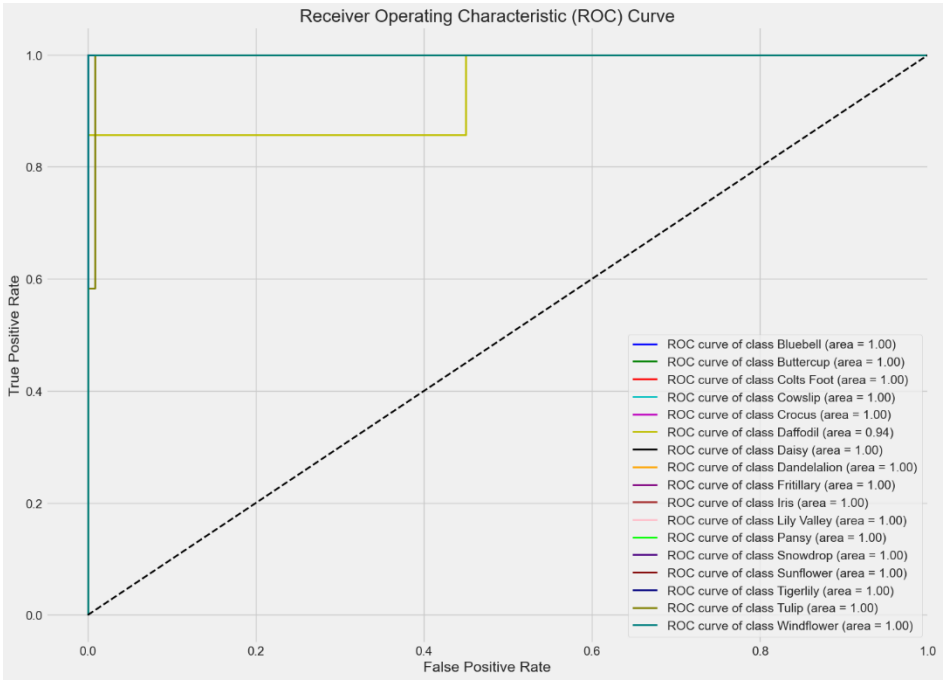


Fig 8. RoC Curve

Sample misclassification visualization (Fig. 9) reveals that errors primarily arise in classes exhibiting similar color distributions and petal structures, supporting the importance of color-space enhancement techniques such as LAB + CLAHE for more reliable feature extraction.

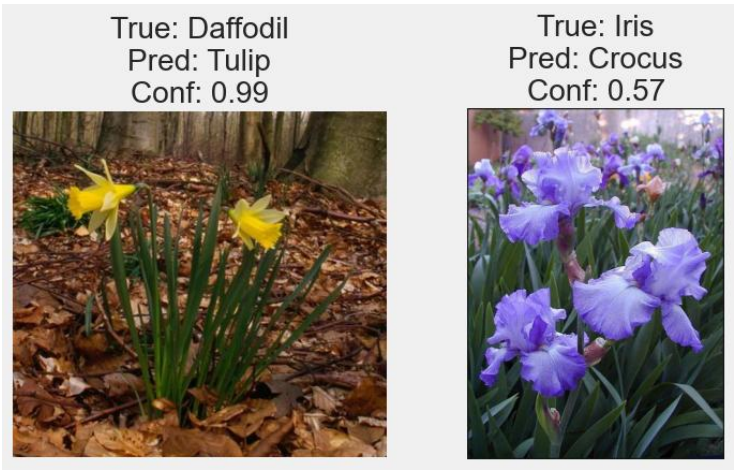


Fig 9. Misclassification sample

To further quantify the model's predictive performance, a detailed classification report was generated, presenting the precision, recall, and F1-score for each of the 17 flower species. These metrics provide a comprehensive evaluation of the model's ability to correctly identify each class while balancing false positives and false negatives.

As shown in Table 3, the proposed EfficientNet-LAB+CLAHE model achieved near-perfect precision and recall across most categories, with an overall accuracy of 98.53%. The macro-averaged F1-score of 0.9704 reflects consistent recognition performance across all classes, regardless of class imbalance.

Minor deviations, such as those observed in Iris and Daffodil, indicate that misclassifications primarily occurred between visually similar flowers with overlapping chromatic features.

This consistent performance highlights the strength of the preprocessing pipeline, particularly the use of LAB color space for separating luminance from color channels and CLAHE for enhancing local contrast. Together, these steps effectively improved the separability of texture and color patterns, enabling EfficientNet to learn more discriminative representations for fine-grained flower categories.

