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Performance evaluation of the multiclass classification of flowers on diverse datasets

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***Abstract*—The accurate classification of flowers plays an important role in our life and researches. Due to the high variation of types and species of flowers, the classification is a challenging task. So far, several classification methods have been proposed. However, the accuracy of the flower classification still needs to be investigated and improved. The paper presents the performance evaluation of flower classification. Both handcrafted feature extraction, traditional machine learning classifiers (e.g., k Nearest Neighbors, Support Vector Machine and Random Forest) and deep neural networks (e.g., Alexnet, Resnet, Inception and Densenet) have been employed to improve the accuracy of the classification. The strategies of using the data augmentation are applied to improve the performance of the classification. The classification methods have been evaluated on four public datasets (Oxford-17, Oxford-102, Kaggle-5 and Iris flower datasets) to compare and analyse the strengths and weaknesses.**

***Index Terms*—Flower classification, Machine learning, Deep neural network, Data augmentation**

I. INTRODUCTION

Flowers play an important role in our life. They support our daily life in the food and pharmaceutical chains. Therefore, having good knowledge and understanding of flowers is necessary. However, each type of flowers has specific color and properties. Some rare flowers look similar and the classification of them is difficult. In some cases, we need expert knowledge to distinguish flowers with high accuracy.

In recent years, the need of automatic classification of flowers by machines becomes more and more necessary (e.g., in smart farming systems). The flower classification aims to categorize flower images based on collected data automatically. However, many challenges exist in the classification of flowers. The difficulties of the flower classification can be mentioned as follows:

- Due to various conditions of image acquisition, flower images can be blur, skew or shadow. Therefore, the flower classification with high accuracy is a non trivial task.
- There exists many classes of flowers and many species of a specific flower. Actually, more than 250,000 known species of flowers exist and they can be classified into about 350 families [1]. Some flowers have similar properties (color and geometry). Therefore, the classification may not be accurate. Fig 1. and 2 demonstrate some classes of flowers.
- The complex backgrounds and overlapped objects (grasses or leaves) in flower images may cause the miss-classification.

Traditional classification methods relied on the low-level feature extraction in flower images and then some classifiers are employed to discriminate flowers [2], [3]. The methods may perform correctly in some cases, however, the accuracy of the classification needs to be improved. In recent years, with the advances of computer vision and deep neural networks (DNNs) techniques, the accuracy of the flower classification is much improved. The paper analyzes and performs the classification of flowers using both handcrafted feature extraction and deep neural networks on large and public datasets. The contributions of the paper are threefold:

(1) We applied and compared the performance of both handcrafted feature extraction and deep neural networks to classify flower images.

(2) To improve the performance of traditional classifiers and DNN models, we apply the augmentation techniques of input flower images.

(3) We evaluate and compare the performance of various flower classification methods on four flower datasets to show the strengths and weaknesses of the methods.

II. RELATED WORK

This section reviews the main approaches of the classification of flowers. Traditional methods attempted to design

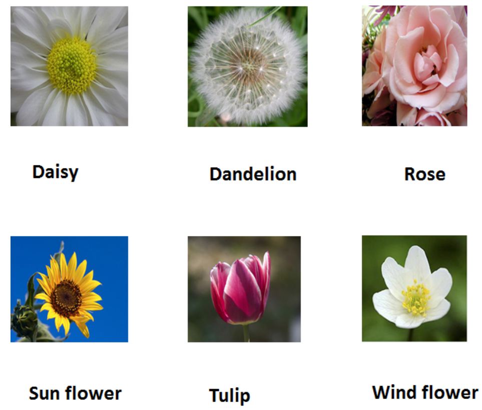

Fig. 1. Examples of different classes of flowers.

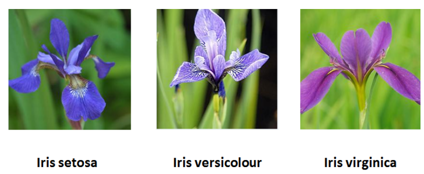

Fig. 2. Examples of different species of Iris flowers.

