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ИНТЕЛЛЕКТУАЛЬНЫЙ МЕТОД ПОЛУЧЕНИЯ ИЗОБРАЖЕНИЯ ТРАВЯНИСТЫХ ЦВЕТОВ НА ОСНОВЕ ТЕМАТИЧЕСКОГО КРАУЛЕРА, ГЛУБОКОГО ОБУЧЕНИЯ И ТЕОРИИ ИГР

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INTELLIGENT ACQUISITION METHOD OF HERBACEOUS FLOWERS IMAGE BASED ON THEME CRAWLER, DEEP LEARNING AND GAME THEORY

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Аннотация: Для того чтобы получить большое количество обучающих данных за короткое время, классификация цветов осуществляется с помощью обработки изображений и алгоритмов глубокого обучения, основанных на теории игр и оптимизации. Технология Python web crawler используется для написания программ краулера изображений и короткого видео на основе китайского названия травяных цветов, а модель обнаружения цели используется для скрининга изображения цветка на основе статического кадра сегментированного видео, чтобы повысить скорость и точность получения изображения. Результаты показывают, что использование технологии тематического краулера может эффективно получить изображение травянистых цветов; обнаружение цели может значительно улучшить использование изображения, количество образцов может быть увеличено в 3~10 раз, а средний коэффициент обнаружения ошибок составляет всего 3,62%; GAN (GenerativeAdversarial Network) - это модель глубокого обучения, основанная на теории игр. Модель GAN может генерировать реалистичные изображения цветов, что дает новую исследовательскую идею для решения проблемы нехватки набора сельскохозяйственных данных в настоящее время, и показывает осуществимость интеллектуального метода сбора данных для травянистых цветов.

Abstract: In order to obtain a large amount of training data in a short time, flower classification is carried out through image processing and deep learning algorithms based on game theory and optimization. The Python web crawler technology is used to write the image and short video crawler programs based on the Chinese name of herbal flowers, and the target detection model is used to screen the flower image on the basis of the static frame of the segmented video, so as to improve the speed and accuracy of image acquisition. The result show that the use of theme crawler technology can obtain the image of herbaceous flowers effectively; target detection can greatly improve the image utilization, the number of samples can be increased by 3~10 times, and the average error detection rate is only 3.62%; the GAN (GenerativeAdversarial Network) is a deep learning model based on game theory. GAN model can generate realistic flower pictures, which provides a new research idea to solve the problem of lack of agriculture data set at present, and shows the feasibility of intelligent data collection method for herbaceous flowers.

Ключевые слова: травянистый цветок; тематический краулер; обнаружение объектов; формирование изображений; глубокое обучение; GAN; теория игр

Keywords: herbaceous flower; topical crawler; object detection; image generation; deep learning; GAN; game theory.

Introduction

Flowers are often used as an important material for urban landscape construction and landscaping. Moreover, flowers also have many economic uses such as spices, raw materials for pharmaceutical factories [1] and for human consumption. In a narrow sense, flowers are defined as herbs with ornamental value [2], such as daisies, sunflowers and tulips. With people's yearning for a better life, many strawberry picking gardens and vegetable picking gardens have appeared in big cities, and the flower picking industry has also gradually emerged [3]. Due to the improvement of production planting input and the insufficient efficiency of manual harvesting, many enterprises have begun to explore new ways of modern agricultural operations. Owing to the complex field environment in which flowers grow and the similarity among different flowers, the subjective judgment and picking method of early farmers not only consumes a lot of labor resources and is inefficient, but also restricts the development of the flower industry to a certain extent. The continuous development of artificial intelligence makes deep learning highlight its great advantages in image classification [4-5], object detection [6-8] and other fields, and has been applied in agriculture such as apple picking [9] and kiwi identification [10]. Automatic feature extraction through convolution neural network can overcome the disadvantages of traditional machine learning methods that require manual design of features, and achieve high-precision flower recognition and classification. However, the shallow networks only have low recognition rate, so they cannot meet the needs of use, and the training of the deep network model requires a large amount of data support. Considering that the open source data set of agricultural images cannot satisfy the personalized research, we try to combine the web crawler and target detection model to make full use of the target flowers in the whole image and effectively increase the training sample data set.

