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RESEARCH ON BAMBOO DEFECT SEGMENTATION AND CLASSIFICATION BASED ON IMPROVED U-NET NETWORK

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ABSTRACT

In this paper, computer vision technology is used to quickly and accurately identify and classify the surface defects of processed bamboo, which overcomes the low efficiency of manual identification. The datasets consist of 6360 defective bamboo mat images of four categories taken by the author at the same position, which are split at a ratio of 8:2 for training and testing. In this experiment, we improved the U-net to segment the datasets and use VGG16, GoogLeNet and ResNet50 with attention mechanism for classification and comparison. The experimental results show that the accuracy of this method is 5.65% higher than the commonly used neural network method. The highest accuracy rate is 99.2%.

KEYWORDS: Deep learning, U-net, ResNet, convolutional neural network.

INTRODUCTION

Many methods have been proposed for the detection and classification of images feature defects. A paper studied the machine vision of bamboo online sorting (Xuemin et al. 2010), used IK030M face scan black-and-white industrial camera for bamboo image acquisition and processing, designed the image processing algorithm and color sorting platform of bamboo color recognition, and used the sorting algorithm based on his and gray mean value to realize the color recognition of bamboo. The method based on HOG feature and support vector machine (Mallik et al. 2011) classifier are used to detect whether there are grape leaves in the image, and the sliding window method is used to search leaves (Felzenszwalb et al. 2010). This method has good detection effect for the leaves with positive position, and poor detection accuracy for the leaves with incorrect position and incomplete surface. Gabor transform was used to recognize the homogeneous texture image in Brodatz (Riaz et al. 2013), and the effect is remarkable. However, the Gabor transform method inevitably extracts the feature noise, which affects the efficiency of the algorithm. A simple k-means algorithm is often used as a texture recognition method, but it is difficult to obtain a better recognition effect because it is easily affected by the initial midpoint to get the local optimal solution (Patgar et al. 2014, Venkateswaran et al. 2013). Lin et al. (2012) proposed an approach to represent and recognize objects with a massive number of local image patches, can directly update the feature weights by defining and calculating feature correlations. This method works well with the task of object detection and localization from images. Differential evolution (DE) algorithm is an evolutionary algorithm based on swarm intelligence, which has been used to solve the optimal cluster center and achieved good results (Kwedlo 2011, Kuo et al. 2013). Dongxu et al. (2014) proposed the recognition of the front and back sides of bamboo based on BP neural network, the accuracy rate reached 97%, but it took a long time and could not identify the defects of bamboo itself. The scope of wood surface defects was determined by 3D image (Sioma. 2015), and the defect area was defined accurately, which enhanced the ability of wood surface defect evaluation. A graph cut method (Rother et al. 2004, Hosang et al. 2016) used Markov random field (MRF) to model the image pixels and their adjacent relations, then minimizes the energy equation through graph cut. This method requires cumbersome human-machine interaction to obtain the target and background. Aimed at the problem of high bit number in Gabor transform (Arivazhagan et al. 2006), the author proposed a method based on the combination of relief and Gabor transform. The relief algorithm is used to select the image twice, and then the optimized k-means algorithm is used to obtain high-precision texture recognition and improve the classification accuracy. To improve the robustness of binary mode to noise, a method was proposed to segment the pixel difference between the center pixel and adjacent pixels of the image object into local ternary mode (Tan et al. 2010). U-net segmentation network was used to detect and mark the infection of COVID-19 CT images with the accuracy was 95% (Saood et al. 2021). Gu et al. (2010) used a tree structured SVM to classify the defective wood board images with the accuracy rate reached 96.5%. Yusof et al. (2013) used a fuzzy logic-based pre-classifier as a means of treating uncertainty to improve the classification accuracy of tropical wood recognition system. The accuracy of wood recognition system is improved by 4%. K-Nearest Neighbor (KNN) classification algorithm has been proposed to classify the wood knot images (Cetiner et al. 2014), knot images are correctly divided into seven different categories with a correct rate of 98% by the authors. Hanbay et al. (2016) proposed that the principal curvature of image has the feature of continuous rotation invariance. The principal curvature of image can not only improve the robustness of classification neural network to image rotation changes, but also obtain the macro structure and micro structure information of target features at the same time, which can improve the effectiveness of classification algorithm. Researchers used a fuzzy pre-classifier to mark the input image as one of four categories based on the pore texture, and used SVM to classify an input image into specific tree species using a set of extracted texture features (Ibrahim et al. 2017). Hong et al. (2021) studied the influence of long-hop connection based on convolutional neural network on bamboo classification. The results show that the network model with long-hop connection has faster convergence speed and will not overfitting, but the classification accuracy is low in the face of large model.

