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Building Models of Flowers Recognition Using Neural Network

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Abstract
Flower recognition plays an important role in image classification research because flower objects often contain complex color and shape characteristics. This study utilizes the Artificial Neural Network (ANN) method to classify lily and ester flower images using four color models, namely HSV, RGB, LAB, and YCbCr. We apply two evaluation approaches, including cross-validation folds and percentage split testing, to analyze classification performance and model stability. The experimental results show that the RGB color model achieves the best overall performance among all evaluated models. In the cross-validation experiment, the RGB model obtains the highest accuracy of 96.8421%, while in the percentage split experiment, the RGB model achieves the highest accuracy of 96.3158%. The LAB and YCbCr color models also demonstrate competitive performance, whereas the HSV model produces the lowest classification accuracy. These findings indicate that color representation significantly influences Neural Network classification performance. This study successfully produces a flower recognition model with high classification accuracy and demonstrates that the ANN method can effectively learn flower image patterns when combined with appropriate color feature representations.

Keywords:
Flower, Recognition, Neural Network, Machine Learning

1. Introduction

Flower recognition has become an important research topic in computer vision because flowers possess diverse visual characteristics, including variations in color, texture, shape, and petal structure. Accurate flower recognition systems support various applications such as smart agriculture, botanical classification, biodiversity preservation, and digital learning systems. However, the recognition process remains challenging because many flower species exhibit highly similar visual appearances, while environmental factors such as lighting conditions, background complexity, and image quality also affect classification accuracy. Traditional image processing approaches often struggle to extract robust features from flower images, particularly when dealing with large-scale datasets and high inter-class similarity. Therefore, researchers increasingly apply artificial intelligence and neural network approaches to improve recognition performance and automate feature extraction processes. [1], [8], [9]

Earlier studies mainly rely on conventional image processing and machine learning methods for object recognition tasks. Rosyani et al. compare several color models for flower recognition and demonstrate that color representation significantly influences recognition accuracy because flowers contain strong color-based characteristics [1]. Although color-based approaches provide promising results, they remain sensitive to illumination variation and background noise. Other traditional classification approaches such as K-Nearest Neighbor also show acceptable performance in pattern recognition problems, including glass type identification and image-based classification tasks [5]. However, these conventional methods still depend heavily on handcrafted feature extraction, which limits their ability to capture complex visual patterns automatically. This limitation encourages researchers to explore neural network-based approaches capable of learning more representative image features directly from training data. [1], [5]

Artificial Neural Networks (ANN) demonstrate strong capability in solving complex classification and prediction problems because they learn nonlinear relationships between input features and output classes. Previous studies successfully apply ANN methods in various domains such as scholarship prediction, rainfall forecasting, and student graduation prediction [11]–[13]. Novita et al. also utilize Backpropagation Neural Networks for coffee type identification and achieve reliable classification performance using sensor-based data [6]. These studies confirm that neural networks effectively model

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complex patterns and improve prediction accuracy compared to conventional statistical approaches. Nevertheless, standard ANN architectures still face limitations when processing high-dimensional image data because they require manual feature extraction before classification. As image datasets become larger and more complex, researchers increasingly shift toward deep learning architectures that can perform automatic feature extraction and classification simultaneously. [6], [11]–[13]

Deep learning, particularly Convolutional Neural Networks (CNN), significantly transforms image recognition research because CNN automatically extracts hierarchical visual features from raw images. LeCun et al. explain that deep learning models effectively learn complex image representations through multilayer neural structures [9]. Krizhevsky et al. further demonstrate that CNN achieves remarkable improvements in large-scale image classification tasks through the AlexNet architecture [8]. Since then, CNN becomes one of the most widely used approaches in computer vision applications due to its ability to recognize shapes, textures, and spatial information with high accuracy. Simonyan and Zisserman also introduce the VGGNet architecture, which improves image classification performance through deeper convolutional layers [10]. These developments motivate researchers to apply CNN architectures in various image recognition domains, including flower recognition problems. [8]–[10]