As an object-oriented programming language, Python has concise code, many standard libraries and third-party libraries, which greatly accelerates the development speed. In fact, Python crawler is a designed program that simulates the behavior of the browser requesting data, and returns the response of the server to user, and extracts the required binary data by parsing the source code of the web page [11-12] (picture/video). In order to prevent crawlers from causing great pressure to the server, websites often adopt some anti-crawler strategies. The most elementary anti-crawler mechanism is that the server judges whether it is browser or code by checking User Agent. When the page view is overloaded, Python-based web crawlers wrap themselves by simulating the User Agent to constructs request header parameters, so as to avoid websites from blocking the IP that the code accesses.

This paper adopts some deep learning models based on game theory and optimization (like GAN). Deep learning is currently an active research direction in the field of AI, scholars at home and abroad dedicated to flower classification and disease diagnosis. Although the application of crawler technology is also widely studied, there are few studies on the preliminary screening and classification of common herbs and flowers using Python crawler technology, the complicated and tedious data collection before training the classification model is often ignored in the past research. Thus, this paper used theme crawler to crawl short videos and images of common herbal flowers firstly, and then divide the video into frames, and use the target detection model to intercept the multi-target flowers in the entire image to improve the image utilization rate, in order to complete the intelligent acquisition of common herbal flower images in a short time. At last, an image generation method of Generative Adversarial Networks is proposed, which provides a new idea for the acquisition of model training data lacking images.

1 Materials and methods

1.1 Materials

Crawler technology, Python interface of OpenCV, Baidu Gallery , Haokan Video and Bilibili and other video websites.

Software operating environment: Python3.6.2, Pytorch1.2.0, Chrome browser.

1.2 Methods

1.2.1 Image Acquisition Based on Theme Crawler

The traditional method of manually collecting image data is time-consuming and labor-intensive, and it is difficult to obtain a large number of samples for training models in a short period of time. However, by relying on Python crawler technology, data can be easily collected within the scope allowed by the website. Generally speaking, in the process of deep model learning and classification, the larger the number of trainable samples in the database, the higher the recognition accuracy will be. In order to reduce the complexity of data construction, this paper discusses a relatively efficient data collection method, and the specific technical route is shown in Fig.1.

