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IMPROVEMENTS OF FLOWER CLASSIFICATION USING DEEP NEURAL NETWORKS WITH VARIOUS SOLVER OPTIMIZATION ALGORITHMS

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Abstract:

Flowers hold significant importance across various fields due to their multifaceted roles and impact, such as agriculture manufacturing and pharmacological research. Therefore, the precise classification of flowers has extensive implications in real life and has attracted more and more researchers. However, the accuracy of the classifiers still needs to be improved. In this work, we present an enhancement in the pipeline of flower image classification, where some state-of-the-art models are performed and compared. In our proposed process, we fine-tuned various Deep neural network models (DNNs) to classify flower images. To improve the accuracy of the classifier, various optimization algorithms are performed and evaluated. We also implemented some traditional approaches to compare the efficiency of classification methods. These methods are evaluated on four public datasets (Oxford-17, Oxford-102, Kaggle-5, and Iris flower datasets). The experimental results showed that the Densenet-121 network combined with the RMSProp optimizer had a competitive advantage in terms of accuracy compared with traditional approaches.

Keywords:

Flower classification, Machine learning, Deep neural network, Data augmentation

1. Introduction

Flowers hold significant importance across various fields due to their multifaceted roles and impact, such as agriculture manufacturing, and pharmacological research [1]. The precise classification of flowers, in particular, has garnered considerable attention from the research community due to its ubiquity in real-world industrial scenarios. Due to the high variety of species of flowers, flower classification is a complex task due to the wide range of flower classes that share similar features: shape, color, and appearance [2]. Recently, with the advances in computer vision and artificial intelligence (AI), automatic classification has become an attractive research area [3]. Based on collected data on flowers, machines can predict the species of flowers without using human knowledge [4]. With the diversity of flower data sets collected, the demand for the most optimal solution has become widespread. In the paper, we present a framework to improve the accuracy of well-known classification models. Within the proposed framework, various deep neural networks (DNNs) are fine-tuned to improve the classification accuracy of flowers. Additionally, various optimization algorithms are performed and evaluated to optimize the DNNs. Our empirical tests on various data sets underscore the efficacy of our framework.

The contributions of our work are threefold.

(1) Several advanced deep neural networks (Alexnet, Resnet, Mobilenet and Densenet-121) are applied to classify flower images. (2) Solver algorithms are performed to improve the accuracy of the classification. We especially focus on the most common algorithms including Stochastic Gradient Descent with Momentum (SGDM), Root Mean Square Propagation (RMSProp) and Adam [5]. (3) We evaluate and compare the performance of various flower classification methods on four flower datasets to show the strengths and weaknesses of several methods.

2 Related work

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

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feature extraction techniques based on image processing techniques [6]. Then, the methods fine-tuned several classifiers to classify the flowers. In recent years, several deep neural networks (DNNs) have been applied and optimized to improve the performance of the classification of flowers. The DNNs enable to classification of flowers in an end-to-end way without the specific domain knowledge [3], [7].

2.1 Traditional handcrafted feature extraction and machine learning classifiers

The work in [4] proposes four different features (e.g. shape/texture, the shape of the boundary, color features) of flowers for classification purposes. 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 [6] 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 [8], 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.

2.2 Deep neural networks

In 2017, the work in [2] applied Google's pre-trained Inception-v3 network for flower classification. They obtained the classification accuracy 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. Recently, the work in [3] investigates neural networks with the attention mechanism to improve the accuracy of flower classification.

3 Proposed system

The overall framework of our proposed system is described in Figure 1.

The framework consists of the following steps:

(1) One of the difficulties in 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 [9]. Figure 2 demonstrates the augmentation techniques based on image processing.

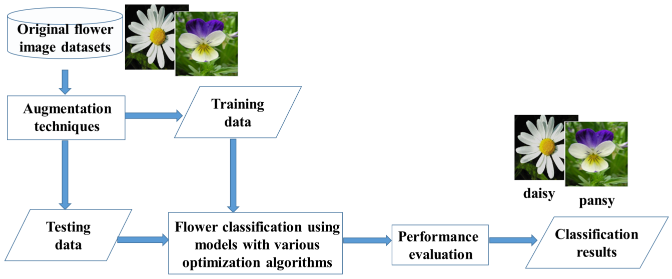

FIGURE 1. Flowchart of the proposed method for the flower classification.

