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An Efficient Classification Algorithm on Orchid Species Based on Data Enhancement

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Abstract
In order to address the issue of low accuracy rate of current orchid type classification methods due to their similarities in the characteristics of orchid types, an effective orchid type classification method using data enhancement is suggested in this work, whose contribution depends on the utilization of data enhancement technologies, which can efficiently enhance the orchid type classification accuracy rate by providing sufficient and balanced sample sets. Specifically, in our approach, firstly, an image set of 12 orchid types containing 12,227 images is established; secondly, the characteristics of the above orchid image dataset are analyzed and studied; thirdly, the reasons for the processing difficulties are identified based on the above orchid image set; at last, some data enhancement technologies are applied to improve the classification accuracy rate of orchid types, which can also enhance the whole performance of orchid type classification. The experimental results display that our suggested classification method using data enhancement in the article can achieve a classification accuracy of 92.65% compared with the one not using data enhancement under the condition of insufficient and unbalanced image datasets.

Keywords
Orchid Types, Classification Algorithm, Data Enhancement

1. Introduction

Orchid is a general term of plants in the monocotyledonous plant family, *Orchidaceae*, belonging to the orchid genus. It is a unique flower due to its unique flower structure, which has been rated as one of the famous flowers in the world [1]. Orchid has various different species and colors, including 22,500 types of orchids, which have white, yellow, red, cyan, purple and other colors. It has a simple, quiet, elegant and noble temperament, which is therefore favored by most people [2]. Orchid has the effects of adjusting breath, relieving cough and improving eyesight, which is generally applied for chest tightness, diarrhea, persistent cough and visual impairments. However, correctly classifying orchid types generally poses a significant challenge due to their similarities in characteristics such as shape, color, texture, and so on [3]. Thus, it will be necessary to develop a more effective classification approach to achieve an accurate classification of orchid types.

The classification of orchid types has predominantly utilized various technologies to achieve an accurate categorization. For instance, approaches such as feature-extraction-based orchid classification,

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machine-learning-based orchid classification and deep-learning-based orchid classification have been proposed to fulfill the classification function of orchid types. However, existing orchid classification methods often suffer from low classification accuracy rates due to their insufficient and imbalanced sample datasets, rendering them unsuitable for an effective orchid type classification.

To settle the above issue, an effective orchid type classification method using data enhancement is proposed in this work, whose primary contribution lies in the utilization of data enhancement technologies, which can efficiently raise the orchid type classification accuracy rate by obtaining sufficient and balanced sample datasets. Specifically, in our approach, firstly, an image set containing 12 orchid types with 12,227 images is established; secondly, the characteristics existing in the above orchid images are analyzed and studied; thirdly, some reasons for the processing difficulties are found based on the above orchid image dataset; at last, some general data enhancement technologies are applied to raise the accuracy rate of orchid type classification, which can enhance orchid type classification performance. As a consequence, the above issue can be effectively addressed by our suggested approach in the article. The test results indicate that our proposed approach in the article can achieve an accuracy rate of 92.65% in classification compared with the baseline method without data enhancement under the condition of insufficient and unbalanced image datasets.

The remainder of the article is organized as follows. The related research is described in Section 2. Our methodology is introduced in Section 3. The experimental tests and results are presented in Section 4. We conclude the study in Section 5.

2. Related Research

Currently, various technologies have been employed by researchers to achieve the classification, identification and recognition functions of orchid species and other plant types, as well as demonstrating notable research advancements.