With the development of deep learning and computer vision technology, the main method for solving bamboo defect detection is to use deep learning technology. Convolution neural network (CNN), as a technical direction of deep learning, has successfully made a great breakthrough in image classification (Krizhevsky et al. 2012), can accurately extract the characteristics of the object in the image, train a large number of extracted object feature data, then it can classify the characteristics of the object quickly and efficiently. One contribution of this paper is proposed an effective deep learning methodology, which is used to identification bamboo slices. The deeper layers of neural network, the higher accuracy of the model achieve in the same datasets (Szegedy et al. 2015, Simonyan et al. 2015). Transfer learning is easy to build a deep layers model and leverage the feature extracting capability of the trained layers (Pan 2013). Fortunately, transfer learning is used in our method, it can classify the bamboo slices effectively. The recognition of bamboo slices made for different varieties and processing technology has strong robustness, which overcomes the shortcomings of traditional methods that need to adjust parameters frequently.

Deep learning

As a new technology in the field of machine learning, the purpose of deep learning is to enable machines to recognize the information of text, sound and image just like human beings. Deep learning has the advantages of strong learning ability, high efficiency, strong adaptability and good portability. However, its disadvantages are obvious, such as large amount of calculation, high cost of hardware and complex model design.

Convolutional neural network (CNN)

Convolutional neural network is composed of convolutions, activations and pooling. Its output is a specific feature space of image. Taking this feature space as input, it outputs a specific category through the fully connected layer, that is to complete the classification task. According to the different functions, the forward and backward connection and intra layer adjustment of each part of CNN are different, and the convolution kernel size, activation function, pooling and weight parameters are also different. At present, the popular convolutional neural networks such as VGG16, GoogLeNet and ResNet50 are all composed of basic convolutional neural networks.

VGG16

VGG16 network was proposed by Oxford University in 2014, which mainly proves that the final performance of the network will be better with the increase of network depth. VGG16 has 16 layers, including 13 convolution layers and 3 fully connected layers. Compared with AlexNet, which won the champion of ImageNet competition in 2012, the biggest improvement of VGG16 is to use continuous 3*3 convolution core instead of 5*5, 7*7 and other larger convolution cores, because there are only 3*3 convolution and 2*2 maximum pooling layers in the network, which can increase the network depth and reduce the amount of parameters. Therefore, the effect of network training is better.

GoogLeNet

GoogLeNet was proposed by Christian Szegedy in 2014. Compared with VGG16. The output layer of GoogLeNet is 1*1 convolution layer, not VGG16 full connection layer. There are different ways to solve the disadvantages of network deepening. GoogLeNet introduces a parallel network structure, in which there are four different lines in each layer to process the network input, focusing on the "wider" structure rather than the "deeper" structure of VGG16. The core of GoogLeNet lies in the emergence structure block. Its main functions are as follows: firstly, 1*1 convolution is used to increase or decrease the dimension, so that more convolutions can be superimposed to obtain richer image features and reduce the computational complexity. Secondly, convolution and regrouping on multiple dimensions at the same time to obtain more abundant features and more accurate classification (Fig. 1).

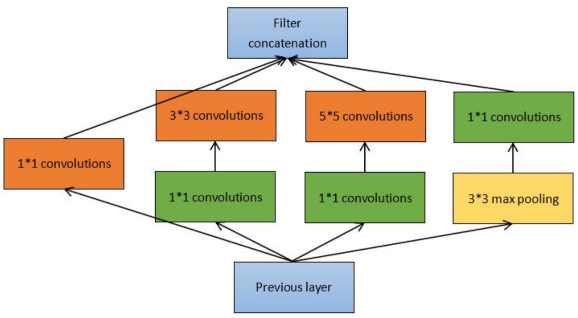


Fig. 1: The inception module of GoogLeNet.

