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RESEARCH ON WOOD DEFECTS CLASSIFICATION BASED ON DEEP LEARNING

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ABSTRACT

Whereas the traditional manual detection method of wood defects is problematic due time-consuming, low efficiency and low accuracy, an derived model based on ResNet-v2 was constructed. The new derived model can accurately point out the types of defects such as wormhole, live joint and dead joint on the surface of plate, improve the accuracy of classification, and greatly reduce the labor force. Compared with the traditional convolutional neural network, ResNet-v2 derived model has better recognition effect and stronger generalization ability. The experimental results show that the classification accuracy of ResNet-v2 derived network model based on different number of layers is more than 80%, and the classification accuracy of ResNet-v2 derived model can reach 97.27%.

KEYWORDS: Deep learning, plate defects, ResNet-v2 derivative model, classification recognition.

INTRODUCTION

Wood defects are easy to occur in the period of natural growth, storage after cutting and later wood processing of trees. Wood defects will affect use and service life of plate materials and wood products (Luo and Sun 2019, Fan et al. 2020, Liu et al. 2019). Wood defect detection is one of the important processes of wood processing. The automatic detection of wood defects is the premise of high-quality plate processing, and the recognition of plate defect image is the difficulty of this technology (Cheng et al. 2018, Zhou et al. 2020). There are many kinds of defects in wood, and the surface shape and color of each kind of wood are different, which makes the diagnosis of wood more difficult.

Regarding the problem of plate defect recognition, traditional algorithms were suggested by authors. Qi and Mou (2013) proposed a wood defect detection algorithm based on Hu moment invariants and BP neural network, and completed the wood defect image segmentation. Wang et al. (2018) proposed a support vector machine method based on texture features and gray histogram to realize the detection and location of wood knot defects. Wu et al. (2010) proposed a wood defect recognition algorithm based on gray level co-occurrence matrix and clustering method. The above three algorithms can effectively recognize the surface defects of wood, but for large sample data, the recognition accuracy is not high.

In recent years, with the improvement of deep learning theory, the pattern recognition algorithms of speech and image have achieved some success. For example, Cheng (2021) proposed the semantic segmentation algorithm of wood defect image based on the platforms OpenCV and Tensorflow. Hu et al. 2019 proposed the wood defect and texture recognition algorithm based on self-learning DBN. Li et al. (2020) proposed the wood automatic defect location model based on MobileNet. Yan and Cheng 2020 proposed a semantic segmentation algorithm of wood defect image based on convolution neural network. Yan et al. (2020) combined deep learning feature extraction method with extreme learning machine (ELM) classification method to establish a deep extreme learning machine model for wood image defect detection. These novel deep learning algorithms have an accuracy rate of more than 80%. Aiming at wood defect classification, this paper attempts to use VGG (Visual Geometry Group) model, GoogLeNet model and ResNet model to detect the types of wood defects, and classify the types of wood defects.

MATERIAL AND METHODS

Sample data acquisition

In this paper, a small sample library was established by selecting the wood sheet materials with three kinds of defects such as wormhole, live joint and dead joint. Because there are only 2630 images in the original sample, it is not suitable for deep learning. So we use the method of data enhancement to deal with the 2630 images by rotation, translation, scale transformation, gray transformation and so on, so as to expand the sample library. After the expansion, there were 10687 images in the sample library, 7480 of which are selected as the training set, 2137 as the validation set, and 1070 as the test set at the ratio of 7:2:1. For illustration some samples of wood defects are shown in Fig. 1.

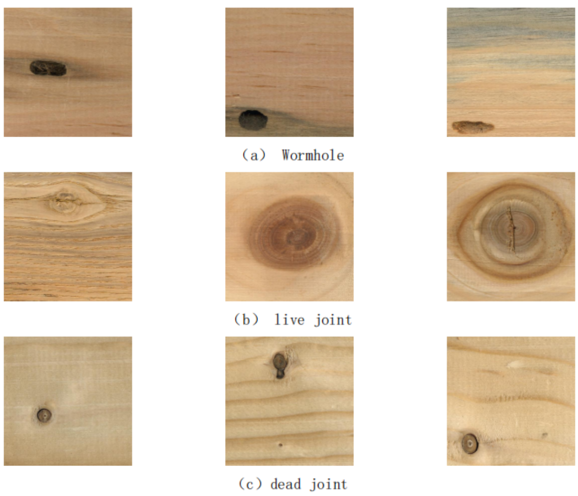

Fig. 1: Samples of wood defects in a sample library.

