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Quality grading of jujubes using composite convolutional neural networks in combination with RGB color space segmentation and deep convolutional generative adversarial networks

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Abstract

As an important link in the processing of jujube products, the qualities classification of jujubes have an important impact on improving the value of commodities. In this study, jujube target was extracted based on the RGB color space characteristics and then put into a black background through a mask. The data augmentation method combined deep convolutional generative adversarial networks and rigid transformation (RT) was used to improve the data richness of defective jujubes, effectively solve the imbalance problem between different types of jujube data. A composite convolutional neural network (CNN) method based on residual networks was designed to effectively solve the problem of misjudgment between jujubes with subtle defects and healthy jujubes. The overall results illustrated that the defect detection accuracy of the proposed scheme was 99.2%, which was superior to the widely used support vector machine and CNN methods. This work could be applied to the actual processing site and greatly improved the quality classification effect of jujubes.

Practical Applications: Cracks, peeling, wrinkles, and other defects have seriously affected the quality and value of jujubes, and the quality classification of jujubes is imperative. This paper proposes a set of deep learning schemes from three aspects of improving data quality, enhancing data richness, and designing more accurate and effective classification models. Experimental results show that this scheme can significantly improve the accuracy of jujube quality grading.

1 | INTRODUCTION

Jujube is delicious and has high edible value and medicinal value (Zhang & Xu, 2015). Jujube is rich in a variety of nutrients, such as trace elements, amino acids, proteins and vitamins, and so forth. It has an important role in enhancing the body's immunity and inhibiting cell cancer. In recent years, the jujube industry has developed rapidly in China, accounting for more than 98% of the world's jujube planting area and output (Hu, Zhu, & Yi, 2019). With the improvement of quality of life, people have higher requirements for the appearance quality and internal nutrients of jujube fruit. However, during the picking and transportation of jujubes, jujubes that suffered from pests, cracks and damage severely affected the overall quality of the jujubes. Therefore, grading jujubes according to different qualities has become the primary and key link for storage, transportation and further processing of large amount of jujubes.

At present, many domestic manufacturers still use manual methods to grade jujubes (Zhong, Cao, & Zhang, 2017), which has the disadvantages of high labor intensity, high cost, and low efficiency. Workers' subjective consciousness often directly affects the quality of jujube sorting, which is prone to missed and wrong inspections. On the one hand, it is not conductive to the formation of standardized products; on the other hand, the processing process is inconsistent with the national food safety and health standards. Therefore, in order to improve the quality of fruit products, meet the needs of modern agricultural product production and processing, and comprehensively improve the level of agricultural product processing technology, it is urgent to develop accurate, efficient and non-destructive jujube quality grading technology.

With the rapid development of high technology and the transformation and upgrading of industrial structure, machine vision technology is widely applied in various filed including fruit detection, harvesting, and quality grading using shape, color features (Tang, Chen, & Wang, 2020; Li et al., 2020a; Chen, Tang, & Zou, 2020; Lin, Tang, & Zou, 2020). Scholars at home have studied the quality classification of jujube and put forward some algorithms. Li Yunzhi extracted the disease area according to the difference between the hue value of normal and diseased jujube, determined the threshold of the diseased area ration through experiments, and established the identification model of diseased jujubes using support vector machine (SVM) (Li, Zhang, & Chen, 2016); Zhao Jiewen extracted the mean value and mean square error of H components in the HIS color space as eigenvalues, and uses SVM to identify defective jujubes (Zhao, Liu, & Zou, 2008); Li Jingbin used Matlab software to process and extracted jujube images, and used syntactic patterns to achieve jujubes' grading (Li, Deng, & Kan, 2014). Generally speaking, the above methods based on machine vision use expert experience for feature extraction, although the research on quality classification methods of jujubes has made great progress, the types of jujube defects are diverse, and the corresponding features are relatively complicated, designing feature extractors one by one makes the development cycle long and time-consuming. At the same time, SVM are easily affected by the quality of image acquisition, the differences in jujube samples and many environmental factors when performing defect identification and classification tasks, resulting in low classification accuracy and efficiency.

As a branch of machine learning, deep learning has made significant progress in recent years and gradually developed into a research hotspot, compared with the machine vision methods, convolution neural networks (Xie, Ma, & Zhao, 2020; Qiao, Li, & Su, 2020; Ji, Zhang, & Zhang, 2020; Hazar, Sahar, & Emna, 2020; Dong, Pan, & Cen, 2020; Xiao, Wu, & Hu, 2020; Yang, HU, & Liu, 2020; Li et al., 2020b; Li & Yang, 2020; Li & Chao, 2020) have more powerful feature learning and representation capabilities, and can automatically learn features, so as to achieve better classification results. Therefore, it has a broad application prospect in quality grading of jujubes. Hai (2019) combined machine vision with deep learning technology, using blob analysis technology and Inception_v3 to identify defects with yellow skin, cracks and black spots; (Geng, Xu, & Zhang, 2018) established a two branch deep fusion convolution neural network combing transfer learning and SqueezeNet to classify healthy jujubes, cracked jujubes and defective jujubes. However, the above methods still have shortcomings, which can be summarized as follows:

First of all, as a data-driven method (Xu, Zheng, & Guo, 2019; Zhang & Tao, 2017; He et al., 2020), the quality of the data set has an important impact on the effect of deep learning algorithm, factors such as color and brightness affect the data quality of jujubes, and the characteristics of different types of jujube defect samples are quite different, it is necessary to improve the quality of jujube data through effective preprocessing to improve the identification effect of convolution neural networks on jujube defects. At present, the traditional preprocessing method (TPM) of jujubes is usually equipped with a white ring light source to provide the light conditions of jujube image acquisition and the acquisition process is as follows: First, the original jujube image with background is grayed, a threshold is set and the original image is converted into a binary image. Then, the binary image is processed by median filtering, the noise is filtered and the edge information is retained. Finally, the minimum circumscribed rectangle of jujube target is obtained to extract region of interest. The above TPM is relatively simple, without considering the influence of complex background, and jujube has a large red channel component, extracting jujube target based on color space can effectively separate it from the background, TPM does not consider color characteristics, resulting in poor data quality and unsatisfactory detection results.

What is more, the number of defective jujube samples is small, which results in the uneven distribution of sample categories. The existing data augmentation method based on rigid transformation (RT) increase the amount of data through rotation, cropping, scaling, and so forth, which can only augment the image with single style or even low signal-noise ratio (SNR), the efficiency is relatively low and the generated image data have a lot of redundant information, which brings more uncertainty to the convolutional neural network (CNN) training (Zhou, Dong, & Liu, 2020; Fu, Li, & Ye, 2020; Li et al., 2020c; Jakub, Michal, & Michal, 2020; Mehran, Purang, & Robert, 2019; Li, Chen, & Meng, 2019; Anabel, Siham, & Julian, 2019), so it needs to be further improved.

Last but not least, the steps of the existing jujube detection methods based on deep learning are usually training data, generating model and classification recognition. These methods easily lead to the misjudgment of unhealthy jujubes with subtle defect characteristics, and lack of further accurate identification, which hinders the improvement of defect detection accuracy.

Aiming at the above-mentioned problems in the quality classification process of jujubes, this paper proposed a method for quality classification of jujubes using composite convolutional neural networks (CCNNs) in combination with RGB color space characteristics and deep convolutional generative adversarial networks (DCGANs). The specific process is as follows.

Firstly, in view of the problems of complex background and strong noise interference in the industrial production environment, jujube target was extracted according to its RGB color space characteristics and placed under the background through the mask, the experimental results shown that the proposed preprocessing method (PPM) can improve the recognition accuracy of CNNs.