FIGURE 2. The data augmentation using image processing. Original image is rotated and added Gausian and pepeper noises.

(2) A wide range of multiclass classification methods of flowers are applied and compared. Both of the handcrafted feature and deep neural networks are investigated and fine-tuned for classification purposes. Various DNN optimization algorithms have been investigated, including Adam and SGDM [5] to improve the classification accuracy.

(3) The method is evaluated and compared on four public datasets to highlight the strengths and weaknesses of each method.

3.1 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 is performed by using DNNs including Alexnet [10], Resnet [11], Inception and Densenet-121 [12]. Detail information of the DNNs is described in Table 1. Figures 3 and 4 demonstrate the accuracy and the loss values of the Alexnet during the training process. Input flower images are 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. 5.

TABLE 1. Structural information of DNNs

DNNs	Layers	Input images	**Features**
Alexnet [10]	25	227x227x3	4096
Resnet-50 [11]	50	224x224x3	512
Densenet-121 [12]	201	224x224x3	1000
Inception-v3 [2]	48	229x229x3	1000

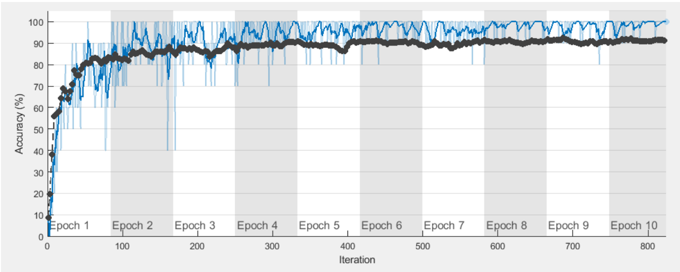

FIGURE 3. Accuracy values during the training process of the Alexnet.

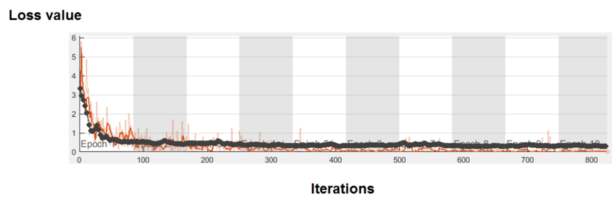

FIGURE 4. Loss values of the training process of the Alexnet.

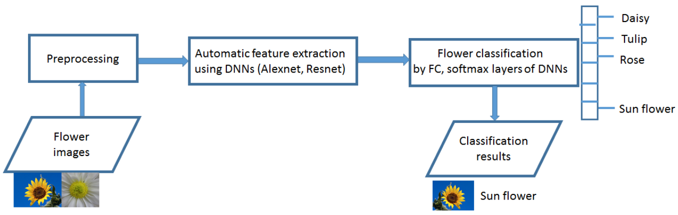

FIGURE 5. Flowchart of the classification of flowers using DNNs.

3.2 The application of solver algorithms to improve the classification accuracy of flower images

In this section, we highlight the most extensively used optimization algorithms such as SGDM, RMSProp and Adam.

Stochastic Gradient Descent (SGD) is a variant of the Gradient Descent algorithm that addresses the computational inefficiency of traditional Gradient Descent methods when dealing with large datasets in practical machine learning problems [13–15]. In [16], they combined a flower segmentation approach with the SGD optimizer to classify flower images. Their method is evaluated on three well-known flower datasets. However, the SGD does not reach the global optimum; instead, it only reaches the local optimum. In the SGDM, a momentum term is added to the regular SGD to overcome the limitation of the SGD algorithm. This term helps accelerate SGD in the relevant direction and dampens oscillations. But if there is a high momentum after reaching the global minimum point, it is still fluctuating and takes some time to get stable at the point.

RMSprop [17] is an algorithm that fixes the issue of slow convergence in the SGDM by adaptively scaling the learning rate for each parameter. During the learning process, a moving average of the squares of gradients for each weight is maintained and the learning rate is divided by this average. It helps stabilize the learning process and prevents oscillations in the optimization trajectory. By adapting the learning rate for each parameter, RMSProp can handle different scales of data and varying curvatures of loss functions. This algorithm can converge faster than SGDM, especially in scenarios with noisy or sparse gradients.