Several studies successfully apply CNN methods in agriculture and object recognition tasks that share similarities with flower classification problems. Rozaqi et al. implement CNN for potato leaf disease detection and obtain effective classification performance despite variations in leaf texture and disease patterns [16]. Putra et al. apply CNN for corn leaf disease classification and demonstrate that deep learning models effectively distinguish visually similar categories [17]. Wardani and Leonardi also use CNN for grape leaf disease classification and report improved recognition accuracy compared with traditional methods [20]. These findings indicate that CNN architectures effectively capture fine-grained visual features from plant-related images. Since flower images also contain complex textures, shapes, and color patterns, CNN-based approaches become highly relevant for flower recognition systems. [16], [17], [20]

Flower recognition specifically benefits from deep learning because flower species often contain subtle visual differences that are difficult to identify manually. Pratiwi et al. develop a flower scanner application using CNN and show that deep learning models effectively recognize flower patterns from image datasets [23]. Their study demonstrates that CNN can learn petal structures, color distributions, and shape characteristics automatically without relying on handcrafted features. However, flower recognition still faces several challenges, including limited datasets, varying image resolutions, overlapping petals, and inconsistent lighting conditions. In addition, visually similar flower species such as lily and ester flowers create additional classification difficulties because their shapes and color distributions often overlap. These conditions require more robust neural network models capable of extracting discriminative features from complex flower images. [1], [23]

Recent advancements in CNN architectures further improve image recognition performance by introducing deeper and more efficient neural network models. MobileNet provides lightweight architectures suitable for image classification with lower computational cost while maintaining competitive accuracy [25]. Other CNN-based studies on doodle recognition, masked face classification, and Javanese script recognition also confirm that deep learning models consistently outperform traditional machine learning approaches in image-based tasks [14], [15], [19]. Despite these advancements, many existing studies focus on general object classification rather than flower-specific recognition problems. Furthermore, limited studies comprehensively evaluate flower recognition performance using neural network approaches under varying dataset conditions. This research gap highlights the need for further investigation into neural network-based flower recognition models capable of handling visually similar flower classes effectively. [14], [15], [19], [25]

Based on these challenges, this study proposes a neural network-based flower recognition model for identifying lily and ester flowers using deep learning techniques. This paper focuses on building an image classification system capable of learning visual characteristics directly from flower images through neural network training. The study addresses the limitations of traditional feature extraction methods by utilizing CNN architectures to improve classification accuracy and robustness. In addition, this study contributes to image recognition research by evaluating the effectiveness of neural network models in handling flower datasets with similar visual characteristics. The proposed approach is expected to support the development of intelligent flower recognition systems that can be applied in agriculture, botanical studies, and educational applications. [8]–[10], [16], [23], [25].

2. Related Works

Rosyani et al. investigated flower recognition by comparing several color models for image classification tasks [1]. The study showed that color representation significantly affected recognition accuracy because flower objects strongly depended on color characteristics. The researchers found that certain color spaces improved object separation better than others under controlled lighting conditions. The main strength of the study lay in its detailed comparison of color feature extraction techniques. However, the method still relied heavily on handcrafted features and traditional image processing approaches. The system also showed sensitivity to illumination changes and complex backgrounds. As a result, the model had limited robustness when applied to more diverse flower image datasets. [1]

Krizhevsky et al. introduced AlexNet and demonstrated the effectiveness of deep convolutional neural networks in large-scale image classification tasks [8]. The study achieved a major breakthrough in ImageNet competitions by significantly reducing classification errors compared with conventional machine learning methods. The architecture utilized multiple convolutional layers and GPU acceleration to improve feature learning performance. The study proved that CNN models automatically extracted hierarchical image features without manual engineering. Its main strength was the ability to learn complex visual patterns directly from raw images. However, AlexNet required large datasets and high computational resources during training. These limitations became challenging for smaller datasets and limited hardware environments. [8]