Then in the aspect of data augmentation, in order to get more abundant image data and alleviated the problem that the generalization ability of CNN model is not strong due to the small data set, this paper proposed a data augmentation method using DCGAN (Ardila-Rey, 2020; Auwal & Deng, 2020; Radford, Metz, & Chintala, 2015) and RT.

It is well known that generatively adversarial network (GAN) (Goodfellow, 2014) is composed of Generator and Discriminator; it generates near-real images based on the competitive idea of generating confrontation, which essentially separates the correlation of generated samples brought by traditional image augmentation methods, and gradually becomes a new data enhancement method. In order to solve the problem of meaningless network output caused by instability in the training process of GAN, DCGAN uses CNN in generator and discriminator to replace multilayer perception (MLP) in GAN, and makes some changes to CNN to improve the quality of generated samples and convergence speed. However, GAN is unstable during training, resulting in meaningless output results. In order to improve defects of GAN, DCGAN was proposed; the discriminators and generators of DCGAN used CNNs to the multi-layer perceptions in GAN, and made some changes to the structure of CNN to improve the quality of generated samples and the speed of convergence. The data augmentation method based on DCGAN and RT is divided into two steps: First, DCGAN was used for the initial augmentation of defective jujubes, so that the jujube samples of various defect types were further balanced to increase the diversity of jujube samples. Second, the data augmentation method based on RT was used to solve the problem of insufficient overall data volume, as a result, the image quality and quantity performance of jujube data were effectively improved.

Finally, aiming at the problem that the subtle defects of jujubes cannot be effectively identified, this paper proposed a framework of CCNN based on ResNet18 (He, Zhang, Ren, & Sun, 2016; Wang, Cheng, & Ying, 2020; Ibrahim, Haworth, & Cheng, 2019), the selection of Resnet18 was determined by comparing the performance of AlexNet (Krizhevsky, Sutskever, & Hinton, 2012; Gasiorowski & Szymak, 2020; Han, Zhong, Cao, & Zhang, 2017),Network in Network (NIN) (Lin, Cheng, & Yan, 2014) and GoogLeNet (Szegedy, 2015) in accuracy, training time and parameter quantity, the framework of CCNN is mainly composed of a coarse classification model for identifying defective jujubes and healthy jujubes, and a fine-grained classification model for identifying defective jujubes misjudged by rough classification model:

The first step was to retrain ResNet18 to classify healthy jujubes and defective jujubes, and defective jujubes that were misjudged were selected; the second step was to retrain Resnet18 to classify jujubes with black spot, jujubes with yellow skin, cracked jujubes, wrinkled jujubes, peeling jujubes and overlapping jujubes, and used the generated CNN model to further identify the defective jujubes that were misjudged in the first step. Experimental results shown that the proposed grading method of jujubes using CCNN in combination with RGB color space characteristics and DCGAN had a significant effect on the detection of jujube defects.

The main contributions of this article are as follows:

1. The RGB color space characteristics of jujubes is used to effectively extract jujube target from background, and the extracted jujube is put under the black background through the mask. Jujubes processed by PPM are more suitable for defect detection by CNNs.
2. A data augmentation method combined DCGAN and RT was proposed. Compared with the traditional and single RT method, the proposed augmentation method can greatly improve the defect detection accuracy.
3. A CCNN based on ResNet18 was proposed to effectively solve the misjudgment caused by subtle defects.

2 | MATERIALS AND METHODS

2.1 | Grading system and image acquisition

The jujube quality grading machine vision system consists of light source, CCD industrial cameras (Hikvision MV-CE013-50GM), roller conveyor, programmable logic controller (PLC), air blowing device and computer, the system framework is shown in Figure 1. The roller conveyor is composed of frame, rollers, driving device, transmission device, electric control device, accessories.

The computer (Intel Core i7-7700HQ CPU @2.80GHz, NVIDIA GTX1070, and 16GB RAM with Ubuntu16.04 operating system) is used to develop the proposed algorithms, and CUDA9.0, CUDNN7.0.5 need be installed for the purpose of deep learning training acceleration; the development environment of jujube target extraction program is Visual Studio code and OpenCV 3.4.0; TPM is completed by the image augmentation library Imgaug; the deep learning framework used for DCGAN is tensorflow-0.14.1; Caffe and Nvidia Digits-6.1.1 are used to train and test CNNs. In the deployment phase, NVIDIA TensorRT 5.0, a high-performance neural network inference engine, is used for inference acceleration. It is built on the basis of NVIDIA's parallel programming model CUDA, which can directly deploy the CNN model in the production environment to provide low latency and high throughput for deep learning inference applications. The ResNet18 model is used for inference performance testing, and the result shows that the inference speed reaches 27 times per second, which meets production requirements.

In the actual sorting process, jujubes are placed between the blue rollers on the roller conveyor for transmission. The roller conveyor contains multiple channels, and each channel has three color CCD industrial cameras above the rollers. When the jujubes pass directly under the industrial camera, the CCD cameras capture the images through its internal sensor. In order to acquire a complete image of the jujube surface, the rollers rotate in the opposite direction to the transmission device while moving together with the transmission device. Under the action of friction, the jujube rotates continuously during the transmission process, by adjusting the rotation speed of the transmission device and the rollers, a complete image of the surface of the jujube can be collected through different cameras on the same channel. When the jujube quality grading software on the computer detects the defective jujubes, it will send the detection result signal to the PLC, and then the PLC will emit trigger signal to control

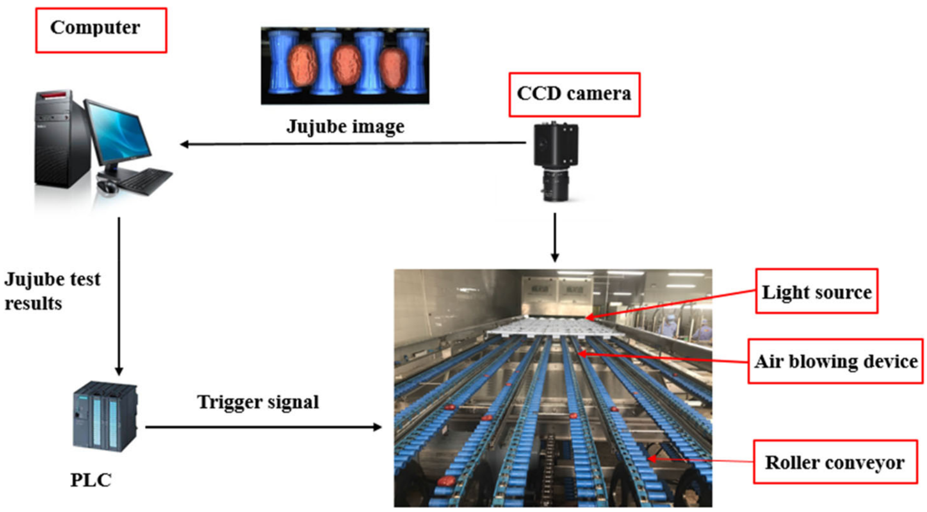

FIGURE 1 Quality grading process of jujubes

the air blowing device, and then the defective jujubes will be blown by the high-speed airflow from the air blowing device to the baffle, and then fall into the jujube grading area, so as to complete the whole grading process.

2.2 | Data preparation

The jujubes in the planting base of Xinjiang Production and Construction Corps were chosen, all the raw material were selected to be naturally dried on the tree and the skin of jujubes was usually red. Defective jujubes are fruits that are damaged due to natural factors such as moisture, temperatures, pest, or the picking process, and can be divided into six categories: Black spot, Yellow skin, Cracked, Peeling, Wrinkled and Overlapping. In total, there were 2,912 healthy jujubes, 366 jujubes with black spot, 118 jujubes with yellow skin, 198 cracked jujubes, 1,135 peeling jujubes, 141 wrinkled jujubes, and 302 overlapping jujubes, respectively, samples are shown in Figure 2.