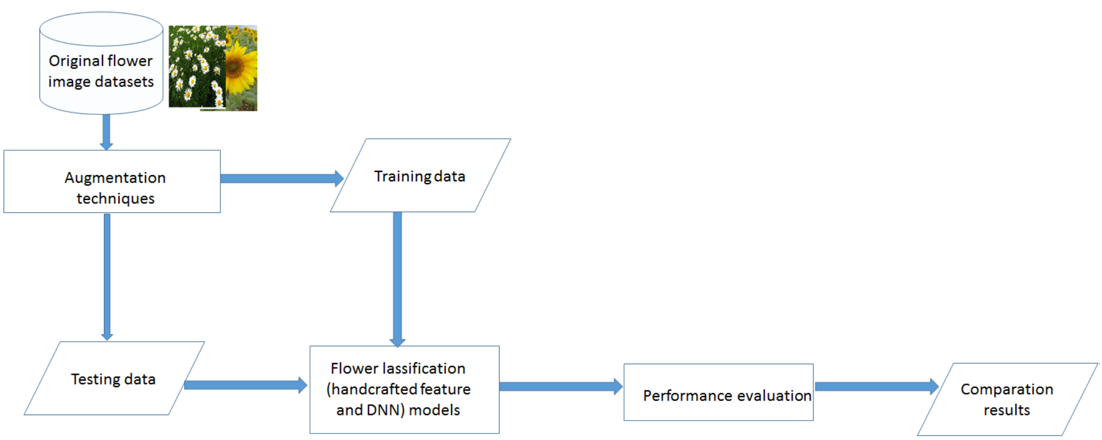

Fig. 3. Flowchart of the performance evaluation of the classification of flowers.

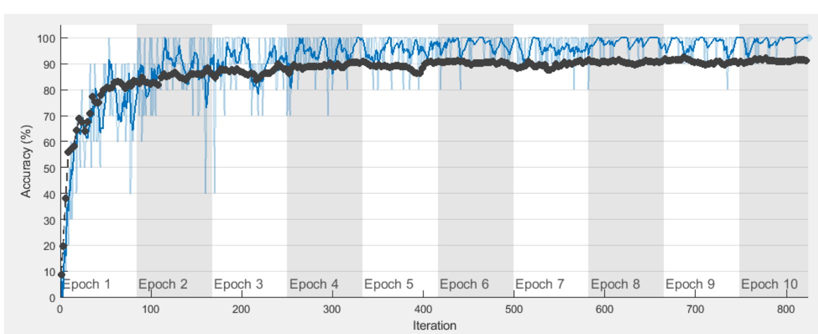

Fig. 4. Accuracy values during the training process of the Alexnet.

feature extraction techniques based on image processing techniques [3]. Then, the methods fine-tuned several classifiers to

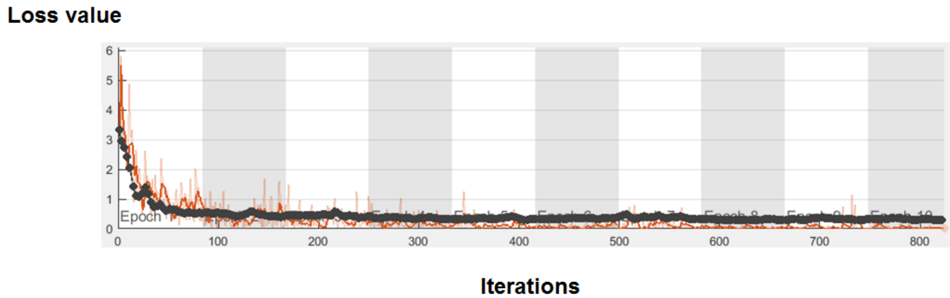

Fig. 5. Loss values of the training process of Alexnet.

classify flowers. In recent years, several deep neural networks (DNNs) are applied and optimized to improve the performance of the classification of flowers. The DNNs enable to classify flowers in an end-to-end way without the specific domain knowledge [4].

A. Traditional handcrafted feature extraction and machine learning classifiers

The work in [2] proposes four different features (e.g. shape/texture, shape of the boundary, colour features) of flowers for the classification purpose. Then, the multiple kernel framework with Support Vector Machine (SVM) classifier is applied. The obtained classification accuracy is 88.33% on the Oxford-102 flower dataset.

The work in [3] extracts color and textual features of flowers. Then, the multi layer perceptron (MLP) is used to classify flower images. The performance evaluation is performed on a private dataset.

In the study [5], the fine-grained classification was proposed on the two datasets that are Oxford-7 and Oxford-102 flower datasets. The work gained the accuracy of 93.14% and 79.1% on the Oxford-17 and Oxford-102 flower datasets, respectively.

B. Deep neural networks

In 2017, the work in [6] applied the Google's pre-trained Inception-v3 network for the flower classification. They obtained the classification acuracy of 95% and 94% on the Oxford-17 and Oxford-102 flower datasets, respectively. The work in [1] firstly segments flower regions in images to improve the quality of images. Then, a CNN is proposed to classify flowers.

More recent, the work in [4] investigates neural networks with the attention mechanism to improve the accuracy of the flower classification.