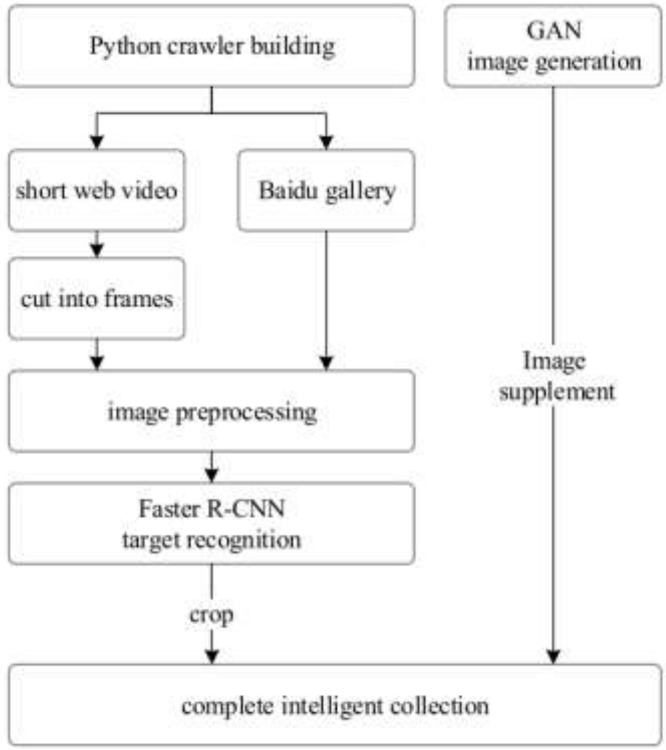

Fig. 1 Technology roadmap

（1）Gallery image acquisition

Taking the data from Baidu gallery as an example of crawling the static image. The crawler code mainly calls the requests, re and os libraries, where requests is used to send requests to the server (Fig.2). There are two ways to request web pages: GET and POST. Baidu gallery adopts the former method, which has a faster response speed; re is the standard library of Python. This library function can use regular expressions to match and extract valid strings to make the code legible; os also serves as a standard library to provide the functions of operating system objects to interact with each other. After calling the above three modules and constructing appropriate request header parameters, the construction of the Baidu gallery theme crawler is initially completed.

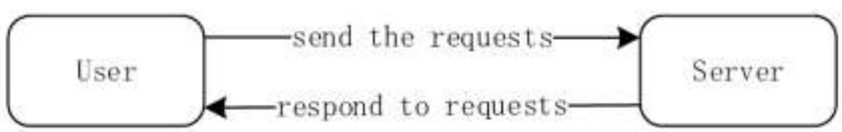

Fig. 2 Web page request

The program is set to obtain 60 images at a time, and four common herbal flowers, daisy, dandelion, sunflowers and tulips are acquired by changing the input theme name parameters.

（2）Short video acquisition

In fact, the amount of data obtained through Baidu gallery is very limited. In order to make full use of network resources, this paper also takes short videos as an important data source. Ordinary requests and urllib2 cannot capture dynamically loaded content, so the selenium crawler technology is used in the short videos retrieval. It can run directly in the browser, and simulate the user's operation according to the access steps. It supports common browsers such as Chrome and FireFox. After parsing the source code of the web page, re matching is used to extract the video title and playing address, and then initiate a GET request again after the address is transcoded to save the binary encoded data locally. In order to deal with anti-crawling mechanism, delay can be added, and the request header of browser can be constructed in headers when access, mainly the creation of User Agent and cookie information.

After crawling the short video, use Python's OpenCV interface to extract video frames, and the video was played at a speed of 30 frames per second. In order to prevent excessive repetition of video frames, the frame time was set to adjust the cutting interval, cut out 20 or so images from each video, which were used for the next step of target recognition after preliminary manual screening.

1.2.2 Target Recognition Based on Faster R-CNN

The image obtained by the Python based crawler depends on the matching degree of the subject words, and there are multiple targets or even multiple types of flowers in each image. In order to improve the utilization rate and the accuracy of the target image, this paper identifies the flowers through the target detection network, judges their categories, and then removes the interference items through manual screening, aiming to improve the efficiency and accuracy of image acquisition of common herbaceous flowers.

Target detection is one of the most basic problems in computer vision, typical application fields include face recognition [13], intelligent transportation [14] and industrial detection [15]. Among them, the recognition algorithm based on region selection is the most mature target detection and recognition framework at this stage. Faster R-CNN [16] extracts target candidate regions by introducing Region Proposal Networks (RPN), and encapsulates them together with deep feature extraction, target recognition and detection processes into the entire model, thus ensuring detection speed and accuracy. The whole process can be shown in Fig.3.