The proportion of calibration set, validation set, and prediction set was close to 3:1:1, and their data distribution is shown in Table 1.

2.3 | Quality grading method of jujubes

The main work of this article was as follows: Jujube target extraction based on RGB color space, data augmentation method of jujubes based on DCGAN and RT, and quality grading of jujubes based on CCNN. The schematic diagram of the proposed method is shown in Figure 3, and the specific process is described as follows.

Firstly, jujube target was extracted according to the RGB color space characteristics (Li, Rao, & Ying, 2011), the background was removed from the original image and the noise was reduced, and the extracted jujube was put under the black background through the mask. And then, DCGAN was used to generate the defective jujubes to solve the problem of sample imbalance, and the data augmentation method based on RT was used to solve the problem of small data volume. At last, a framework of CCNN based on ResNet18 was constructed to realize the fine-grained identification of jujube defects.

2.3.1 | Jujube target extraction based on RGB color space characteristics

Firstly, the jujube image was processed by the weighted average gray method, the proportion of the three primary colors was set according to the RGB color space of the jujube, and the background was initially removed by setting the threshold value; Then, the jujube and background were changed into white and black, respectively, by binary processing, and the jujube mask was extracted by the method of maximum contour extraction; Finally, the other image pixel values other than mask were set to 0, and the mask was applied to the original image to extract the jujube target successfully; The detailed process is as follows and the image processing result of each step is shown in Figure 4.

2.4 | Grayscale

The commonly used grayscale methods include maximum method, average method and weighted average method. The red component of jujube is relatively large. Reasonably increasing the weight of the red component can effectively highlight the difference between the jujube and the background. Therefore, in this paper, the weighted average method was used to gray the jujube image. The formula of weighted average method is as follows.

$$Gray = (W*R + V*G + U*B)/3 \tag{1}$$

where R, G, and B represent the brightness of red, green and blue channels in RGB color space, respectively, and W, V, and U represent the weight of red, green and blue, respectively, the above three components are weighted by different weights according to the importance and index. Considering the characteristics of human eyes, people have the highest sensitivity to green and the lowest sensitivity to blue, so for general images, V > W > U. Jujube is mainly red, so the weight of red component is increased during weighted average. Many experiments shown that setting W, V, and U to 4:5:1 made the jujube image more

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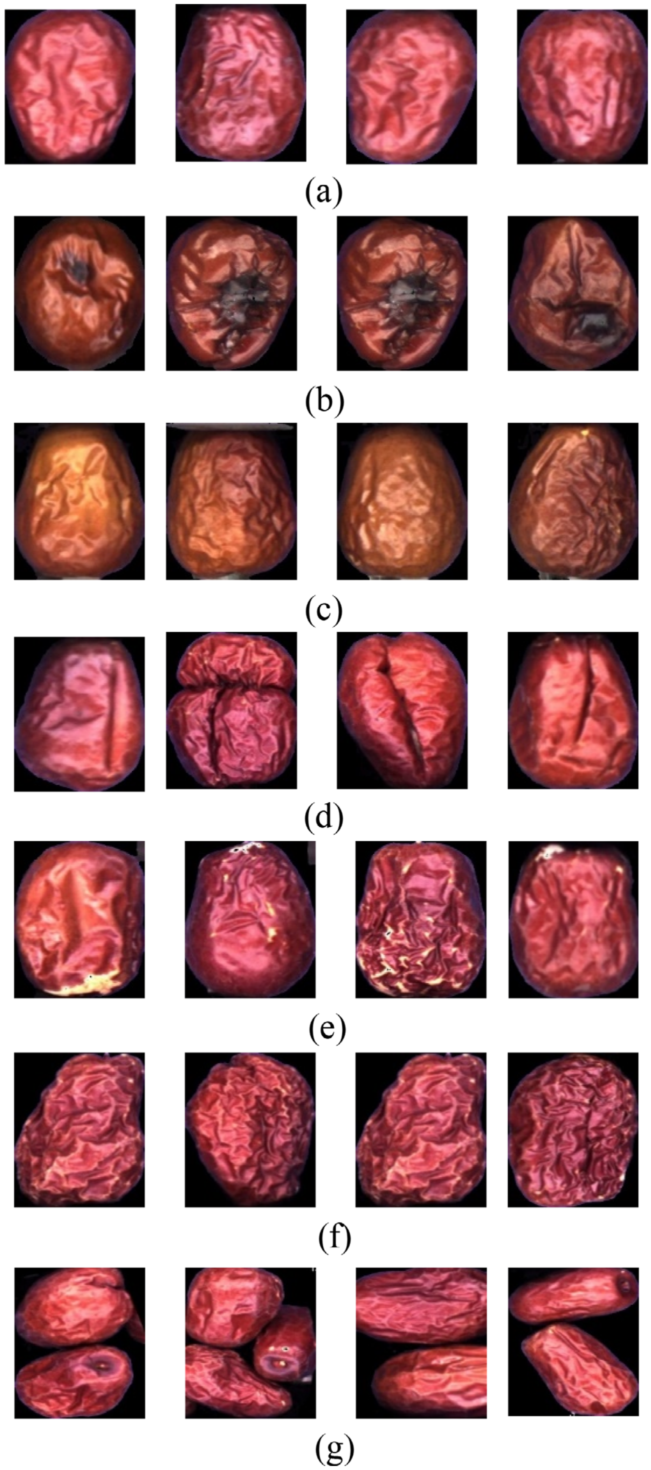

FIGURE 2 Jujube samples: (a) healthy, (b) black spot, (c) yellow skin, (d) cracked, (e) peeling, (f) wrinkled, and (g) overlapping

fault-tolerant and targeted. In addition, the red component of jujube is much larger than the background, the value of R + G-B*2.0 of the jujube target must be higher than 0, while the value of R + G-B*2.0 of the background must be smaller than 0. Therefore, in the experiment, the pixel value whose R + G-B*2.0 was less than 0 was set to 0, and the pixel value whose R + G-B*2.0 was greater than 0 was set to the value calculated by Formula 1, then the background can be preliminary removed.

2.5 | Binarization

The gray level of the jujube target and the background in the image has been distinguished after grayscale. Therefore, selection of a suitable threshold value can change the jujube target into white pixels and the background into black pixels, thus jujube target can be separated from the background. The binarization formula is as follows.

$$g(x,y)=\begin{cases}1 & f(x,y)\geq T\\ 0 & f(x,y)<T\end{cases} \tag{2}$$

where $f(x, y)$ represents the gray value of the pixel in the coordinate (x, y) of the image, and $g(x, y)$ represents the gray value of the pixel after binarization, and T is the threshold value. In this study, the threshold value was set to 30 can achieve good results.

2.6 | Denoising and mask extraction

The binary image was relatively messy, mixed with some noise. In order to remove the noise, the maximum contour of the image was extracted, and the value of the pixels outside the contour changed into 0, so the image denoising completed and the effective mask was obtained, then the mask was applied to the original image to get the jujube target with black background.