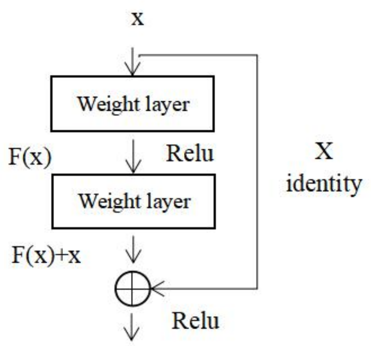


Fig. 2: Basic unit of residual model.

ResNet50

ResNet50 network was proposed by Kaiming et al. (2015). The characteristic of ResNet50 network is that it adds residual structure. By using multiple parameter layers to learn the residual structure of input and output, it not only has faster convergence speed, but also can avoid the gradient disappearing, and has higher classification accuracy. As the main part of ResNet, the residual learning unit is shown in Fig. 2. The residual structure can learn the input of each layer to form a residual function. The residual function of the first layer is defined:

$$F = \omega_2 \sigma(\omega_1 x) \tag{1}$$

where: σ - represents the ReLu function. After shortcut and the second function of ReLu, the output y is:

$$y = F(x, \{\omega_i\}) + x \tag{2}$$

If it is necessary to change the dimension of input and output, that is, to change the number of channels, the linear transformation of x can be performed at the time of shortcut:

$$y = F(x, \{\omega_i\}) + \omega_s x \tag{3}$$

U-net

U-net was proposed in 2015 by Olaf Ronneberger of Fitzburg University. It is a full convolution deep learning network without full connection layers, which is used for semantic segmentation of images. It adopts the architecture of encoder and decoder, performs four down sampling and four up sampling operations respectively. It can not only increase the robustness to the small disturbance of the input image, but also reduce the overfitting and the amount of computation, get better segmentation results. The structure of U-net network is shown in Fig. 3.

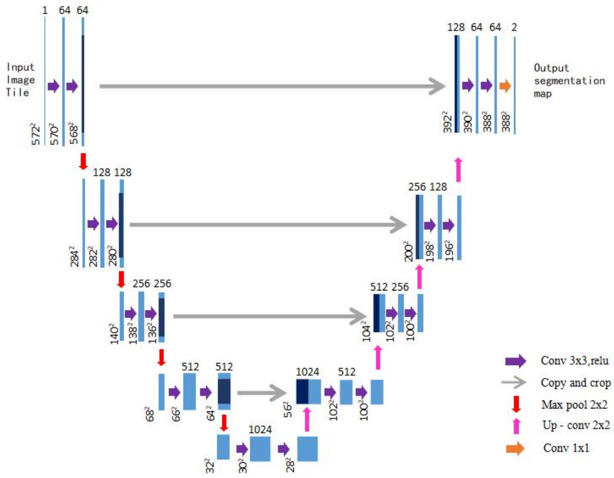


Fig. 3: U-net network structure.

Attention mechanism

Attention mechanism is a kind of resource allocation mechanism, which enables the computer to get the target area that needs attention just like human attention, and allocate more attention to the target area, ignoring the information of irrelevant areas. Attention mechanism includes soft attention mechanism and hard attention mechanism. Soft attention mechanism allocates a weight between [0,1] according to the attention degree of features in the image region, that is, most information is considered, but the degree of consideration is not. Soft attention pays more attention to the channel, which is deterministic attention and differentiable and ensures that soft attention can calculate the size of the gradient through deep learning algorithm, get the weight of attention through forward propagation and backward propagation. Strong attention pays more attention to point, which is a random prediction process and emphasizes dynamic change. At the same time, strong attention is not differentiable, the weight parameters are obtained by reinforcement learning.

Channel attention and spatial attention

Channel attention can be used to automatically obtain the importance of each channel feature through deep learning, and assign different weight parameters to each channel, so as to enhance the important features and weaken the unimportant features.