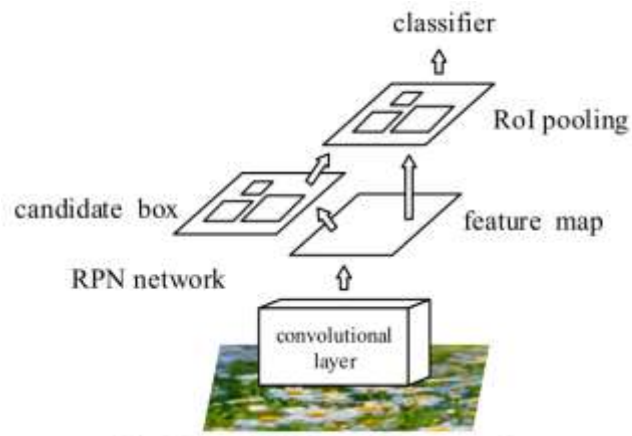

Fig. 3 Faster R-CNN model framework

After inputting an image, the backbone feature extraction network is used to extract the features of the image to obtain the common feature map, and then the output features are used to predict candidate regions and RoI pooling with RPN. Finally the target recognition and bounding box regression are realized. The new RPN network generates candidate region instead of Selective Search (SS) to reduce computational redundancy, improve detection speed, and adopt an end-to-end training process. The optimization methods are back propagation and Stochastic Gradient Descent (SGD). Classification and the joint loss of regression error is taken as the loss function, calculated as Eq. 1.

$$L(\{p_i\}+\{t_i\}) = \frac{1}{N_{cls}} \cdot \sum_i \quad L_{cls}(p_i, p_i^*) + \frac{\lambda}{N_{reg}} \cdot \sum_i \quad p_i^* \cdot L_{reg}(t_i, t_i^*) \qquad \text{Eq. 1}$$

Where *i* represents the i^{th} anchor point, $p_i^* = 1$ represents the i^{th} anchor point is a positive sample, t_i^* is the error between the candidate region and the real box, IoU (Intersection over Union) measures the correlation between the real value and the predicted result by calculating the quotient of the overlapping and the union parts of the two regions. During the training, a threshold was set, and the border with IoU greater than the threshold was defined as positive sample, while those less than the threshold were negative samples. The IoU was used to measure the accuracy of model prediction, and the higher the value, the better the detection and recognition performance of the model was.

Considering the distribution of training data, the Average Precision Value (AP) varies greatly in different categories. In order to fully prove the generalization ability of the model, this paper measures the quality of the model by calculating the Mean Average Precision (mAP), which is the most important index of target detection. In addition, in the problem of target detection, the detected images will contain targets of different categories, so it is necessary to calculate the classification and positioning accuracy of the model at the same time. The calculation of mAP value is shown in Eq. 2, and the higher the value, the better the average recognition performance of the model in various types of flowers. In order to collect as many samples as possible from limited data, the trained model was used for the detection of four types of common herbal flowers.

$$\begin{cases} Precision_c = \dfrac{\sum TP_c}{(TP+FP)_c} \\ mAP = \dfrac{\sum_1^c Precision_c}{C} \end{cases}$$ Eq. 2