2.6.1 | Data augmentation based on DCGAN and RT

Data augmentation of defective jujubes based on DCGAN

DCGAN is made of two neural networks, the generator (G) and discriminator (D), which are introduced as follows:

G is mainly used to capture data information of real samples and then generate images, its structure is shown in Figure 5, and has the following characteristics:

TABLE 1 Distribution of the calibration set, the validation set, and the prediction set

	Healthy	Black spot	Yellow skin	Cracked	Peeling	Wrinkled	Overlapping
Calibration set	1758	220	70	120	683	85	182
Validation set	577	73	24	39	226	28	60
Prediction set	577	73	24	39	226	28	60

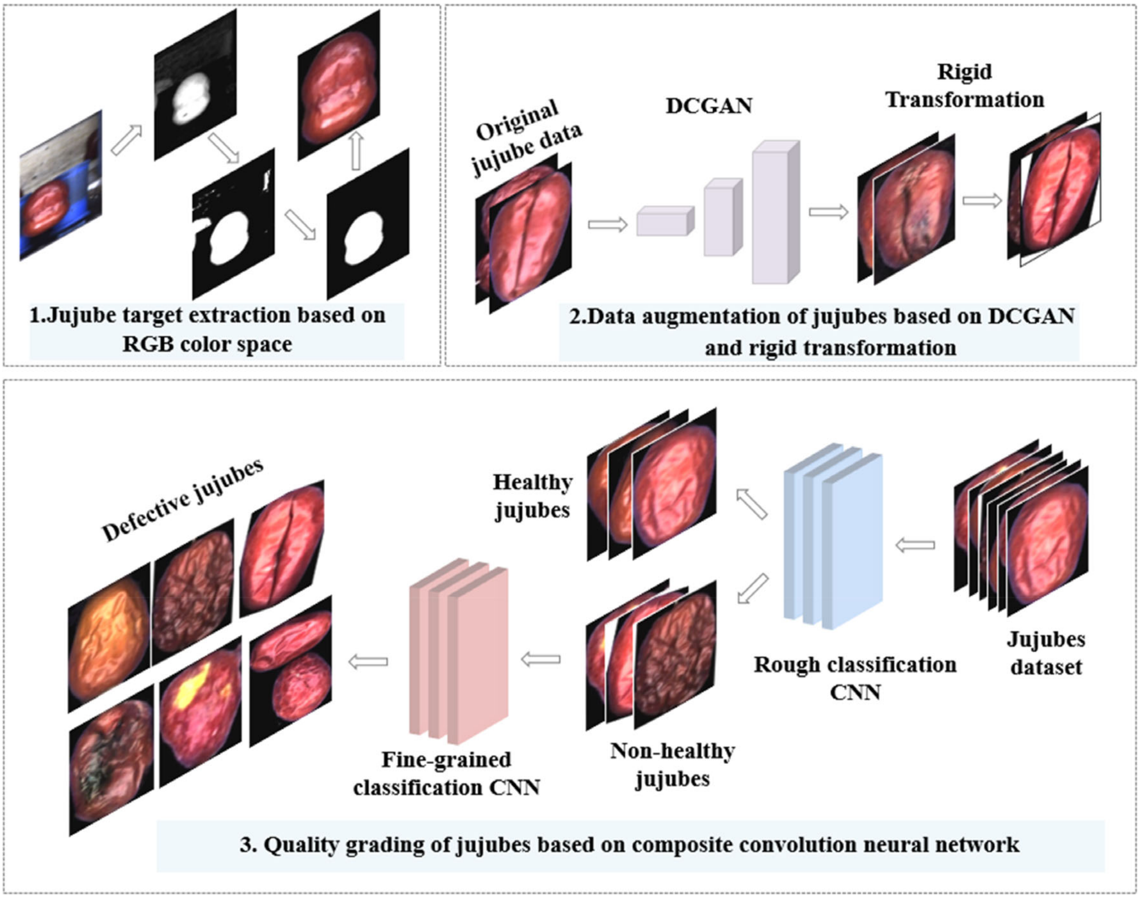

FIGURE 3 The schematic diagram of quality grading method of jujubes

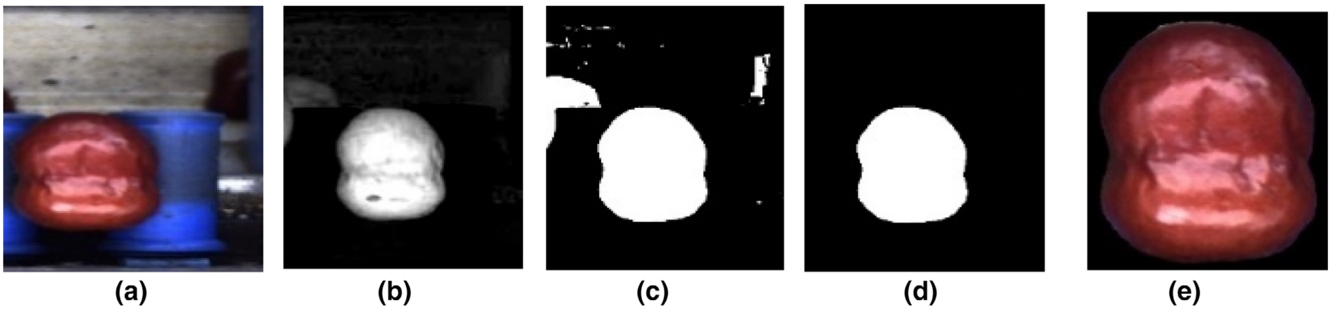

FIGURE 4 Jujube target extraction: (a) original image; (b) grayscale; (c) binarization; (d) denoising and extraction; (e) result

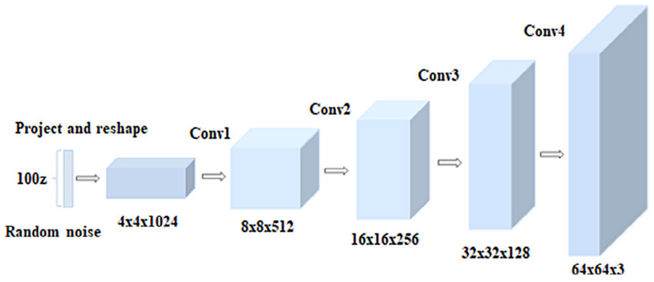

FIGURE 5 The structure of the generator

- Input layer is 100-dimensional random noise which obeys uniform distribution.
- Four fractionally-strided convolution layers are used to replace pooling layers for spatial downsampling, the strides of fractionally-strided convolution layer is set to 2, so each time the fractionally-strided convolution layer is performed, the number of channels is halved and the image size is doubled;
- Batchnorm is used in all convolutional layers except for output layer, which can solve the poor initialization problem and avoid the collapse of G; the output of feature layer is normalized to make the

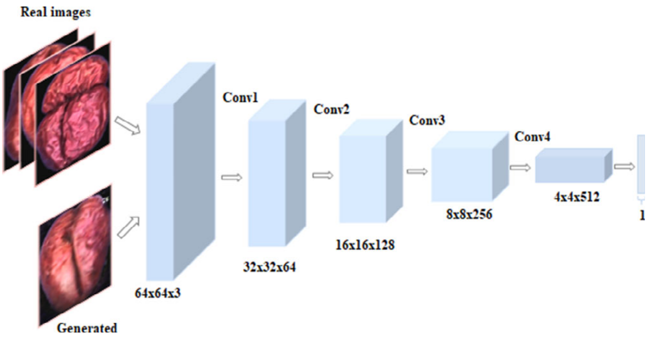

FIGURE 6 The structure of the discriminator

training more stable, and also allows gradient flow in deeper models;

- ReLU activation is used in all layers except for output layer, which uses Tanh.

D is mainly used to determine whether the input data *x* belong to the pseudo sample *p*(*z*) generated by G or comes from the real sample p_{data}, its structure is shown in Figure 6 and has the following characteristics.

- Strided convolution layers are used to replace pooling layers for spatial up-sampling。
- Batchnorm is used in all convolutional layers except for input layer to have unit variance and zero mean, which alleviates the disappearance of the gradient in the training process and speeds up the training speed of the model.
- Leaky ReLU activation is used for all layers in D to prevent gradient sparseness.
- A full connected layer outputs a scalar ranging from 0 to 1 to indicate the probability that input data belong to the real data.