Spatial attention can transform the spatial information in the original image to another space after using the spatial transfer module, retain the important feature information while transferring, and generate a weight mask for each position. After weighted output, it can enhance the important features and weaken the unimportant features.

Continuous block attention module (CBAM) is a hybrid attention mechanism module which combines space and channel. Compared with the attention mechanism which only focus on channel or space, it can achieve better effect, and can be embedded into deep learning networks as a plug and play module: *(1)* The CBAM module based on VGG16 network is added after each build-up layer. *(2)* The CBAM module based on GoogLeNet, like VGG16, adds this module after each build-up layer. *(3)* CBAM module based on ResNet50 is added after each residual structure. The relevant illustration are shown in Figs. 4 and 5.

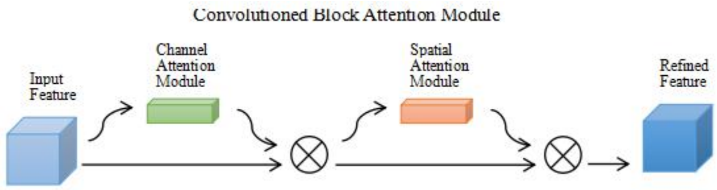


Fig. 4: Convolution layer of attention module.

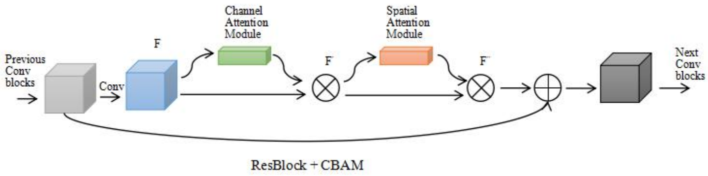


Fig. 5: Residual structure of attention module.

MATERIAL AND METHODS

Datasets

In order to ensure that the image quality will not be affected by the external factors, 6360 images were selected for the experiment after screening out some blurred images on the premise of ensuring that only the bamboo itself is different and other conditions are the same. According to the different types of defects, it can be divided into four categories, type *(a)* 1713 pictures, type *(b)* 1727 pictures, type *(c)* 1718 pictures, and type *(d)* 1202 pictures. The representative features of the four types are shown in the Fig. 6 and named Banpiancai, Feipiancai, Huapiancai, Lantoucai separately. Each photo is manually cropped to 256*256 pixels, which makes it easier to be processed by deep learning network. Each image in the datasets is uniquely numbered according to its defect category, which ensures that the defect category of the image can be quickly and accurately identified by numbering.

(a) (b) (c) (d)

Fig. 6: Datasets image: (a) Banpiancai,(b) Feipiancai, (c) Huapiancai, (d) Lantoucai.

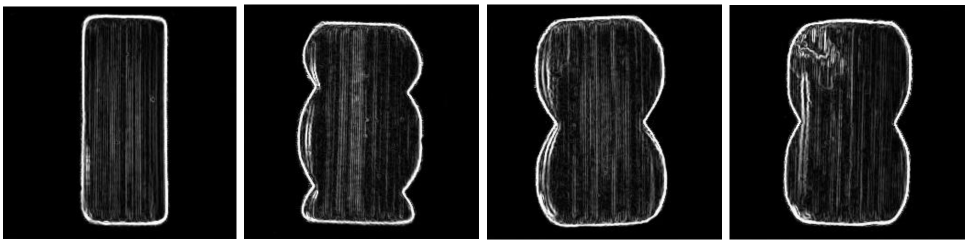
Experimental environment

In this experiment, using PyCharm software, PyTorch1.8.0 framework for bamboo defect segmentation and classification. The experiment adopts windows 10, the CPU is the ninth generation of Intel Core i7-9750H, the RAM is 16GB, the GPU is NVIDIA GeForce GTX 1660Ti, and the CUDA version is 10.2.141.

Research methods

Edge detection

In computer vision, the edge and contour of image objects contain important information. In this experiment, Sobel operator is used to process the original image to obtain the edge contour of bamboo defects. The image obtained is shown in Fig. 7.