Simonyan and Zisserman proposed the VGGNet architecture to improve CNN performance through deeper convolutional layers [10]. Their work demonstrated that increasing network depth enhanced image recognition accuracy and feature representation capability. The study became one of the most influential works in deep learning because of its simple yet effective architecture design. VGGNet successfully captured fine-grained visual details in image classification tasks. This strength made the model suitable for recognizing objects with similar appearances, including flowers and plant species. However, the architecture required large memory consumption and long training times due to its massive number of parameters. The computational complexity also limited its efficiency for lightweight applications. [10]

Pratiwi et al. implemented a CNN-based flower scanner system for automatic flower recognition [23]. The study showed that CNN effectively recognized flower images by learning petal patterns, shapes, and color distributions automatically. The proposed system improved recognition accuracy compared with traditional feature extraction methods. The researchers highlighted the capability of deep learning models in handling complex flower image characteristics. The study also demonstrated the practical implementation of CNN in flower-related applications. However, the dataset size remained relatively limited, which potentially reduced model generalization ability. In addition, the study did not extensively evaluate the effect of environmental variations such as lighting and background complexity on classification performance. [23]

Rozaqi et al. applied CNN methods for potato leaf disease detection using image processing techniques [16]. The study successfully classified several disease categories with high accuracy despite the visual similarity between leaf patterns. The researchers demonstrated that CNN effectively extracted texture and shape features from agricultural images. The study contributed valuable insights into plant-related image classification problems that shared similarities with flower recognition tasks. Its main strength was the ability to recognize subtle visual differences among classes. However, the model performance still depended heavily on dataset quality and image consistency. The study also lacked analysis regarding model performance under real-world environmental conditions. [16]

Wardani and Leonardi developed a CNN-based model for grape leaf disease classification [20]. The study reported strong classification accuracy and demonstrated that deep learning methods outperformed conventional machine learning techniques in plant image recognition. The researchers emphasized the importance of convolutional layers in capturing local visual features such as texture and disease spots. The study showed that CNN models effectively handled complex image patterns and inter-class similarities. However, the system still encountered challenges when processing images with overlapping objects and inconsistent lighting conditions. The study also did not explore lightweight architectures for computational efficiency. [20]

Putra et al. investigated corn leaf disease classification using convolutional neural networks [17]. The study demonstrated that CNN models effectively distinguished disease categories with visually similar symptoms. The researchers showed that deep learning approaches reduced dependency on manual feature extraction processes. The main strength of the work was its ability to improve recognition accuracy through automatic feature learning. However, the study primarily focused on disease classification and did not evaluate broader object recognition problems such as flower species identification. Furthermore, the dataset diversity remained limited, which potentially affected the robustness of the trained model. [17]

Howard et al. introduced MobileNet as an efficient CNN architecture for mobile and embedded vision applications [25]. The study proposed depthwise separable convolutions to reduce computational complexity while maintaining competitive classification accuracy. MobileNet became widely adopted because it balanced performance and efficiency effectively. The architecture demonstrated strong potential for lightweight image recognition systems with limited computational resources. This advantage became highly relevant for practical flower recognition applications deployed on mobile devices or embedded systems. However, MobileNet generally produced slightly lower accuracy than deeper architectures such as VGGNet and ResNet in highly complex classification tasks. The trade-off between efficiency and recognition performance remained one of the key limitations of the approach. [25].

3. Proposed Method

1. Dataset

This study utilized 12 species from two families and software to process the dataset and the proposed method for testing using WeKa 3.8.3. The flower image material used in this study is a flower image dataset that researchers obtained from previous research which consists of 2 types of flowers, namely lilies and ester flowers.