The objective function adopted by DCGAN is as follows.

$$\min_G \max_D V(D,G) = E_{x\tilde{p}_{\text{data}}(x)}[\log D(x)] + E_{z\tilde{p}_z(z)}[\log(1-D(G(z)))] \quad (3)$$

wherex is the real image data, $p_{data}(x)$ represents the distribution of real data, *D*(*x*)represents the probability of real data,*z*represents 100-dimensional random noise, $p_z(z)$ represents the distribution of the random noise, and *G*(*z*) represents generated data.

In this study, jujube defect samples were used as real images and DCGAN was used for training to generate samples, the training of DCGAN is an alternating process, which is essentially a maximum and minimum optimization problem and is divided into two parts, the flow chart is show in Figure 7.

Train the generator network. The parameters of *D*are fixed, and the parameters of the generator *G*are optimized, the formula is as follows

$$\min_G V(D,G) = E_{z\tilde{p}_z(z)}[\log(1-D(G(z)))] \quad (4)$$

Since *D*(*G*(*z*)) represents the probability that D judges whether the images generated by the generator G is true, so *D*(*G*(*z*)) should be maximized, which is to minimize*V*(*D*, *G*). D will send its gradient back to update the parameters of G after discriminating.

Train the generator network. The parameters of D are fixed and the parameters of G are optimized, the formula is as follows

$$\max_D V(D,G) = E_{x\tilde{p}_{data}(x)}[\log D(x)] + E_{z\tilde{p}_z(z)}[\log(1-D(G(z)))] \quad (5)$$

For the generated samples, *D*(*G*(*z*)) should be minimized, that is, 1 – *D*(*G*(*z*)) should be maximized, therefore, when training D, *V*(*D*, *G*) should be maximized. The parameters of D are updated by the back propagation of the error.

In the whole training process, the goal of G is to generate an image of approximately positive samples so that D cannot be distinguished, and finally G and D reach balance in a dynamic game.

Data augmentation based on RT

The augmentation steps based on RT are as follows.

1. Rotate randomly at an angle of −20 to 20
2. Horizontally flip 50% of the images
3. Vertically flip 30% of the images
4. Using a method of Gaussian blur, Average blur and Median blur to process images: (Gaussian blur with a sigma of 0 to 1, Average blur with a kernel of 1 to 2, Median blur with a kernel of 1 to 3)
5. Normalized image size to 224 x 224

A certain probability was given to the flip, rotation and noise of the space, so that each sample can perform angle flip and noise according to the probability. In addition, according to the number of each type of jujubes, the corresponding multiples were expand to balance the amount of various types of jujubes.

2.6.2 | Quality grading of jujubes based on CCNNs

Judging from the actual needs of jujube defect identification, a major problem was that the differences between defective jujubes with subtle defects and healthy jujubes was relatively small and not obvious, which was easy to cause misjudgment when grading jujubes. When defective jujubes were misjudged as healthy jujubes, sales of healthy jujubes were seriously affected. Therefore, it was urgent to further improve the accuracy of defect identification.

The current deep learning classification method divided jujubes into healthy, peeling, cracked, yellow skin, blackspot, and so forth, used CNN for training and classification, although the above one-step method was simple and quick, the misjudgment problem had not been effectively solved. In view of the above problem, this paper innovatively proposed a fine-grained CCNN scheme for jujube defects, the

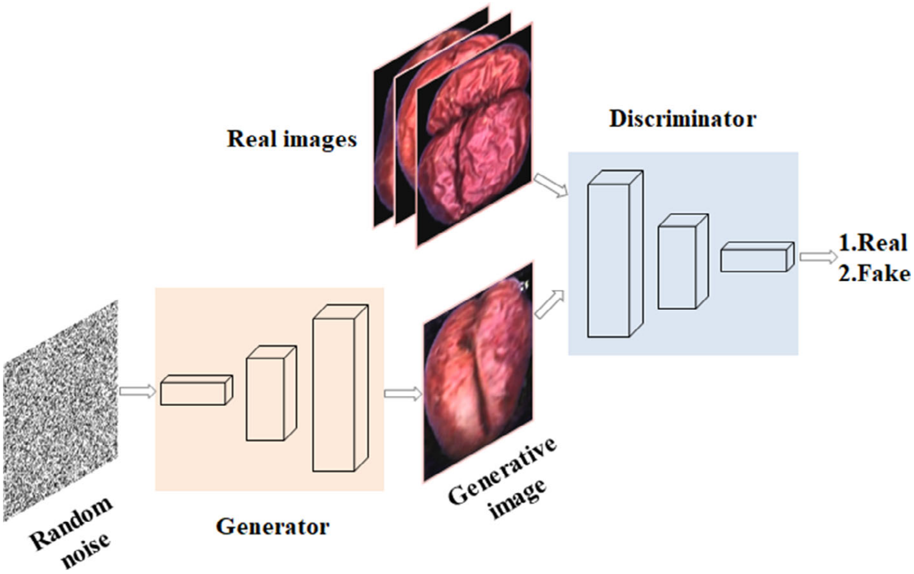

FIGURE 7 The schematic diagram of deep convolutional generative adversarial network (DCGAN)

reason for choosing ResNet18 was that it has excellent recognition accuracy on large public data sets compared with AlexNet, Network in Network and GoogLeNet, and its structural complexity was also moderate.

The principle of ResNet18 is as follows:

When CNN reaches a certain depth, blindly increasing the number of layers will not bring about further improvement in classification performance, instead, it will make the network convergence slower and the classification accuracy of the test set will become worse. In response to the above problems, the author of ResNet introduced the concept of residual representation commonly used in the field of computer vision to the construction of CNN models, and designed a building block using skip connection, its structure is shown in Figure 8.

The output formula of the building block is expressed as follows:

$$H(x) = F(x) + x \tag{6}$$

The above formula can be rewritten as follows:

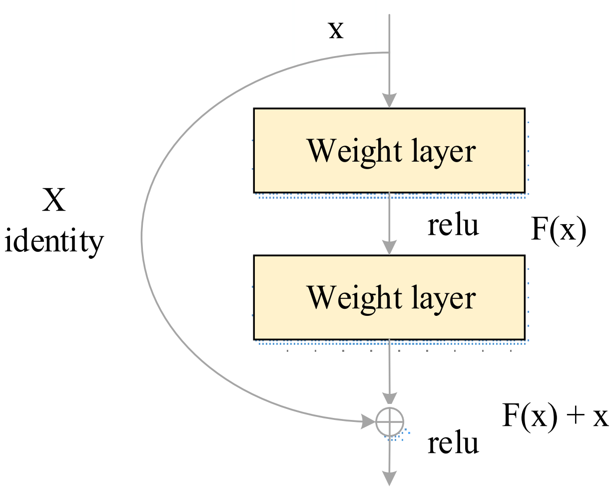

FIGURE 8 A building block of ResNet18

$$F(x) = H(x) - x \tag{7}$$

From the above analysis, it can be seen that the building block can be regarded as learning the residual representation between the actual output and the input, Resnet18 uses multiple building blocks to make the network have a stronger identity mapping capability, thereby expanding the depth of the network and improving the performance of the network. Experiments show that using a parameterized layer in the general sense to directly learn the residuals is faster than directly learning the input and output mappings, and that higher classification accuracy can be obtained.

The proposed CCNN scheme mainly included three steps:

2.7 | Established a coarse classification recognition model for healthy jujubes and non-healthy jujubes

First of all, the rough classification data set of jujubes were made, including healthy jujubes and defective jujubes, the defective jujubes included six types: cracked, peeling, wrinkled, black spot, yellow skin and overlapping. The training set, validation set and test set were divided according to the proportion close to 3:1:1. Then ResNet18 was used in the way of training from scratch and the rough classification model was obtained through optimization. Finally, the rough classification model was used to identify the test set, and the misjudged defective jujubes were selected for further identification.