(a) (b) (c) (d)

Fig. 7: Edge detection image of datasets after Sobel operator.

Since the obtained image is RGB three channel image, when using U-net network for image segmentation, we need to choose to gray the image and process it into single channel mode. In this experiment, the commonly used weighted average algorithm is used to gray the datasets, that is, the pixel values of R, G and B channels are weighted average according to a certain weight. The calculation formula is shown in Eq. 4:

$$\mathrm{gray} = R * 0.229 + G * 0.587 + B * 0.114 \quad (4)$$

where: R - red channel, G - green channel and B - blue channel.

Improving U-net

In this paper, the improved U-net network adds residual structure to the decoding block, which can not only reduce the loss of image features in the convolution process and suppress the phenomenon of gradient disappearance and gradient explosion in the training process effectively, but also improve the ability of the decoder to recover features.

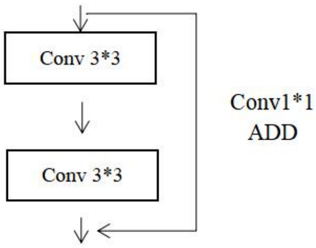


Fig. 8: Residual structure of U-net network.

The residual structure added in U-net is shown in Fig. 8. The residual block connects the output of the shallow network to the deep network and takes it as a part of the convolution input of the deep network. This method can effectively reduce the loss of image features in the convolution process, retain more useful information and improve the utilization of features. When the dimensions of the two images linked by the residual structure are the same, we use the residual structure shown in Fig. 2. When the dimensions are different, it is necessary to convert the dimensions through a one-dimensional convolution layer shown in Fig. 8 and then overlay the images. The improved U-net is shown in Fig. 9 .

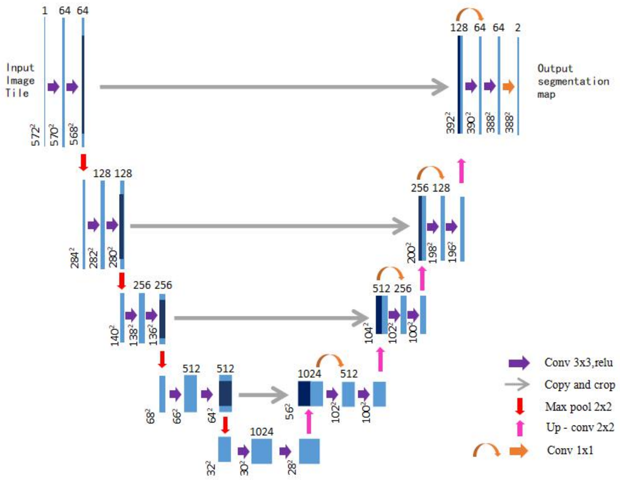
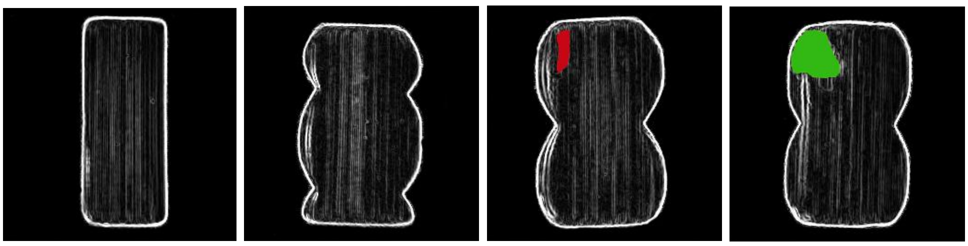


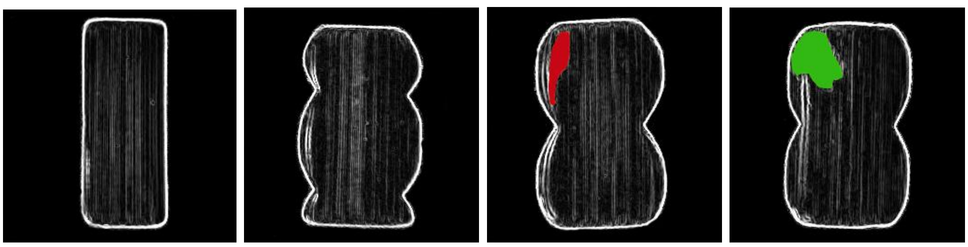
Fig. 9: Improved U-net network structure.