1.2.3 Image Generation Based on GAN Model

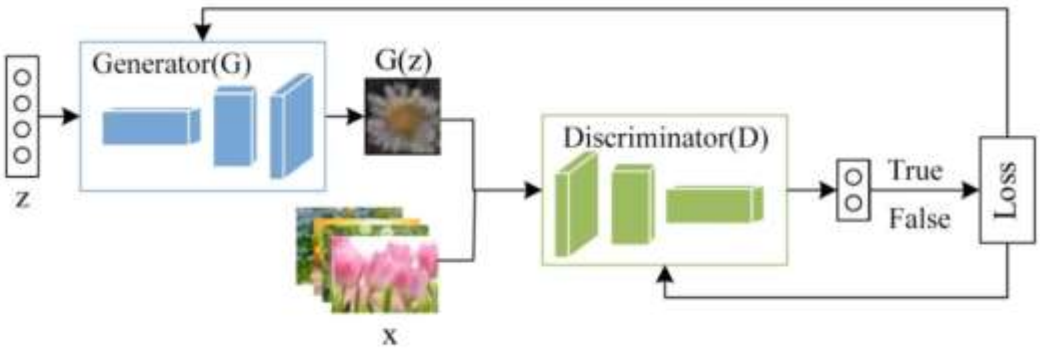

Fig. 4GAN model structure diagram

GAN is a deep learning model, which is inspired by the two-person zero-sum game in game theory[27]. The two players in the GAN model are played by the generative model and the discriminative model. The generative model G captures the distribution of the sample data, and uses the noise z that obeys a certain distribution (uniform distribution, Gaussian distribution, etc.) to generate a sample similar to the real training data, and the pursuit effect is that the more like the real sample, the better; A classifier that estimates the probability that a sample comes from training data (rather than generated data). If the sample comes from real training data, D outputs a high probability, otherwise, D outputs a small probability. GAN is a generative model with strong learning ability, which consists of two modules: generator *G* and discriminator *D*. Its model structure is shown in Fig.4. The generator *G* converts the random noise vector z obeying the distribution p(z) into an output $G(z)$ similar to the real data, and the discriminator *D* is used to predict the real sample *x* and the label of the generated sample $G(x)$. When *x* is entered into the discriminator, it should be judged as a real sample and the class label is 1, and when the data received by the discriminator is $G(z)$, the class label 0 is given, that is, the data is a generated fake sample .

During the training process, the discriminator *D* is committed to maximizing the results of the binary prediction, and the generator *G* constantly improves the quality of generated data, so that $G(z)$ is mixed with the real training data *x*, making it difficult for *D* to distinguish. The performance of the two is strengthened in the game of confrontation and finally reaches the Nash equilibrium [18]. In this case, it is difficult for the discriminator to make a decision on the category of the current sample, so the classification probability tends to be 1/2. The loss function of the GAN model is calculated as shown in Eq. 3.

$$L_{GAN}(G,D) = E_{x\sim p_{data}}[logD(x)] + E_{z\sim p_z}\left[\log\left(1-D\left(G(z)\right)\right)\right]$$ Eq. 3

In the formula, p_{data} and p_z *represent the distribution of real data and random noise vector respectively*, $E_{x\sim pdata}[logD(x)]$ is the mathematical expectation of the discriminator for the classification probability result of the real data *x*, $E_{z\sim pz}[log(1\text{-}D(G(z)))]$ is the mathematical expectation of generating data $G(z)$, and the objective function is $\min_G \max_D L_{GAN}(G,D)$. In fact, the generator and discriminator can be any learning model with generation and discrimination capabilities. Due to the powerful feature learning capabilities of deep models, especially the advantages of convolutional neural networks in image data processing, GAN is used to generate image data, the combined mechanism of transpose convolution and up sampling is often used as the generator and CNN is used as the discriminator.

2 Results and Analysis

2.1 Crawler Based Image Acquisition

Baidu gallery image acquisition

Using the theme-based Python crawler to collect herbal flowers can quickly obtain a large number of target images, which has significant advantages over manual work. During the download process, because the loading time of some images is too long, the page will not be turned before the download is completed, which will cause the image repetition. In addition, the network delay will cause the loss of the image. There will also be non-category flowers in the images crawled based on the keywords. Therefore, in this paper, the preset value of the number of images required for each type of flower is set as 60, and only the first image in the repeated images is considered as a valid image. Finally, the number of valid images will be determined manually. The statistical results of the data are shown in Tab.1. It can be seen from Tab.1 that the number of valid images is slightly lower than the preset value. Among the four types of common herbal flowers selected in this study, tulips has the highest collection, reaching 96.67%, and the extraction efficiency of other flowers is also above 90%, indicating the feasibility of this method.

Tab. 1 Results of herbal flowers obtained from Baidu gallery by Python crawler technology

herbal flowers	Baidu gallery crawls preset number	valid images	efficiency/%
daisy	60	56	93.33
dandelion	60	55	91.67
sunflowers	60	56	93.33
tulips	60	58	96.67

Network short video image acquisition

Most of the gallery image data captured by crawlers have high pixel and recognition degree. In order to make the collected data more suitable to the actual situation, this paper also crawls the short videos uploaded to the network by users and expands the training image set by extracting video frames. The specific method is as follows: firstly, six short network videos of each type of flowers are selected, and then about 20 frames are extracted from each short video according to the length of the video. Finally, filter out the frames without flowers. The experiment is set to extract 17~25 frames from each video. Taking into account the user's behavior of recording videos, the device will remain stationary for a short period of time during the shooting process, so the difference between the segmented images is small, which can be approximated as repeated frames. The efficiency of segmented images in short videos of herbal flowers can be calculated by Eq. 4.