2.8 | Established a fine-grained identification model for defective jujubes

Firstly, the data set of defective jujubes were made, that is, the defect jujubes were divided into six categories: cracked, peeling, wrinkled, black spot, yellow skin and stacked. The training set, validation set and test set were divided according to the proportion close to 3:1:1.

Then ResNet18 was retrained to get a high-precision defective jujubes classification model, and the misjudged defective jujubes in the rough classification process were further classified.

2.9 | Calculate the error rate

The number of healthy jujubes misjudged by the rough classification model and the number of defectives jujubes misjudged by the fine classification model were accumulated and divided by the total number of tested jujubes to get the error rate.

3 | RESULTS AND DISCUSSIONS

3.1 | Performance of algorithm

3.1.1 | Comparison of preprocessing methods

The original data in Table 1 were processed according to TPM and PPM, respectively, the control variate method was used, the jujube data processed by the two preprocessing methods were augmented using RT, and the augmented details were completely the same. Since the number of jujubes between different categories was quite different, in order to achieve balance, different types of jujubes were augmented by different multiples and further filtered to make the numbers consistent, the numbers of augmented jujubes are shown in Table 2.

Four kinds of neural networks, AlexNet, NIN, GoogLeNet and ResNet were used to train the data processed by two preprocessing methods in the way of training from scratch, parameters of each network are shown in Table 3.

The test results are shown in Figure 9, the test accuracy of the data processed by TPM on AlexNet, NIN, GoogLeNet, and ResNet were 94.68, 93.05, 94.14, and 87.83%, respectively, and the test accuracy of the data processed by PPM on the above four CNNs was 94.78, 93.73, 94.58, and 94.89%, respectively. By comparing the experimental results, it can be seen that the data processed by PPM was better than that of TPM, especially when ResNet18 was used for quality grading, PPM shown a great advantage over TPM, which verified the effectiveness of PPM.

3.1.2 | Comparison of data augmentation methods

The method of controlling variables was adopted, and jujube data were processed by PPM, the number of original jujube samples was shown in Table 1, and the number of augmented samples processed by RT was shown in Table 2. The proposed augmentation method combined DCGAN and RT was mainly described as below.

First, DCGAN was used to generate jujube samples to increase the diversity and richness of data set, each type of jujubes must be trained separately to generate samples of the corresponding category, it is worth mentioning that due to the large number of healthy jujubes, they were not taken into account. The basic parameters of DCGAN were set as follows: the batch size was 4, the input size was 256 x 256, the output size were 256 x 256, the number of epochs were 5,000, and the learning rate were 0.0002. The trained model of ResNet18 in Section 3.1 was used to test the samples generated by DCGAN to ensure that they can be correctly classified by CNNs. The comparison between the images generated by DCGAN and the real images are shown in Figure 10, where (a)–(f) represent the jujube samples generated by DCGAN, and (g)–(l) represent the real jujube samples. It can be seen from the Figure 9 that the samples generated by DCGAN are very similar to the real jujubes, with subtle differences in details. .

The numbers of correctly tested defective jujubes generated by DCGAN were as follows: the number of jujubes with black spot, jujubes with yellow skin, cracked jujubes, peeling jujubes, wrinkled jujubes and stacked jujubes were 902, 478, 314, 1982, 291, and 365, respectively.

Then these defective jujubes generated by DCGAN and the original jujube data set in Table **1** were put together, and the training set, validation set and test set were divided according to a ratio close to 3:1:1, and the method based on RT was used for further augmentation, the final data distribution of each type of jujubes was the same as Table **2** through further screening.

Finally, four kinds of neural networks, AlexNet, NIN, GoogLeNet and ResNet were used to train the data processed by two data augmentation methods in the way of training from scratch, parameters of each network are shown in Table 3 and the results are shown in Figure 11, the test accuracy of the data augmented by RT on AlexNet, NIN, GoogLeNet and ResNet were 94.78, 93.73, 94.14, and 94.89%, respectively, while the test accuracy of the data augmented by DCGAN and RT on the above four CNNs was 96.96, 96.99, 97.04, and 98.10%, respectively. The experimental results shown that when DCGAN was used for preliminary augmentation, the data richness was improved and the redundancy of information was reduced, which greatly improved the accuracy of CNNs in quality classification of jujubes.

3.1.3 | Comparison of CCNN and other CNN methods

The control variate method was used, jujube samples were preprocessed by PPM, and then they were augmented by the data

TABLE 2 Data distribution of augmented jujubes

	Healthy	Black spot	Yellow skin	Cracked	Peeling	Wrinkled	Overlapping
Calibration set	3,516	3,552	3,672	3,600	3,415	3,654	3,720
Validation set	1,170	1,184	1,275	1,200	1,135	1,260	1,200
Prediction set	1,166	1,120	1,071	1,140	1,125	1,095	1,200

TABLE 3 Parameter setting of four convolutional neural networks

CNNs	Parameters						
	Epochs	Base_lr	Solver type	Lr_policy	Gamma	Momentum	Weight_decay
AlexNet	30	0.01	SGD	Step down	0.1	0.9	0.0001
NIN	30	0.01	SGD	Step down	0.1	0.9	0.0001
GoogLeNet	30	0.001	SGD	Step down	0.1	0.9	0.00001
ResNet	30	0.01	SGD	Step down	0.1	0.9	0.0001

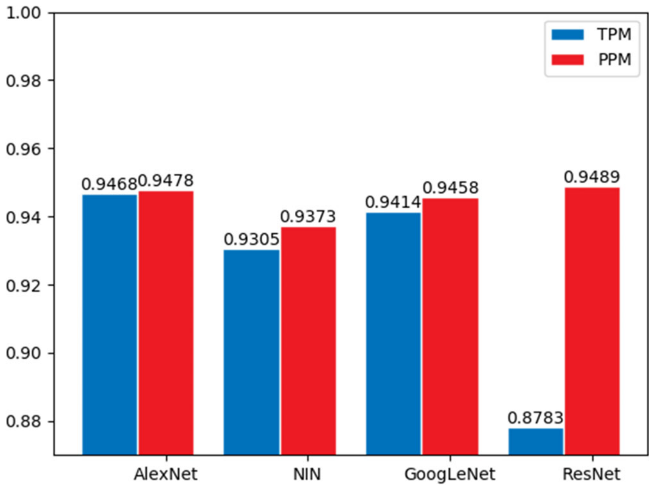

FIGURE 9 Comparison of recognition accuracy of jujube defects under two preprocessing methods

augmentation method combined DCGAN and RT, CCNN scheme includes rough classification model for identifying healthy jujubes and defective jujubes and fine-grained classification model for identifying various defective jujubes. Accordingly, a coarse classification data set and a fine-grained classification data set needed to be established.

1. The rough classification experiment was done and all jujube samples were divided into healthy jujubes and defective jujubes, data distribution is shown in Table 4 and the total amounts of jujubes used was consistent with that of traditional CNNs, which are shown in Table **2**. ResNet18 was used to train and classify, and the test results were shown in Table 5, it can be seen that 46 defective jujubes were misjudged as healthy jujubes, so they should be selected for further identification.

2. The fine-grained classification experiments of defective jujubes was done and defective jujubes were divided into six categories, included jujubes with black spot, jujubes with yellow skin, cracked jujubes, peeling jujubes, wrinkled jujubes and stacked jujubes, so the number of defective jujubes in the calibration set, validation set and prediction set in Table 4 was divided by 6, which were 2094, 705, and 658, respectively.

ResNet18 was trained in the way of training of scratch and 46 misjudged defective.

jujubes were tested, the experimental result was shown in Table 6, it can be seen that only 8 defective jujubes were misjudged.