The grayed image is segmented by U-net network (Fig. 10). The image is segmented by the improved U-net network, and the effect is shown in Fig. 11.



(a) (b) (c) (d)

Fig. 10: U-net network segmentation image of datasets.



(a) (b) (c) (d)

Fig. 11: Image segmentation based on improved U-net network of datasets.

Because the shape of the bamboo pieces with *(a)* and *(b)* defects is different from that of the normal mahjong bamboo pieces, the types of the defects can be distinguished by their shapes. Compared with *(d)* and *(c)*, the color of most *(c)* defects is darker than the primary color of the bamboo pieces, which is indicated by red *(d)* The color of the defect is lighter than the primary color, which is indicated by green. It can be seen from the visual comparison chart that the improved U-net network can segment the defects of *(c)* and *(d)* bamboo pieces more accurately and the effect is better on the basis of accurately segmenting bamboo pieces.

After the improved U-net segmentation processing, the output of four types of defects are divided by the ratio of training: testing = 8 : 2. By adding three classification networks VGG16, GoogLeNet and ResNet50 of CBAM attention mechanism module to classify defects, the classification accuracy of the three is compared. During the experiment, in order to ensure the reliability and fairness of the experimental results, after using several rounds of tests, the final three kinds of classification network para-meters are as follows: learning rate is 0.0001, optimizer is Adam, batch size is 32, epoch is 60.

RESULTS AND DISCUSSION

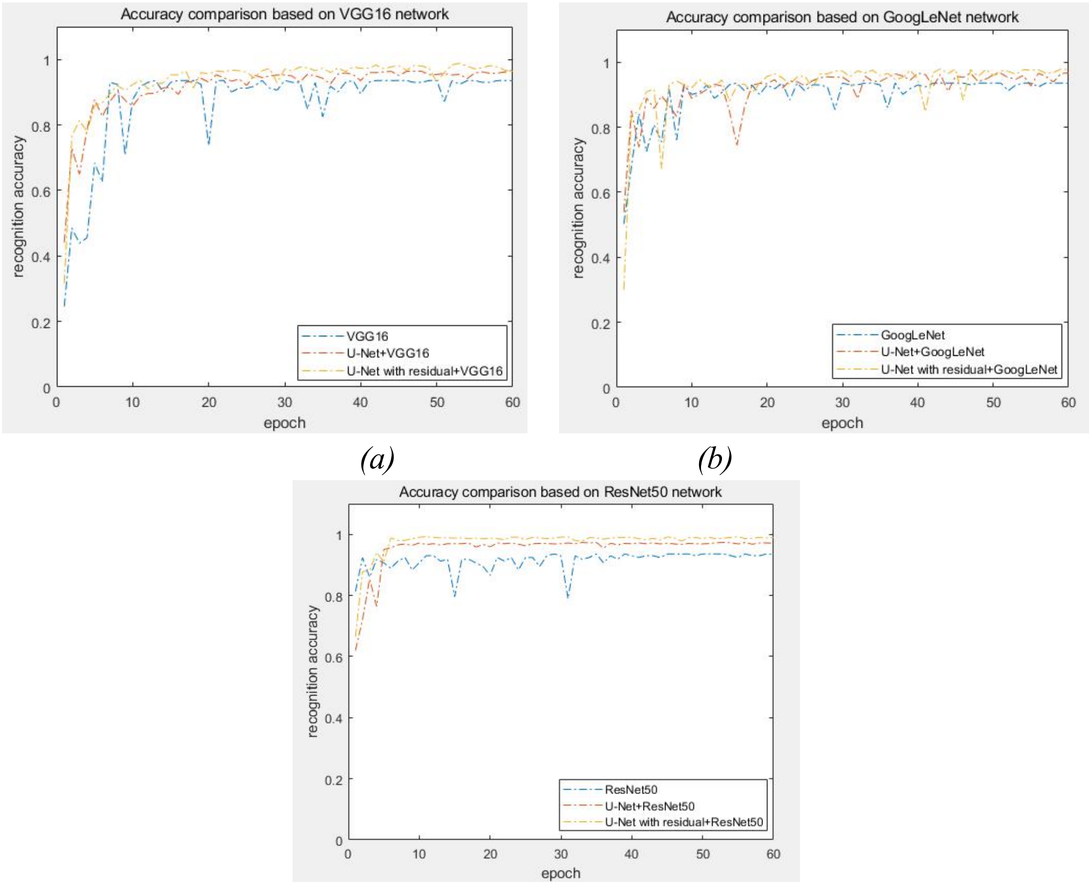
The classification accuracy of neural network model based on transfer learning in different segmentation networks and classification network models are shown in Tab. 1. It can be seen that the highest accuracy of the three classification networks is 93.57% of ResNet50 when the segmentation network model is none, but there is little difference compared with the other two networks. When the basic U-net segmentation network is used, the highest accuracy is 97.12% of ResNet50, compared with the accuracy of 93.57% without segmentation network model, the accuracy of ResNet50 is improved by at least 3%, the improvement effect is obvious. Compared with VGG16 and GoogLeNet under the same conditions, the accuracy is improved by 1-2%, and the improvement is obvious. When using the improved U-net segmentation network with residual structure, the accuracy of the three kinds of classification neural networks has been significantly improved compared with the previous ones. The most improved one is GoogLeNet, which has increased by 3.26%, and the highest recognition rate is ResNet50, which has reached 99.22%. Compared with the U-net network before the improvement, the recognition rate has increased by 2.1%.