III. Proposed system

The overall framework of our proposed system is described in Fig. 3. The framework consists of the following steps:

(1) One of the difficulties in the flower classification is the lack of datasets. Moreover, the number of flower species is imbalanced. Therefore, the augmentation techniques based on image processing are applied for input datasets to increase and balance the number of input images. Fig. 6 demonstrates the augmentation techniques based on image processing. The original datasets are enlarged using the rotation and noise addition techniques.

Fig. 6. The augmentation techniques using the rotation and noise addition image processing.

(2) A wide range of multiclass classification methods of flowers are applied and compare. Both of the handcrafted feature and deep neural networks are investigated and fine-tuned for the classification purposes.

(3) The methods are evaluated and compared on four public datasets to point out the strengths and weaknesses of each method.

A. The classification of flowers using handcrafted feature extraction and machine learning classifiers

1) Handcrafted feature extraction: In the section, several handcrafted feature extraction techniques are applied to extract visual features of flower images such as: Scale-invariant feature transform (SIFT) [10], Histogram of gradient (HOG) and Discrete Wavelet Transformation (DWT) feature extraction.

2) Machine learning classifiers: After obtaining visual features, several classifiers are fine-tuned to categorize flower images into classes: such as SVM, k Nearest Neighbors (kNN) and Random Forest (RF) [11]. The process of the classification using the handcrafted feature extraction and machine learning classifiers is shown in Fig. 7.

B. The classification of flowers using deep neural networks

In the paper, advanced DNNs have been applied and fine-tuned to classify flower images in an end-to-end way. The feature extraction and classification are performed by using DNNs including Alexnet [7], Resnet [8], Inception and Densenet [9]. Detail information of the DNNs is described in Table I. Fig. 4 and 5 demonstrate the accuracy and the loss values of the Alexnet during the training process. Input flower images are

TABLE I.
STRUCTURAL INFORMATION OF DNNS

DNNs	Number of layers	Sizes of input images	**Number of extracted features**
Alexnet [7]	25	227x227x3	4096
Resnet-50 [8]	50	224x224x3	512
Densenet-201 [9]	201	224x224x3	1000
Inception-v3 [6]	48	299x299x3	1000

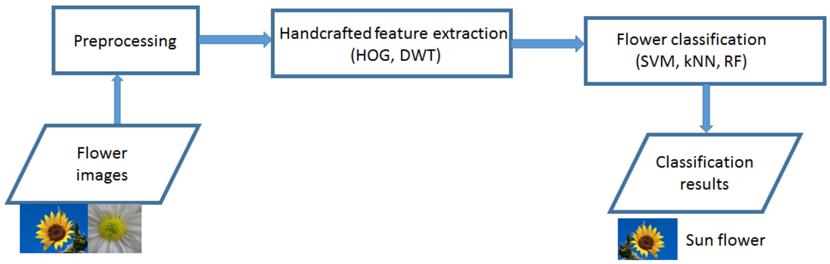

Fig. 7. Flowchart of the classification of flowers using handcrafted feature extraction.

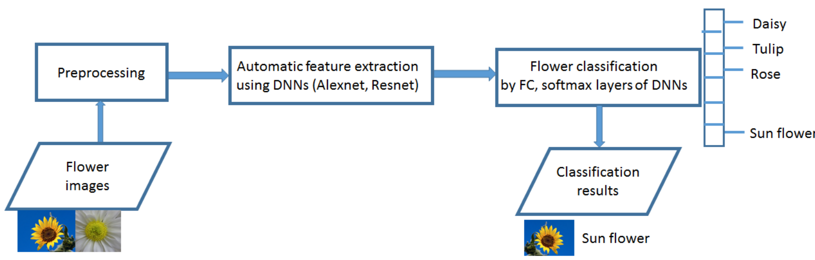

Fig. 8. Flowchart of the classification of flowers using DNNs.

resized as the requirement of the DNNs. The implementation of the DNNs is supported by the Matlab 2021b environment with the 8GB RAM and core-i5 processor. The process of the classification using the DNNs is shown in Fig. 8.

IV. EXPERIMENTAL RESULTS

A. Datasets and evaluation metric

1) Datasets: We performed the evaluation of framework on four public datasets. The Kaggle-5 flower [12] dataset consists of about 800 images (5 species of flowers). The Oxford-17 flower dataset [13] consists of 80 images in which 70 images for training and 10 images for testing (17 species of flowers). The Oxford-102 flower dataset [2] consists of 80 images in which 70 images for training and 10 images for testing (102 species of flowers). The Iris flower dataset consists of 80 images for each kind of Iris flower. Detail information of the datasets is shown in table II. Fig. 9, 10 and 11 show the information of classes of flowers in the Oxford-102, Oxford-17 and Iris datasets, respectively.