Andono et al. [4] applied supervised learning to classify 15 orchid species, achieving an accuracy of 98.13%. Chen et al. [5] combined FTIS with SSAE (Fourier transform infrared spectroscopic technique with a stacked sparse auto-encoder) for 13-orchid variety identification, with experimental validation demonstrating method effectiveness. Arwatchananukul et al. [6] implemented deep-learning-based visual recognition for *Paphiopedilum* orchids, supported by empirical results. Sabri et al. [7] utilized the color, shape and texture features of three-species orchid classification, attaining an accuracy of 82.22%. Post [8] employed multilabel classifiers with transfer learning for six-orchid feature classification, experimentally validating their approach. Susanto et al. [9] adopted HSV models and a Naive Bayes classifier to realize the quality and identification classification of shallot in size, which could realize a classification accuracy rate of 91.67%. Fu et al. [10] developed an improved model of YOLOv3-tiny to complete the detection of kiwifruit, who verified the effectiveness of their method with experimental results. Koirala et al. [11] made use of the region-based convolutional neural network (R-CNN) technology to detect mango fruit, which could achieve a F1-score of 0.89 for their method. Wang et al. [12] implemented a segmentation technology based on mask R-CNN to achieve the detection of waxberry images in an orchard environment, which could realize an average detection accuracy rate of 97%. Liu et al. [13] evaluated two deep learning neural networks, namely VGG16 and ResNet-50, to realize the recognition function of chrysanthemums, and evaluated the recognition performance of these networks in an experimental way. Chen et al. [14] applied the self-supervised learning technology to detect the growth status of orchids in greenhouses, which could achieve a recognition accuracy rate of about 98.6%. Hu et al. [15] created a self-supervised learning technology to realize an orchid classification platform, which could classify hundreds of orchid species. Fu et al. [16] proposed a CNN-based classification model GL-CNN to classify *Cymbidium* species, which realized a classification accuracy rate of 94.13%. Tsai et al. [17] developed intelligent image analysis technologies to realize the identification of common viral diseases suffered by orchids, which could realize an identification rate of 91.8%. Sarachai et al. [18] designed a hybrid model based on a small deep CNN to achieve the classification function of 52 in-house orchids, and they also verified its superiority in an experimental way. Andrio et al. [19] implemented the template matching technology to realize the classification of orchid images, which achieved an accuracy rate of about 76% in classification. Andayani and Kusneti [20] combined a support vector machine and the histogram of oriented gradients (HOG) feature technology to classify five orchid types, which could realize a classification accuracy rate of 98%. Ideastari et al. [21] utilized a ResNet-50 CNN to classify four orchid types, which could complete a classification accuracy rate of 97.75%. Chen et al. [22] applied a deep-learning-based technology to achieve the classification function of 58 orchid species, which could reach an accuracy rate of 91.4% in classification. Our previous work [23] employed the feature fusion technology to achieve the classification function of 12 orchid types, and our approach could complete a classification accuracy rate of 92.98%, while in this work [24], we implemented the transfer learning technology to realize the classification function of 12 orchid types, and this approach could achieve a classification accuracy rate of 96.16%.

Although the above methods are well-designed, the further development of more effective orchid classification methods remains necessary for improving the overall orchid type classification accuracy rate. Unlike previous classification approaches, we applied the data enhancement technology to enhance the classification accuracy rate of orchid types. Through analyses and research on internal relationships within the orchid image datasets established in this study, we developed an effective orchid classification approach utilizing the data enhancement technology, thereby improving the overall classification performance.

3. Methodology

3.1 Establishing Image Sets of Orchid Types

In this subsection, we present an image dataset comprising 12 orchid types with 12,227 images. The dataset was collected through both web sourcing and field photography, following the same acquisition methodology described in our previous works [23,24]. For the field photography component, each captured image exhibited distinct variations in their shooting background, content, angle, scale, perspective and lighting conditions. The detailed naming conventions and quantitative distribution of images across the 12 orchid species can be found in our prior publications [23,24].

3.2 Motivation for Data Enhancement

The classification of orchid types is a fine-grained image classification task, which can efficiently classify an orchid from a large number of different orchid type images. There are many different kinds of orchid species in real life, whose morphologies, shapes and colors are variable. However, there is a certain similarity in the characteristics of different kinds of orchids above in terms of their morphology and color, that is, inter-species similarity among orchid types. Fig. 1 shows the inter-species similarity between *Cymbidium faberi* and *Cymbidium ensifolium*. There are also differences in the shape, morphology and color of orchids belonging to the same orchid types, that is, intra-species variations of orchid types. Fig. 2 shows the intra-species variations of *Phalaenopsis aphrodite*.

If applying existing coarse-grained image classification algorithms directly to the classification of orchid types, it may be difficult to achieve a required classification performance. Orchid images have not only inter-species similarities and intra-species variations, but also different lighting intensities, shooting equipment, shooting angles and complex backgrounds in the real world, which lead to great classification differences in the feature extraction of orchid types because of their similar colors, textures, shapes and other features in the same images. Consequently, it is very essential to exploit an efficient orchid type classification algorithm using the data enhancement technology that can classify orchid types more accurately.