The experimental results show that the ResNet50 classification network has the highest recognition accuracy under the same condition, whether the segmentation network model is used or not. When the basic segmentation network and the improved segmentation network are used, the recognition accuracy of ResNet50 classification network is significantly improved, and the highest recognition rate reaches 99.22%.

Tab. 1: Accuracy of image recognition of bamboo defects (%).

Segmentation network model	**Classification network model**		
	VGG16	GoogLeNet	ResNet50
None	93.15	93.56	93.57
U-net	95.81	94.63	97.12
U-net+residual	97.24	97.89	99.22

Fig. 12 shows the broken line graph of bamboo defect recognition accuracy based on VGG16, GoogLeNet and ResNet50 networks respectively. From the graph, we can see the difference in recognition accuracy under different segmentation network models easily and intuitively. The blue line indicates that the segmentation network model is not adopted, the red line indicates that the basic U-net segmentation model is adopted, and the orange line indicates that the improved U-net segmentation model is adopted.



(a) *(b)*

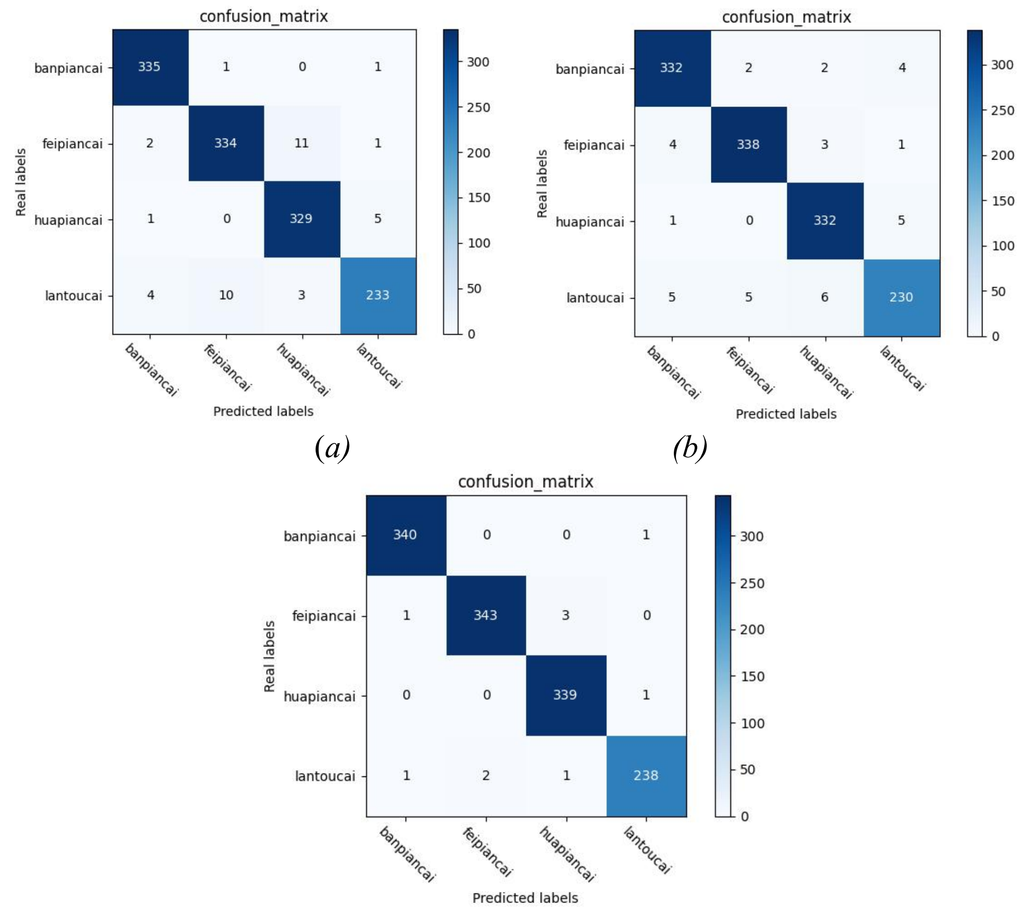
(c)

Fig. 12: Comparison of recognition accuracy of different classification networks: (a) comparison of recognition accuracy based on VGG16 network, (b) comparison of recognition accuracy based on GoogLeNet network, (c) comparison of recognition accuracy based on ResNet50 network.

Confusion matrix

Confusion matrix, also known as error matrix, is a visual tool used to evaluate the classification accuracy. The columns of confusion matrix are classification categories, and the total number of each column is the number of network prediction categories. Each row represents the real category of the image, and the total number of each row is the actual number of classified images of the category. In the matrix diagram, the depth of background color represents the accuracy of classification recognition. The deeper the color is, the higher the accuracy of model recognition is.