2) Evaluation metric: For the performance evaluation, the precision (P), recall (R) and F1 score metrics are widely applied for the classification classification task. Mathematically, F1 score is the harmonic mean of precision and recall. The score can be calculated as follows:

$$F1 - score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (1)$$

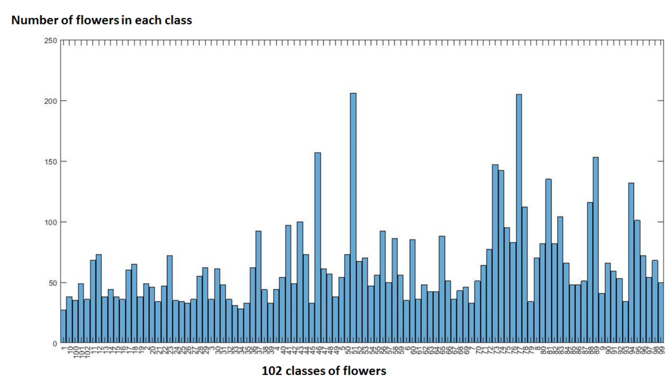

Fig. 9. Number of flowers of each class in Oxford-102 dataset.

B. Performance evaluation of various flower classification methods

As our results, the classification of flowers using the Densenet achieves the highest accuracy thanks to the powerful network architecture. The classification of DNNs obtain higher accuracy than those of handcrafted feature extraction. The data augmentation technique allows the DNNs performs better. The HOG feature extraction gains better results compared to the DWT feature extraction. Tables III, IV, V and VI compare the performance of various classification methods on the four

TABLE II.
STATISTIC INFORMATION OF FLOWER DATASETS.

Dataset	Number of classes of flowers	Training (Number images)	Testing (Number images)
Kaggle-5 flower dataset	5	500 / class	250 / class
Oxford-17 flower dataset	17	60 / class	20 / class
Iris flower dataset	3	50 / class	35 / class
Oxford-102	102	50 / class	35 / class

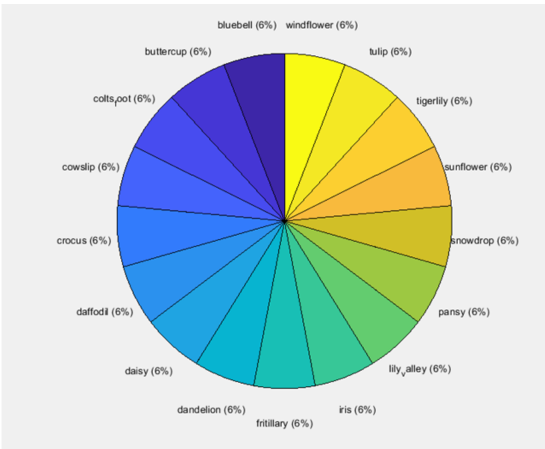

Fig. 10. Percentage of flower classes in the Oxford-17 dataset.

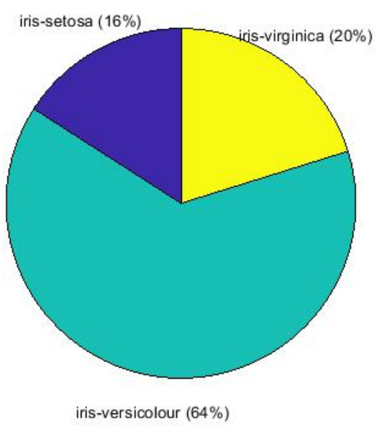

Fig. 11. Percentage of flower classes in Iris dataset.

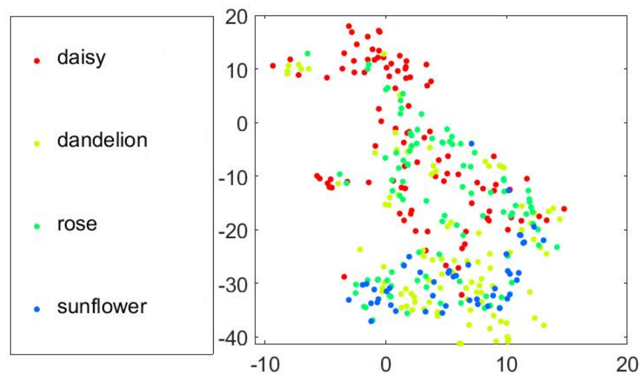

Fig. 12. Feature visualization of flower classes in the Kaggle-5 dataset extracted by Alexnet