Fig. 1. Inter-species similarity between *Cymbidium faberi* and *Cymbidium ensifolium*. (a) Shapes and colors of *Cymbidium faberi*. (b) Shapes and colors of *Cymbidium ensifolium*.

Fig. 2. Intra-species variations of *Phalaenopsis Aphrodite*. (a) Oval *Phalaenopsis aphrodite*. (b) Falcate oblong *Phalaenopsis aphrodite*. (c) Rhomboid round *Phalaenopsis aphrodite*.

3.3 Processing Method based on Data Enhancement

3.3.1 Divide and preprocess orchid image datasets

To better manage the orchid image datasets described above, this article divides the orchid image dataset into training and testing sets at a ratio of 8:2. The training set contains 9,777 images, the testing set comprises 2,450 images, maintaining the same division methodology as our prior studies [23,24]. To ensure dimensional consistency, all images in the training set were normalized to 256×256 pixels, addressing variations in the original image sizes across the dataset.

3.3.2 Introduce general data enhancement method

As is widely recognized, the improvement of classification effect depends on not only the design and optimization of the network, but also data enhancement. It is easy to cause over fitting problems if the training set is insufficient and the samples are imbalanced during the training process of network models. Therefore, it becomes our important problem how to obtain more image datasets in a more efficient way when the image sets are insufficient and the samples are unbalanced. Using our proposed methodology, we employ the data enhancement technology to mitigate overfitting risks through training set expansion, thereby improving classification accuracy rate. Common data enhancement approaches include the following key technologies:

1) Vertical flip: flips the orchid images vertically along their horizontal axis;
2) Horizontal flip: flips the orchid images horizontally along their vertical axis;
3) Fancy principal component analysis (PCA): converts orchid images into three-dimensional vectors and performs PCA to obtain covariance matrices. This method calculates eigenvalues and eigenvectors from these matrices. The mathematical implementation of Fancy PCA can be represented by the following Formula (1):

$$[\mathrm{p1}, \mathrm{p2}, \mathrm{p3}][\alpha 1\lambda 1, \alpha 2\lambda 2, \alpha 3\lambda 3]\mathrm{T} \tag{1}$$

where p is the principal component eigenvector, λ is the corresponding eigenvalue, and α is a random value following a specified distribution. For an RGB orchid image, the formula generates a 3×1 vector, which is then added to new images following an RGB channel order;
4) Salt-and-pepper noise: randomly replaces pixels in an image with black/white pixels. The key parameter of this augmentation is the noise ratio, which determines the proportion of corrupted pixels;
5) Rotation: rotates an orchid image by a specified angle around its image center;
6) Random cropping: crops an orchid image randomly to specified dimensions. The processing results using different data enhancement methods are shown in Fig. 3.

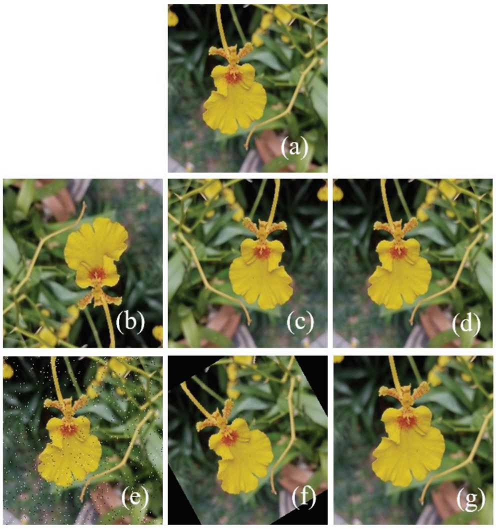

Fig. 3. Processing results using different data enhancement methods: (a) the original orchid image, (b) orchid image using the vertical flip approach, (c) orchid image using the horizontal flip approach, (d) orchid image using the Fancy PCA approach, (e) orchid image using the approach with a pepper salt noise of 0.99, (f) orchid image using the rotation approach; and (g) orchid image using the random crop approach.

3.3.3 Improved method based on data enhancement

To enhance the original training set, our approach adopts a combination of the aforementioned data enhancement strategies, which consists of the following two steps:

(a) In the first step of data enhancement process, a training set X is created by vertically flipping images of several orchid species with particularly-limited image samples, including *Cymbidium eburneum*, *Cymbidium lowianum*, *Cymbidium aloifolium*, and *Cymbidium tracyanum*.