Figure 1. Lilies and Esther Flowers

The research design serves as a pre-designed guideline. If the research implementation encounters any obstacles, the research design needs to be reviewed to determine which processes can be improved or developed to achieve objective research results. The design flow for this research is shown

2. Proposed Method

This study utilizes an ANN combined with k-Fold Cross-Validation to improve model reliability and evaluate generalization performance. The dataset is divided into (k) subsets, where one subset is used as testing data and the remaining subsets are used for training. This process is repeated k times until all subsets have been used as testing data. The average performance is calculated as:

$$CV_{score} = \frac{1}{k}\sum_{i=1}^{k} Acc_i \tag{1}$$

where Acc_i represents the accuracy obtained in the i-th fold and k denotes the total number of folds. The ANN model processes the input feature vector using weighted summation:

$$z = \sum_{i=1}^{n} w_i x_i + b \tag{2}$$

The neuron output is activated using the sigmoid activation function:

$$f(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

For classification, the model minimizes the categorical cross-entropy loss function during training:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \quad (4)$$

where y_i denotes the actual label and $\hat{y}_i$ represents the predicted probability. The final model performance is evaluated using the average results from all cross-validation folds to ensure stable and unbiased flower recognition performance.

This study uses secondary image data collected from previous research. We utilize a dataset consisting of two flower categories, namely lily flowers and ester flowers, as input data for the classification process. Before training the model, we perform image preprocessing to standardize data quality and improve the effectiveness of feature learning in the classification stage. This study applies the NN method to classify flower images and achieve better accuracy compared with previous studies. The model learns visual patterns from the flower images and predicts the corresponding flower category. Furthermore, we analyze the classification results to evaluate the performance of the proposed model. We use the evaluation results as the basis for measuring classification accuracy and drawing conclusions regarding the effectiveness of the proposed method.

4. Result and Analysis

In this study, there are several color models that are usually used such as RGB (Red, Green, Blue), YcbCr (Luminance Chrominance_Blue Chrominance_Red), HSV (Hue Saturation Value), XYS, LAB (Luminance A and B), and CMY colors, but among the various color models, there is certainly the best one based on the highest level of accuracy in the process of flower recognition based on this color feature. Therefore, the author compares 4 color models for flower color recognition, namely RGB (Red, Green, Blue), HSV (Hue Saturation Value), LAB (Luminance A and B), and YcbCr (Luminance Chrominance_Blue Chrominance_Red).

Table 1. Accuracy Comparison of Color Models Using Neural Network with Cross-Validation

No	Color Model	Cross-Validation Folds					Nilai Max	Nilai Min
		10	20	30	40	50		
1	HSV	90.5263	93.6842	91.3158	92.3684	91.0526	93.6842	90.5263
2	RGB	96.8421	95.5263	96.5789	96.5789	96.0526	96.8421	95.5263
3	LAB	96.0526	96.5789	95	96.8421	96.8421	96.8421	95
4	YcbCr	94.2105	95.7895	95.2632	96.3158	95.5263	96.3158	94.2105
Nilai Max dan Min							96.8421	90.5263

Table 1 presents the classification accuracy results obtained from four color models, namely HSV, RGB, LAB, and YCbCr, using the Artificial Neural Network (ANN) method with different cross-validation folds. The results show that the RGB color model achieves the highest and most stable performance among all tested models. The RGB model obtains accuracy values ranging from 95.5263% to 96.8421%, with the highest accuracy achieved at 10-fold cross-validation. The LAB model also demonstrates competitive performance, producing maximum accuracy of 96.8421% at 40-fold and 50-fold cross-validation. Meanwhile, the YCbCr model achieves accuracy values between 94.2105% and 96.3158%, indicating good classification capability but slightly lower stability compared with RGB and LAB.