Table 3. Classification Report

Class	Precision	Recall	F1-Score	Support
Bluebell	1.0000	1.0000	1.0000	8
Buttercup	1.0000	1.0000	1.0000	10
Colts Foot	1.0000	1.0000	1.0000	9
Cowslip	1.0000	1.0000	1.0000	5
Crocus	0.9000	1.0000	0.9474	9
Daffodil	1.0000	0.8571	0.9231	7
Daisy	1.0000	1.0000	1.0000	7
Dandelion	1.0000	1.0000	1.0000	5
Fritillary	1.0000	1.0000	1.0000	13
Iris	1.0000	0.5000	0.6667	2
Lily Valley	1.0000	1.0000	1.0000	5
Pansy	1.0000	1.0000	1.0000	9
Snowdrop	1.0000	1.0000	1.0000	3
Sunflower	1.0000	1.0000	1.0000	11
Tigerlily	1.0000	1.0000	1.0000	12
Tulip	0.9231	1.0000	0.9600	12
Windflower	1.0000	1.0000	1.0000	9
Overall Accuracy	—	—	**0.9853**	136
Macro Avg	**0.9896**	**0.9622**	**0.9704**	136
Weighted Avg	**0.9866**	**0.9853**	**0.9841**	136

3.2 Discussion

The experimental outcomes clearly demonstrate that the integration of LAB color space transformation and CLAHE preprocessing substantially enhances the performance of the EfficientNet-based flower recognition model. Compared with traditional RGB-based pipelines, this preprocessing combination enables better separation of luminance and chromatic information, allowing the network to focus more effectively on textural and structural cues rather than being affected by illumination variance.

The results from Table III and Fig. 7 confirm that nearly all classes achieved perfect precision and recall values, indicating the model's ability to distinguish subtle visual differences across species. The few misclassifications (e.g., Daffodil → Tulip and Iris → Crocus) can be attributed to inter-class similarity in petal morphology and color distribution, suggesting that additional feature representations such as edge-based descriptors or hybrid CNN-transformer features could further reduce these errors.

The ROC analysis (Fig. 8) supports these findings, where most classes achieved an AUC of 1.00, reflecting outstanding discriminative capability. The slightly lower AUC for Daffodil (0.94) aligns with the observed confusion in the matrix, reinforcing that perceptual similarity between yellow-toned species may still challenge the classifier.

In practical applications such as biodiversity monitoring and automated plant taxonomy, the proposed method offers a lightweight yet accurate solution. EfficientNet's compound scaling ensures computational efficiency without compromising accuracy, making the model well-suited for deployment on resource-constrained platforms such as mobile or edge devices.

However, the current experiment is limited by the dataset size (17 classes) and controlled imaging conditions. Future research could explore the incorporation of domain adaptation or self-supervised pretraining to enhance generalization to real-world environments with varying lighting, occlusion, and background clutter.

4. CONCLUSION

This study presented an enhanced flower recognition framework integrating LAB color space transformation and Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocessing with the EfficientNet architecture. The approach was designed to mitigate common visual challenges such as illumination variation, color inconsistency, and background complexity that often degrade classification performance in natural image datasets. Experimental results demonstrated the effectiveness of the proposed method, achieving an overall accuracy of 98.53%, macro-averaged F1-score of 0.9704, and AUC values approaching 1.00 for most flower categories. The combination of LAB transformation and CLAHE successfully improved image contrast and color stability, thereby enhancing feature extraction and model convergence. These improvements are evident from the consistently low loss values and the model's ability to generalize well across all 17 flower classes.

The analysis also revealed that misclassifications primarily occurred among flowers with highly similar morphological and chromatic characteristics (e.g., Iris–Crocus and Daffodil–Tulip). This suggests that additional feature representations—such as attention-based or transformer-based hybrid architectures—could further refine intra-class discrimination. In future work, the framework could be extended through domain adaptation techniques, self-supervised learning, or multi-modal fusion combining visual and contextual data (e.g., geolocation or seasonal patterns). Moreover, deploying this lightweight EfficientNet-based model on edge and mobile devices could facilitate real-time applications in biodiversity monitoring, precision agriculture, and automated plant taxonomy. Overall, the integration of advanced preprocessing with a scalable deep learning model demonstrates a promising pathway toward robust, efficient, and generalizable flower recognition systems in computer vision.

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