Because the ratio of training and testing is 8:2, the number of defect images of *(a)* Banpiancai, *(b)* Feipiancai, *(c)* Huapiancai and *(d)* Lantoucai is 342, 345, 343 and 240, resp. Fig. 13 shows the confusion matrix of different classification networks. It can be seen that the recognition accuracy of *(c)* is the highest. In 1270 testing photos, 1260 photos are accurately identified, and the recognition accuracy is 99.2%. A small part of the image classification errors may be due to the similar texture between the bamboo defects.



(*a*) (*b*)

(c)

Fig. 13: Confusion matrix of different classification networks: (a) VGG16, (b) GoogLeNet, (c) ResNet50.

CONCLUSION

In order to realize the accurate classification of bamboo defects, we proposes a two-stage method for datasets segmentation before classification. In order to achieve better image segmentation, the traditional U-net segmentation network is improved by adding residual blocks to achieve more accurate defect segmentation. The experimental results show that after using the improved segmentation network, the accuracy of the three kinds of classification neural networks has been significantly improved compared with the previous ones. The highest improvement is GoogLeNet, which increases by 3.26%, and the highest recognition accuracy is ResNet50, which reaches 99.22%. Compared with the U-net network before the improvement, the recognition accuracy increases by 2.1%, It is proved that the improved model can improve the accuracy of defect classification. From the confusion matrix, we can see that there are still some shortcomings in this research. On the one hand, some images in the datasets have similarity in the shape and texture of defects, on the other hand, some images must be divided into a certain category when there are two kinds of defects at the same time, which affects the accuracy of classification. In view of the above problems, the author will carefully select the datasets to ensure that a picture has only one kind of defects. At the same time, the author will continue to learn and choose a new deep learning algorithm for verification.

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