$$E_i = \frac{Valid_i}{Seg_i} \quad \text{Eq. 4}$$

In the above formula, Seg_i is the total number of video frames segmented from the videos of category i, and the frames that actually contain flowers will be used for the target detection in the next step. $Valid_i$ represents the number of valid images of class i flowers that can be identified by the detection model as target flowers. Tab.2 shows the statistics of short videos and segmentation results of herbal flowers. Compared with the analysis results in Tab.1, the extraction efficiency of valid frames from videos is not as well as that of gallery crawling, but except for sunflowers, the extraction efficiency is higher than 50%, of which dandelion has the best extraction effect, reaching 71.54%.

Tab. 2 Short video and segmentation results of herbaceous flowers

herbal flowers	crop frames	frams contain the flower	valid frames	efficiency/%
daisy	123	99	84	68.29%
dandelion	130	98	93	71.54%
sunflowers	119	63	55	46.22%
tulips	133	84	76	57.14%

2.2 Data Augmentation Based on Object Detection Model

Target detection not only includes the judgment and confidence calculation of the target category, but also locates the position of the object in the image. After the images are cropped by the positioning coordinates, the amount of training data is greatly expanded, and each image is fully utilized, the anti-jamming ability of identifying multiple types of targets in a single image under a complex background is also improved. The experiment adopts the transfer learning method to accelerate the model training speed. Freeze the backbone before training 50 epochs, set the learning rate to 10-

4 at the same time. The learning rate is reduced to 10^{-5} when under unfreezing training. The mAP of the model after training is over 85% on the test set. Based on the above collection method, the results of the number of targets and the average false detection rate of four common herbal flowers are shown in Tab.3. It can be seen from the table that the false detection of video frames is significantly higher than that of the gallery, which also proves the efficiency and accuracy of the image acquisition based on the theme crawler.

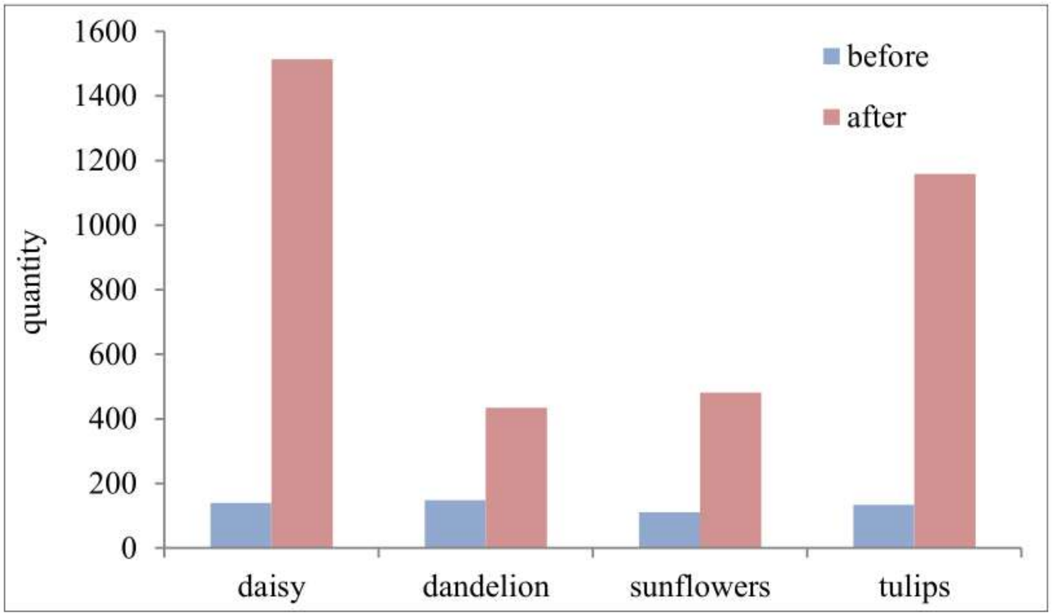

Fig. 5 Data distribution results of herbaceous flowers

Tab. 3 Results of herbaceous flower images after target recognition

herbal flowers	gallery crop quantity	gallery false detection	short video crop quantity	video frame false detection	average false detection rate%
daisy	671	11	842	34	2.84%
dandelion	166	1	269	20	4.02%
sunflowers	271	2	211	20	5.11%
tulips	685	0	474	24	2.53%