(b) In the second step of data enhancement process, all orchid species in the training set X undergo the following transformations: a horizontal rotation, Fancy PCA with a mean of 0 and a standard deviation of 100, a salt-and-pepper noise at a signal-to-noise ratio of 0.99, and a 30° left rotation, so as to generate training set Y. Through these data enhancements, the total number of images in the training dataset is expanded from 9,777 to 56,095. Table 1 presents the distribution and quantities of both the original and enhanced training image datasets based on the data enhancement methodology.

Note that, in our proposed scheme, a random cropping process is performed before data is fed into the model. Specifically, 256×256 training images are randomly cropped to 224×224 patches, which are then input into the model for training.

Table 1. Distribution and number of original training sets and enhanced training dataset

Name of Orchid types [23,24]	Original training image sets [23,24]	Enhanced image sets X	Enhanced image sets Y
Cymbidium sinense	1,144	1,144	5,720
Cymbidium floribundum	665	665	3,325
Cymbidium kanran makino	1,217	1,217	6,085
Cymbidium ensifolium	1,240	1,240	6,200
Oncidium hybridum	767	767	3,835
Cymbidium goeringii	1,204	1,204	6,020
Cymbidium eburneum	352	704	3,520
Cymbidium lowianum	322	644	3,220
Cymbidium aloifolium	393	786	3,930
Cymbidium faberi	852	852	4,260
Phalaenopsis aphrodite	1,246	1,246	6,230
Cymbidium tracyanum	375	750	3,750
Total number of image sets	9,777	11,219	56,095

4. Experimental Test and Results

To validate the effectiveness of our method presented in this study, a series of experiments were designed in this section, which mainly included the following two key contents: the establishment of an experimental environment and parameters, and the testing and analyses of experimental results.

4.1 Establishment of an Experimental Environment and Parameters

Our experiments were executed on an Ubuntu operating system with an AMDRyzen CPU, an NVIDIAGTX GPU, a PyTorch deep learning framework, and so on. To ensure the reproducibility and consistency with our proposed methodology, we adopted the same experimental environment and parameter configurations as those described in our prior work [23,24]. For a performance evaluation, we employed classification accuracy as the primary metric under identical testing set conditions. These evaluation protocols aligned with the definitions established in our previous studies [23,24].

4.2 Testing and Analysis of Experimental Results

In this subsection, we present experimental evaluations and analyses on our proposed method. The test results are summarized in Table 2, where a classification method “a” that uses the original training sets, a classification method “b” that employs the original training sets augments with crop, a classification method “c” that uses the original training set Y with clipping operations, and a classification method “d” that incorporates the original training set X using the clipping technology are used.

Table 2 clearly shows that, the accuracy rate of only the cropping-based classification method “b”, the first stage of data enhancement plus cropping-based classification method “c” and the second stage of data enhancement plus cropping-based classification method “d” increased by 4.82%, 5.55%, and 9.18% respectively, compared with classification method “a” that does not use data enhancement. This improvement can be primarily attributed to the application of data enhancement technology in our scheme, which enhances both the quality and quantity of orchid image datasets. Such enhancement effectively improves the overall classification accuracy of orchid species.

Table 2. Accuracy and training time in experimental results

Classification approach	Data enhancement technology	Accuracy	Average training time of an epoch
a	Nothing	0.8347	1 m 37 s
b	Crop	0.8829	1 m 38 s
c	Flip vertically (partial species) + crop	0.8902	1 m 47 s
d	Vertical flip (partial species) + horizontal flip + fancy PCA + salt and pepper noise + left rotation 30° + crop	0.9265	6 m 40 s

Additionally, Table 2 demonstrates that the data enhancement technology helps alleviate sample imbalance issues, particularly for orchid species with limited samples. The expanded dataset not only enhances the network model classification accuracy but also reduces the risk of overfitting. However, it should be noted that data-enhancement-based methods incur a longer training time for the network model. Corresponding experimental results regarding accuracy versus epoch for all the four schemes are presented in Fig. 4.