Adam [17] is a first-order gradient-based optimization algorithm that is appropriate for stochastic objective functions. It estimates lower-order moments adaptively and customizes the learning rate based on its gradient history. This customization helps the neural network learn more efficiently. The Adam combined with DNNs is straightforward to implement due to only requiring first-order gradients. Moreover, one of Adam's advantages is that it requires storing just the first and second moments of the gradients, therefore, keeping little memory requirements. Adam is widely used in the deep learning domain due to its rapid training convergence for high-dimensional parametric models.

These algorithms are commonly used in other DNN-based applications such as image classification, object detection, segmentation, LSTMs and transformers for language modeling. For example, both SGDM and Adam are used in [18, 19] to detect and classify common diseases in rice plants. In [20], the authors showed that SGDM helps improve the performance of the citrus diseases classification model significantly. However, we admit that no optimization algorithm, including Adam, is guaranteed to work best for all problems. Thus, the main motivation behind this study is to compare various optimization algorithms to find the appropriate algorithm for solving the considered problem without the need for human intervention. The best algorithm is implemented in the proposed framework and tested on various data sets.

4 Experimental results

4.1 Datasets and evaluation metric

4.1.1 Datasets

The proposed method has been evaluated on four public datasets. The first dataset is the Kaggle-5 [21] that consist of 800 images of 5 species of flowers. The second dataset is the Oxford-17 flower [22] that consists of 80 images for each kind of flowers. There are 17 species of flowers in the dataset. The third dataset is the Oxford-102 [4] consists of 80 images for each kind of flowers. There are 102 species of flowers in the dataset. Finally, the proposed method is validated on the Iris flower dataset. The dataset consists of 80 images for each kind of Iris flowers. Detail information of the datasets is shown in Table 2.

4.1.2 Evaluation metric

To obtain a clear evaluation of the proposed method, the precision (P), recall (R) and F1 score metrics are applied in the work. The F1 score is the harmonic mean of precision and recall that can be calculated as follows:

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

4.2 Performance evaluation of various flower classification methods

First, we compare various optimizer algorithms to find the appropriate algorithm for solving the considered problem. We combine classification models with optimal algorithms and test on the Oxford 102 dataset which is the most challenging dataset. Fig. 6 shows that the RMSProp algorithm gives the best results and is appropriate for DNN classification models. Tables 3, 4, 5 and 6 compare the performance of various classification methods on the four datasets. As our results, the HOG feature extraction gains better results compared to the DWT feature extraction. However, the execution time of DWT is better than other methods. The classification of DNNs obtains higher accuracy than those of handcrafted feature extraction. The data augmentation technique allows the DNNs to perform better. The classification of flowers using the Densenet-121 achieves the highest accuracy thanks to the powerful network architecture. Figure 7 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,

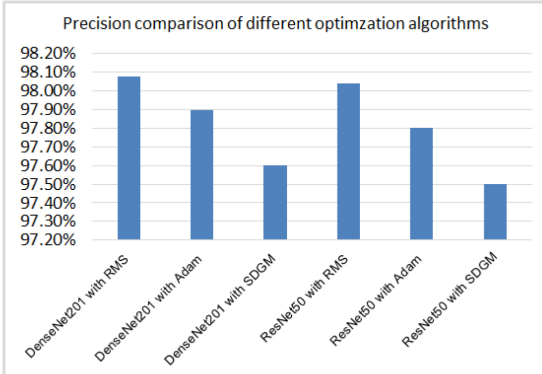

FIGURE 6. Comparison of classification accuracy of different DNNs using various optimization algorithms.

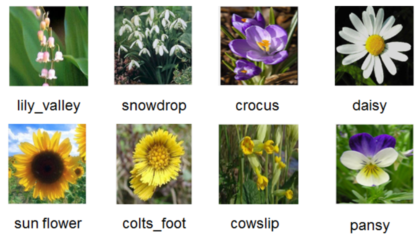

FIGURE 7. Results of flower classification in Oxford-17 flower dataset

the obtained results are lowest. In contrast, the accuracy of the classification of flowers on the Iris datasets is the highest.