As can be seen from Tab3, after target detection model to identify the targets and crop the image, the data volume of each common herb flower significantly increased. The distribution of visual data volume is shown in Fig.5, among which the number before and after detection of daisy and tulips increased by nearly 10 times, while dandelion and sunflowers increase relatively low, but also increased by nearly 3 to 4 times. The reason is that sunflowers have large flower faceplate, so sparse sowing is adopted for better growth, while dandelion propagated seeds by wind, so the location of seeds in the soil will have great uncertainty; daisy and tulips as herbs with higher ornamental value, tend to be planted more tightly and thus have more targets in the captured images.

2.3 Image Generation Extension

Fig. 6 Flower images generated by GAN network after 10 rounds (left) and 400 rounds (right)

The experiment was run under the Windows10 operating system, NVIDIA GeForce GTX1650 processor, and accelerated with CUDA10.0, using the Pytorch framework to build the network, collecting 26194 (daisy: 6533, dandelion: 5881, sunflowers: 7154, tulips: 6626) herbal flower images data. Each image was uniformly scaled to 96 × 96, and based on this dataset, the image training and generation of herbal flowers were carried out.. During the training, set the learning rate of both the generator and the discriminator to 0.0002, choose Adam as the optimizer, and set the regularization coefficient of the optimizer to 0.5. Fig.6 shows the partially generated images of each type of flower after using the GAN model to train 10 epochs (left) and 800 epochs (right). We can see that with the increase of training rounds, the outline of the flower is more and more clear, after 10 iterations can only see the outline of the fuzzy and color, and after 800 iterations, we have been able to obtain a more realistic generated samples, indicating that it is feasible to use image generation method to realize data set augmentation to a certain extent.

3. Conclusion and discussion

Identifying common herbal flowers is of great significance for automatic picking. Its essence is image classification. Some studies are based on artificially designed features and use machine learning methods to classify images. The performance of this method depends on the quality of feature design, which requires high professional knowledge and experience and has certain subjectivity. Although the use of deep learning realizes automatic feature extraction, it requires a large amount of training data as support. In order to make better use of network resources to complete the construction of the training set and cope with the problem of large number of images required by the classification model. In this paper, a variety of methods are used to collect common herbal flowers, which greatly increased the number of flower images. On the other hand, in view of the limitations of crawling images, target detection is used to further improve the accuracy of data and achieve the purpose of expanding the data set. In order to enhance the robustness and generalization ability of the classifier in the case of limited data, an image generation method is proposed to generate high-quality images that look like the "real" to expand the training set of flowers. Experiments show that the intelligent collection method based on the theme crawler can obtain images with high accuracy and quality in a short period of time. After the target detection, the number of images is further increased, which not only solves the problem of multiple types of targets in a single image, but also effectively reduces the interference of complex background on the later classification. The image generation algorithm based on GAN can synthesize more realistic images, and can generate different types of flower images according to the expected direction. This method provides a new research idea for the lack of original sample.

However, this study also has some shortcomings. In terms of data acquisition, the resolution of the captured images is uncertain, resulting in poor target detection and false detection of flowers; in the crawler program, the number of captured images is lower than the expected target due to the anti-crawling rules of the website. In addition, the delicacy of the images generated by GAN still needs to be further improved through algorithm improvement to make them closer to real images. Therefore, the improvement of model algorithm will be the key technology to realize the rapid and accurate acquisition of herbal flower images in the follow-up research.

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