In contrast, the HSV color model produces the lowest classification performance among all evaluated models. The HSV model achieves accuracy values ranging from 90.5263% to 93.6842%, indicating that this color representation is less effective for distinguishing flower image characteristics in this study. Overall, the experimental results demonstrate that color representation significantly affects Neural Network classification performance. The RGB model provides the best overall accuracy with a maximum value of 96.8421%, while the lowest accuracy value recorded in the experiments is 90.5263% using the HSV model. These findings indicate that RGB and LAB color models are more suitable for flower recognition tasks using ANN-based classification.

Table 2. Accuracy Comparison of Color Models Using Percentage Split Testing

No	Color Model	Percentage Split					Nilai Max	Nilai Min
		10 %	20 %	30 %	40 %	50 %		
1	HSV	71.6374	84.8684	87.5940	86.8421	86.8421	87.5940	71.6374
2	RGB	78.0702	91.7764	93.6090	95.5439	96.3158	96.3158	78.0702
3	LAB	80.4094	92.1053	93.2331	92.1053	93.1579	93.2331	80.4094
4	YcbCr	78.9474	92.4342	93.9850	92.1053	94.2105	93.985	78.9474
Nilai Max dan Min							96.3158	71.6374

Table 2 presents the classification accuracy results of the Neural Network model using four different color models, namely HSV, RGB, LAB, and YCbCr, under several percentage split testing scenarios. The experimental results show that the RGB color model achieves the best overall performance compared with the other color models. The RGB model produces accuracy values ranging from 78.0702% to 96.3158%, where the highest accuracy is obtained at the 50% percentage split scenario. The YCbCr model also demonstrates strong performance, achieving a maximum accuracy of 94.2105%, followed by the LAB model with a maximum accuracy of 93.2331%. These results indicate that RGB, LAB, and YCbCr color representations effectively capture important visual characteristics of flower images for the classification process.

Meanwhile, the HSV color model produces the lowest performance among all evaluated color models. The HSV model records accuracy values between 71.6374% and 87.5940%, indicating lower consistency and weaker classification capability compared with the other models. The overall results demonstrate that the selection of color models significantly influences the performance of the Neural Network classifier. The highest accuracy value achieved in this experiment is 96.3158% using the RGB model, while the lowest accuracy value is 71.6374% using the HSV model. These findings suggest that RGB and YCbCr provide more effective color information for flower recognition tasks using ANN-based classification methods.

5. Conclusion

This paper utilizes the Artificial Neural Network (ANN) method to classify flower images using four different color models, namely HSV, RGB, LAB, and YCbCr. We apply two evaluation approaches, including cross-validation folds and percentage split testing, to measure the classification performance and model consistency. Based on the experimental results, the RGB color model achieves the best overall performance in both evaluation scenarios. In the cross-validation experiment, the RGB model obtains the highest accuracy value of 96.8421%, while in the percentage split experiment, the RGB model achieves the highest accuracy of 96.3158%. These results indicate that the RGB color representation effectively captures important visual characteristics of flower images and provides more stable classification performance compared with the other color models.

We also demonstrates that the selection of color models significantly influences Neural Network classification performance. The LAB and YCbCr color models show competitive results with relatively high accuracy values, indicating that both models can preserve useful color information for flower recognition tasks. However, the HSV model consistently produces the lowest performance in both experiments, with minimum accuracy values of 90.5263% in cross-validation and 71.6374% in percentage split testing. These findings suggest that the HSV representation is less suitable for distinguishing flower image characteristics in this study. Furthermore, we observe that larger percentage split scenarios generally improve classification accuracy because the model learns more representative training patterns from the dataset.

Our proposed model successfully produces a flower recognition model with high classification accuracy using the ANN method. We demonstrate that ANN can effectively learn flower image patterns and perform accurate classification when combined with an appropriate color representation model.

Among all evaluated models, RGB provides the best balance between accuracy and stability, making it the most suitable color model for this flower recognition task. The findings of this study contribute to the development of image-based flower classification systems and provide useful references for future research involving Neural Network methods and color feature extraction techniques.

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