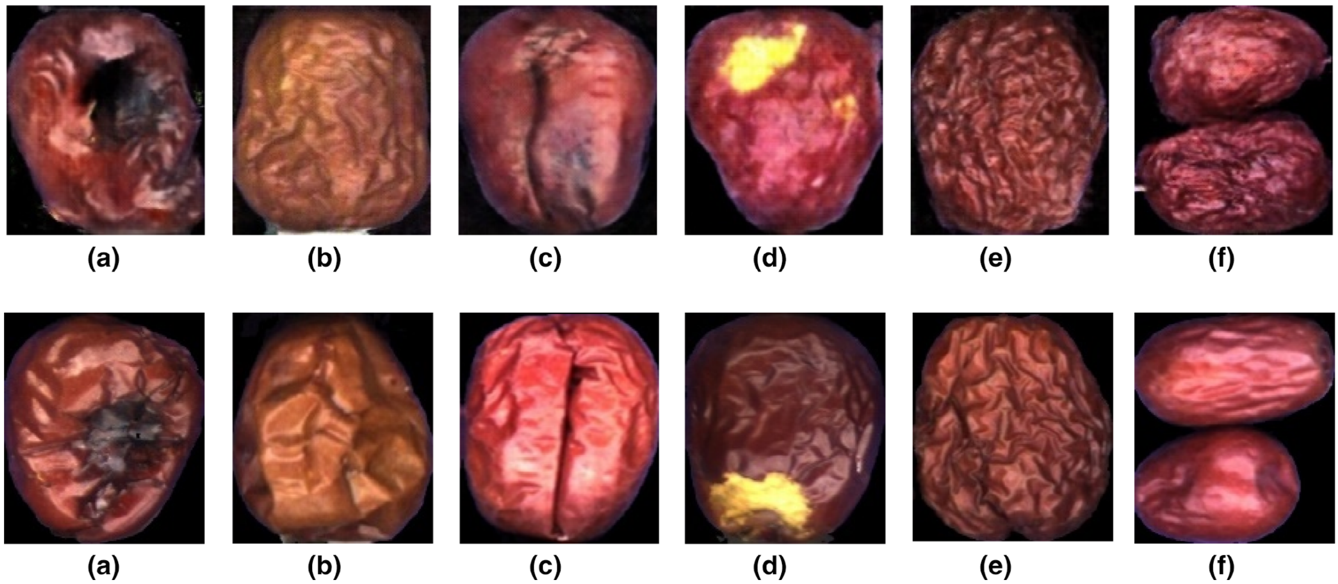

FIGURE 10 Comparison figure between actual generated images and original images. (a)–(f) Defective jujube samples generated by DCGAN. (g)–(l) Original defective jujubes samples

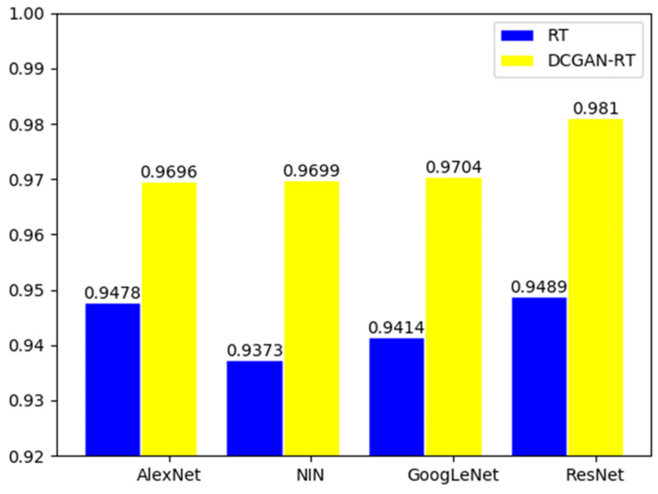

FIGURE 11 Comparison of recognition accuracy of jujube defects under different data augmentation methods

TABLE 4 Distribution of the coarse classification dataset after data augmentation

	Healthy Jujubes	Defective jujubes
Calibration set	12,565	12,565
Validation set	4,227	4,227
Prediction set	3,948	3,948

TABLE 5 Confusion matrix of coarse classification

	Healthy	Defect
Healthy	3,894	54
Defect	46	3,902

3. The number of healthy jujubes misjudged by coarse classification model and the numberof defective jujubes misjudged by fine-grained classification were accumulated and divided by the total test number of jujubes.

$$\text{Error} = \frac{54+8}{3948+3948} = 0.79\% \tag{8}$$

So the overall accuracy of the proposed CCNN scheme was calculated as follows:

$$\text{Accuracy} = 1 - \text{Error} = 99.21\% \tag{9}$$

4. Finally, four CNNS of AlexNet, GoogLeNet, NIN and ResNet18 were used to comparewith the proposed CCNN scheme, the result is shown in Figure 12. In order to facilitate the discussions, this paper made the following abbreviations: The scheme combined PPM, DCGAN-RT and AlexNet was called PD-AlexNet, and the other CNNs combine PPM and DCGAN-RT were called PD-NIN, PD-GoogLeNet, PD-ResNet and PD-CCNN.

It can be seen that the accuracy of PD-AlexNet, PD-NIN, PD-GoogLeNet and PD-ResNet were 96.96, 96.99, 97.04, and 98.10%, respectively, while accuracy of PD-CCNN was 99.21%, the experimental results proved that the proposed CCNN scheme can effectively reduce the misjudgment of defective jujubes and improve the overall recognition accuracy.

3.1.4 | Comparison between the proposed scheme and other schemes

After using the control variable method to demonstrate the improvement effects of PPM, DCGAN-RT and CCNN scheme, the final result was clear at a glance. In order to facilitate the discussions, this paper made the following abbreviations for several schemes:

The traditional AlexNet based on TPM and RT was called TR-AlexNet, the other traditional CNNs based on TPM and RT were called TR-NIN, TR-GoogLeNet, and TR-ResNet. For the convenience of analysis in subsequent discussions, the above methods can be collectively referred to as TR-CNNs. It is worth mentioning that this paper also introduced the commonly used jujube quality classification method based on manual feature extraction and SVM, which mainly extracted the mean value and mean square error through color models such as RGB and HSV, and then uses gray-level co-occurrence matrix and Gabor features to perform texture feature extraction, and finally SVM was used to classify the feature vectors extracted above to identify various defects.

The Precision, Recall and F1 score of the proposed PD-CCNN scheme and other schemes is shown in Table 7.

It can be seen that in terms of Precision index, except that the TR-ResNet in TR-CNNs performed 0.15 lower than the SVM method on peeling jujubes, the identification performance of TR-CNNs was better than the SVM method; and the proposed PD-CCNN performed

TABLE 6 Confusion matrix of fine-grained classification

	Black spot	Yellow skin	Cracked	Peeling	Wrinkled	Overlapping
Black spot	3	0	0	0	0	0
Yellow skin	0	1	0	0	0	0
Cracked	1	0	24	0	0	0
Peeling	1	0	0	7	0	0
Wrinkled	6	0	0	0	3	0
Overlapping	0	0	0	0	0	0

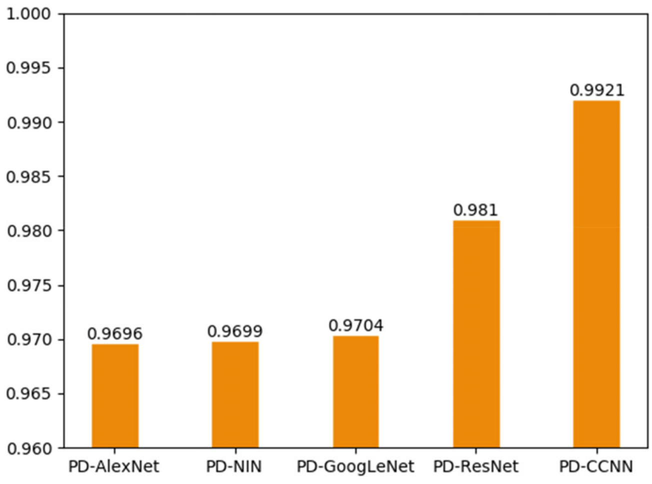

FIGURE 12 Comparison of recognition accuracy of PD-CCNN and other PD-CNN methods

slightly lower than TR-GoogLeNet and TR-ResNet in black spot jujubes, but its performance was the best in the other five type of jujubes.