As is shown in Fig. 4, classification scheme “d” achieves the best classification performance among the four methods, with the classification accuracy plateauing around epoch 40 for all approaches. A persistent accuracy gap between the training and testing sets indicates overfitting, which is most likely attributable to either insufficient training data or class imbalance in the orchid datasets.

These experimental results demonstrate that the data enhancement technology proposed in this study effectively improves classification accuracy rate while mitigating the overfitting risk through dataset expansion. This methodology proves particularly valuable when working with limited and imbalanced image datasets: a common challenge in botanical studies where sample collection constraints may exist. Notably, the proposed approach shows a promising generalizability and can be adapted for the classification of other flowering plant species.

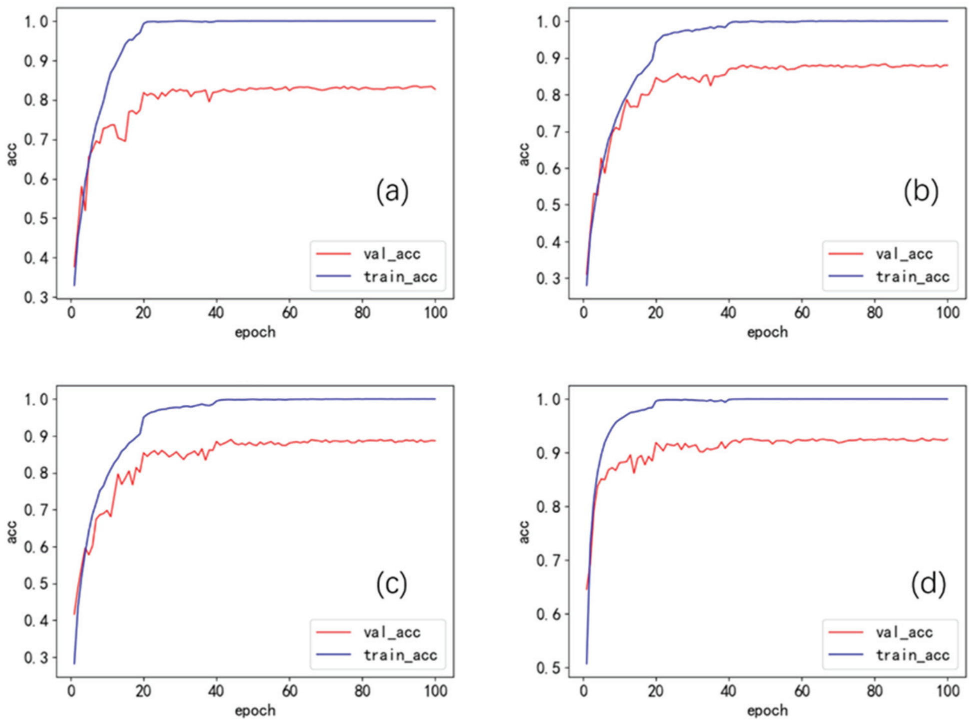

Fig. 4. Experimental results between accuracy and epoch for the four approaches: (a) approach “a,” (b) approach “b,” (c) approach “c,” and (d) approach “d.”

5. Conclusion

In this work, an effective orchid type classification approach using data enhancement is developed to improve the accuracy rate of classification through expanding image datasets. Our methodology consists of four key stages: first of all, we constructed a dataset containing 12 orchid species with 12,227 images. Secondly, we conducted a comprehensive analysis of the visual characteristics presented in these orchid image datasets. Thirdly, we identified processing challenges specific to these orchid image datasets. Finally, we implemented a generalized data enhancement technology to enhance classification accuracy of orchid species. Experimental results demonstrate that our proposed method achieves a classification accuracy rate of 92.65% under the conditions of insufficient and imbalanced image datasets, significantly outperforming non- enhancement approaches.

The primary limitation of this work lies in its specific application scenario: our method mainly improves orchid classification performance when dealing with inadequate and unbalanced samples. When sufficient training data is available, this enhancement approach becomes unnecessary. Future research will focus on two directions: 1) implementing more advanced data enhancement technologies to further enhance classification performance using our expanded datasets and 2) exploring complementary technologies to optimize orchid classification based on the enhanced image datasets developed in this study.

Conflict of Interest

The authors declare that they have no competing interests.

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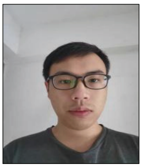

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