We apply the t-SNE dimensional reduction [23] to reduce the extracted features of flower images by Resnet-50. The feature reduction allows to visualize the distribution of extracted features. The network extracts 512 visual features of input images, and then the number of features is reduced to three. Figure 8 demonstrates the feature distribution of the Oxford-17 flower datasets. As shown in the figure, the extracted features allow to separate the classes of flowers efficiently.

Obtained results have shown the efficiency of the classifi-

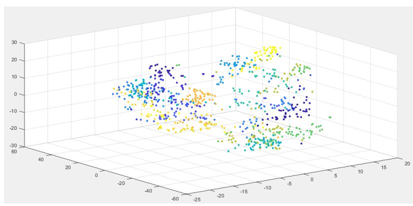

FIGURE 8. The distribution of extracted features of Oxford-17 dataset using Resnet-50. Colored dots represent the extracted featured of flowers in the dataset.

TABLE 2. Detail information of flower datasets used for the training and testing DNNs.

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

TABLE 3. Performance comparison of the classification of flowers on the Oxford-17 flower dataset.

Methods	**P**	**R**	**F1**
HOG	41%	39%	39.98%
DWT	35%	33%	33.97%
SIFT	44%	41%	42.45%
Alexnet	91%	89%	89.99%
Inception-v3	93%	92%	92.50%
Resnet-50	95%	93%	93.99%
Densenet-121	96%	94%	94.99%

TABLE 4. Performance comparison of the classification of flowers on the Oxford-102 flower dataset.

Methods	**P**	**R**	**F1**
HOG	40%	38%	38.97%
DWT	33.4%	31.6%	32.48%
SIFT	43%	40%	41.45%
Alexnet	89%	86%	87.47%
Inception-v3	90.5%	88.5%	89.49%
Resnet-50	93%	91%	91.99%
Densenet-121	94%	92%	92.99%

TABLE 5. Performance comparison of the classification of flowers on the Kaggle-5 flower dataset.

Methods	**P**	**R**	**F1**
HOG	45%	40%	42.35%
DWT	39%	37%	37.97%
SIFT	48%	45%	46.45%
Alexnet	92%	89%	80.45%
Inception-v3	93%	91%	91.99%
Resnet-50	94%	92%	92.99%
Densenet-121	97%	95%	95.99%

TABLE 6. Performance comparison of the classification of flowers on the Iris flower dataset.

Methods	**P**	**R**	**F1**
HOG	46.5%	41%	43.58%
DWT	42%	39%	40.44%
SIFT	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-121	97.5%	95.5%	96.49%

TABLE 7. Confusion matrix of the classification of flowers in Kaggle-5 dataset

Prediction	Ground truth				
	daisy	dandelion	sunflower	tulip	rose
daisy	**247**	2	1	3	0
dandelion	2	**244**	1	3	0
sunflower	0	2	**245**	3	1
tulip	0	2	0	**241**	0
rose	1	0	3	0	**249**

cation of flowers. However, some errors of the flower classification still existed: (1) Quality of some flower images are not high. (2) Several images contain complicated background, grasses and overlapped objects. The issues caused the errors of the classification. Table 7 shows the confusion matrix of the classification of flowers in Kaggle-5 dataset. As shown in the table, the classification of Rose flower obtains the highest accuracy. Meanwhile, the classification of Dandelion flower obtains the lowest accuracy.

5 Conclusion and Future Works

The paper investigates and proposes the improvements of the classification of flowers. The paper applied various DNN model with three solver algorithms. The performance evaluation is carried out on various datasets. The testing on four datasets shows that the deep neural networks obtain higher accuracy compared to traditional methods. The experimental results show that the advanced neural networks outperform traditional handcrafted feature extraction methods. The data augmentation techniques allow us to obtain higher performance. The application of various solver algorithms during training the DNNs allows to obtain higher classification accuracy. In the future, obtained results of flower classification can be developed with Internet of Things (IoT) systems. The solutions can be applied for intelligent agriculture.

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