Then there was the performance on the Recall index. The TR-NIN, TR-GoogLeNet and TR-ResNet on healthy jujubes were 0.054, 0.033, and 0.505 lower than the SVM method, respectively, the TR-AlexNet was 0.063 higher than the SVM method, and the proposed PD-CCNN performed best, reaching 0.986. In terms of the recognition of yellow skin jujubes, the performance of TR-CNNs was better the SVM method, and the performance of the TR-AlexNet, TR-NIN, and TR-GoogLeNet was slightly higher than the proposed PD-CCNN. In the recognition of black spot jujubes, cracked jujubes, peeling jujubes, wrinkled jujubes and stacked jujubes, the performance of the PD-CCNN proposed in this study was the best.

Finally, in terms of F1 Score, the TR-ResNet on healthy jujubes was 0.226 lower than the SVM method, while the TR-AlexNet, TR-NIN, TR-GoogLeNet on healthy jujubes were 0.388, 0.340, 0.353 higher than the SVM method, respectively, the proposed PD-CCNN had the highest score, reaching 0.987. The performance of TR-CNNs on the black spot jujubes was better than the SVM method, and the performance of TR-ResNet and TR-ResNet was slightly than that of the proposed PD-CCNN. In the other five types of jujubes, the performance of the proposed PD-CCNN method was the best.

The overall recognition accuracy comparison of several methods is shown in Figure 13. The overall recognition accuracy of the method based on manual feature extraction and SVM, TR-AlexNet, TR-NIN, TR-GoogLeNet and TR-ResNet were 84.06, 94.68, 93.05, 94.14, and 87.83%, respectively, while the accuracy of PD-CCNN was 99.21%. Experimental results shown that when the amount of jujube data was relatively sufficient, compared with the traditional machine learning method based on manual feature extraction and SVM, the TR-CNNs had obvious advantages; after improved preprocessing method, data augmentation method and CNN scheme, the proposed CCNN scheme in combination with PPM and DCGAN-RT has a significant defect recognition effect compared with the traditional CNN methods combined TPM and RT.

4 | DISCUSSIONS

While theoretical analysis and experimental results show that the proposed scheme can achieve a high detection rate, there is still room for improvement.

TABLE 7 The precision, recall, and F1 score of the proposed PD-CCNN scheme and other schemes

Jujube type	Indicators	SVM	TR-AlexNet	TR-NIN	TR-GoogLeNet	TR-ResNet	PD-CCNN
Healthy	Precision	0.618	0.848	0.815	0.875	0.893	0.998
	Recall	0.837	0.900	0.783	0.804	0.333	0.986
	F1-score	0.711	0.873	0.825	0.838	0.485	0.987
Black spot	Precision	0.856	0.983	0.972	0.989	0.995	0.984
	Recall	0.812	0.995	0.980	0.992	0.989	0.997
	F1-score	0.833	0.989	0.976	0.991	0.992	0.990
Yellow skin	Precision	0.959	0.999	0.993	0.995	0.970	0.999
	Recall	0.880	0.999	1.000	1.000	0.961	0.997
	F1-score	0.918	0.999	0.996	0.998	0.965	0.998
Cracked	Precision	0.862	0.971	0.929	0.951	0.907	0.991
	Recall	0.848	0.869	0.877	0.906	0.949	0.973
	F1-score	0.855	0.917	0.902	0.928	0.927	0.982
Peeling	Precision	0.798	0.903	0.878	0.832	0.648	0.962
	Recall	0.729	0.973	0.984	0.982	0.982	0.988
	F1-score	0.762	0.937	0.928	0.901	0.781	0.975
Wrinkled	Precision	0.770	0.929	0.919	0.965	0.850	0.997
	Recall	0.711	0.911	0.893	0.910	0.937	0.974
	F1-score	0.7393	0.920	0.906	0.937	0.891	0.985
Overlapping	Precision	0.847	0.999	0.992	0.993	0.999	0.999
	Recall	0.819	0.987	0.989	1.000	0.981	1.000
	F1-score	0.833	0.993	0.990	0.996	0.990	0.999

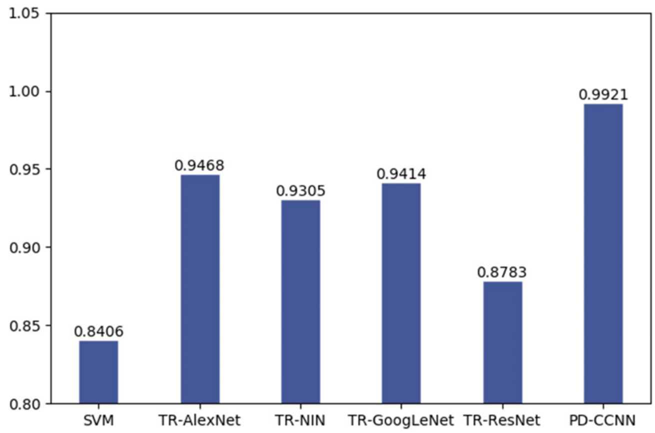

FIGURE 13 Comparison of overall recognition accuracy between the proposed PD-CCNN scheme and other schemes

1. The proposed method in this paper introduces a combination of coarse-grained and fine-grained schemes in the design of CNN schemes, which makes the design of the jujube classification scheme more in line with the actual situation and can effectively avoid the misjudgment of the jujubes with minor defects, but it also leads to more parameters and increases the cost of detection. Therefore, the network structure needs to be improved in the future work.
2. The proposed method is mainly tested on the jujube data set of the Xinjiang

Production and Construction Crops planting base, there are many varieties of jujube, in the next step, it should be extended to other varieties of jujube and other types of fruit.

5 | CONCLUSIONS

This paper proposes a quality grading method of jujubes using CCNNs in combination with RGB color space segmentation and DCGANs. The proposed method first improves the quality of jujube data by extracting the raw data using the RGB color space characteristics of jujubes; And then, in order to address the imbalance of the number of defect categories, DCGAN is used to generate defective samples to improve the richness and diversity of data set, the rigid transformation method is used to make the number of jujubes between various categories reach equilibrium; finally, a fine-grained identification scheme of jujube defects using composite convolution neural network based on ResNet18 is proposed. The control variable method is used to conduct experimental analysis and comparison to demonstrate the effectiveness of the proposed improvement points. The experimental results show that the classification of the proposed PD-CCNN scheme is 99.21%, 15.15% higher than the method based on manual feature extraction and SVM, and 4.53, 6.16, 5.07, and 11.38% higher than TR-AlexNet, TR-NIN, TR-GoogLeNet and TR-ResNet, respectively. The method proposed in this study can be extend to other fruits, such as apples, pears, and so forth. Future work will focus on the improvement of the CNN architecture.

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AUTHOR CONTRIBUTIONS

Zhongyuan Guo: Conceptualization; formal analysis; methodology; software; validation; visualization; writing-original draft; writing-review and editing. **Hong Zheng:** Conceptualization; funding acquisition; methodology; project administration; resources; supervision; writing-review and editing. **Xiaohang Xu:** Methodology; software. **Jianping Ju:** Writing-review and editing. **Zhaohui Zheng:** Writing-review and editing. **Changhui You:** Writing-review and editing. **Yu Gu:** Writing-review and editing.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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