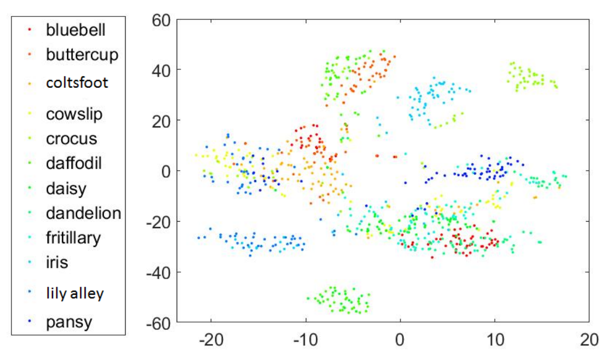

Fig. 13. Feature visualization of flower classes in the Oxford-17 dataset extracted by Alexnet

datasets. However, the execution time of DWT is better than other methods. Fig. 14 shows examples of the classification of flowers in the Oxford-17 dataset. The classification of flowers in the Oxford-102 dataset is the most challenging. Therefore, the obtained results are lowest. In contrast, the accuracy of the classification of flowers on the Iris datasets is the highest.

To visualize the distribution of extracted features, the t-distributed stochastic neighbor embedding (t-SNE) dimensional reduction [14] is applied to reduce the extracted features of flower images by Alexnet. Alexnet extracts 4096 visual features of images, then the number of features are reduced to 2. The t-SNE aims to reduce the number of features to efficiently display extracted features. Fig. 12 and 13 demonstrate the feature distribution of the Kaggle-5 and Oxford-17 flower datasets. As shown in the figures, the classes of flowers can be possibly separated for the classification using the extracted features.

Some errors in the flower classification can be caused by the following reasons: (1) Some flower images are blur. (2) Several flower images contain background and grasses. The

Fig. 14. Examples of the classification of flowers in Oxford-17 flower dataset

TABLE III.
PERFORMANCE COMPARISON OF THE CLASSIFICATION OF FLOWERS ON THE OXFORD-17 FLOWER DATASET.

Methods	P	R	F1
HOG and SVM	41%	39%	39.98%
DWT and kNN	35%	33%	33.97%
SIFT and RF	44%	41%	42.45%
Alexnet	91%	89%	89.99%
Inception-v3	93%	92%	92.50%
Resnet-50	95%	93%	93.99%
Densenet-201	96%	94%	94.99%

factors cause the miss-classification.

V. CONCLUSION AND FUTURE WORKS

The paper has presented the performance evaluation of the classification of flowers. Both handcrafted feature extraction and deep neural network methods are applied. The performance evaluation is carried out on four public datasets. The experimental results show that the advanced neural networks outperform traditional handcrafted feature extraction methods. The data augmentation techniques allow to obtain higher performance. In the future, the flower classification methods can be considered to integrate with internet of thing (IoT) systems to support real applications of intelligent agriculture.

TABLE IV.
PERFORMANCE COMPARISON OF THE CLASSIFICATION OF FLOWERS ON THE OXFORD-102 FLOWER DATASET.

Methods	P	R	F1
HOG and SVM	40%	38%	38.97%
DWT and kNN	33.4%	31.6%	32.48%
SIFT and RF	43%	40%	41.45%
Alexnet	89%	86%	87.47%
Inception-v3	90.5%	88.5%	89.49%
Resnet-50	93%	91%	91.99%
Densenet-201	94%	92%	92.99%

TABLE V.
PERFORMANCE COMPARISON OF THE CLASSIFICATION OF FLOWERS ON THE KAGGLE-5 FLOWER DATASET.

Methods	P	R	F1
HOG and SVM	45%	40%	42.35%
DWT and kNN	39%	37%	37.97%
SIFT and RF	48%	45%	46.45%
Alexnet	92%	89%	80.45%
Inception-v3	93%	91%	91.99%
Resnet-50	94%	92%	92.99%
Densenet-201	97%	95%	95.99%

TABLE VI.
PERFORMANCE COMPARISON OF THE CLASSIFICATION OF FLOWERS ON THE IRIS FLOWER DATASET.

Methods	P	R	F1
HOG and SVM	46.5%	41%	43.58%
DWT and kNN	42%	39%	40.44%
SIFT and RF	51%	48.5%	49.72%
Alexnet	92.5%	89.5%	90.98%
Inception-v3	94%	92.5%	93.24%
Resnet-50	94.5%	93%	93.74%
Densenet-201	97.5%	95.5%	96.49%

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