Visual geometry group model (VGG)

VGG model was proposed by Visual Geometry Group of Oxford University in 2014, so this model algorithm is named Visual Geometry Group, abbreviated as VGG model. It is derived from the AlexNet model. On the basis of the AlexNet model, the LRN layer is removed, and the convolution kernel of 7×7 is removed. The size of convolution kernel and pooled kernel is 3×3, and the parameters are reduced to get the VGG network model. Among them, VGG-16 network is the network model with the best classification performance (Zhang et al. 2018, Bao et al. 2021). VGG-16 has 16 layers of network structure, which is composed of 13 layers of convolution layer and 3 layers of full connection layer. Firstly, the pixels of the plate defect sample image are converted into $224 \times 224 \times 3$ and input into the network. Firstly, after two layers of convolution layer, the convolution core size is $3 \times 3 \times 64$, and the maximum pooling processing is adopted; secondly, after two layers of convolution layer, the convolution core size is $3 \times 3 \times 128$, and the maximum pooling processing is adopted; thirdly, after three layers of convolution layer, the convolution core size is $3 \times 3 \times 512$, and the maximum pooling processing is adopted. Finally, the data are processed by softmax function for three times, and the classification of plate defect sample images is realized. The experimental results of VGG model are shown in Fig. 4.

GoogLeNet model

The GoogLeNet model was proposed by Christian Szegedy in 2014, which is a 22 layer neural network based on the perception network. A $224 \times 224 \times 3$ sheet defect image is input into GoogLeNet network (Xue et al. 2020, Huang et al. 2020, Peng and Wang 2019). First, it goes through the first layer of convolution layer, convolution core size is $7 \times 7 \times 64$, convolution is followed by ReLU operation, and then through the maximum pooling process of 3×3, then, it goes through the second layer of convolution layer, convolution core size is $3 \times 3 \times 192$, convolution is followed by ReLU operation, and then through the maximum pooling process of 3×3, finally, it goes through the third layer of intrusion 3A layer, which is divided into four branches, which are processed by convolution kernels of different scales. The convolution kernels of three convolution processing are resp. $1 \times 1 \times 64$, $1 \times 1 \times 96$, $1 \times 1 \times 16$ and $5 \times 5 \times 32$, and the other branch is 3 x 3 pooling layer, which connects the results of the four branches. The third dimension of the output results of the four branches is parallel, which is the dimension of the output image; the third layer is perception 3b layer, this layer is divided into four branches, which are processed by convolution kernels of different scales. The convolution kernels of three convolution processing are $1 \times 1 \times 128$, $1 \times 1 \times 128$, $3 \times 3 \times 192$ and $1 \times 1 \times 32$, $5 \times 5 \times 96$ and another branch is 3×3 pooling layer processing and $1 \times 1 \times 64$ convolution processing (Liu et al. 2020). The results of the four branches are connected, and the third dimension of the output results of the four branches is parallel, which is the output of the data dimension: the fourth level of perception (4a-e) and the fifth level of perception (5a,b) are similar to the third level, so we will not repeat them. Finally, the output data is the type label of the plate defect image, so as to achieve the purpose of classification. The algorithm covers convolution layer and pooling layer of different scales, which can effectively alleviate the problem of training gradient dispersion caused by large amount of data processing. The experimental results of GoogLeNet model are shown in Fig. 5.

ResNet model structure

CNN model will enhance the detection effect with the increase of learning layers. However, there are many problems in deep CNN, such as huge model structure and heavy computation, which affect the speed and accuracy of training. Therefore, this paper uses residual neural network to learn and recognize wood samples. In the ordinary convolution model, the series mechanism is added to form ResNet model. It effectively reduces the training difficulty of network parameters, and will not cause the decline of accuracy (Zhang et al. 2021). The following figure is the schematic diagram of two-layer basic block unit. The three-layer basic block structure is based on the two-layer structure, adding a layer of convolution layer structure on the main branch. Basic block units are connected in series to form res block module, which is the smallest unit of ResNet model (Xie and Dong 2021, Tong and Xu 2021, Jin et al. 2021, Wang and Hi 2019). The schematic diagram of basic block unit is shown in Fig. 2.

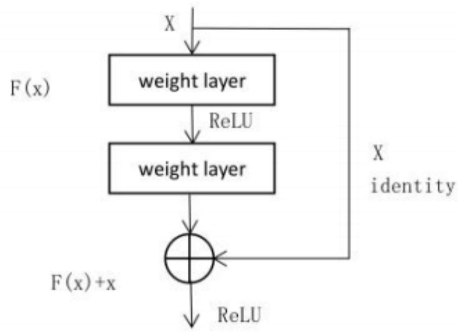

Fig. 2: Schematic diagram of basic block unit.

Due to the different layers of ResNet network, the unit structure of residual block is also slightly different. Therefore, the network structure of ResNet can be roughly divided into two categories: one is based on two-layer structure of basic block, such as ResNet-18 and ResNet-34; the other is based on three-layer structure of basic block, such as ResNet-50, ResNet-101, ResNet-152 and higher-layer ResNet network structure (Zhang and Hu 2019). In ResNet network, the structure sequence of residual block is convolution processing, BN processing, and ReLU activation processing. After processing results are superimposed, ReLU activation processing is performed. The specific network structure configuration is shown in Tab. 1.

Tab. 1: ResNet network configuration table.

Layer	Output size	ResNet-18	ResNet-34	ResNet-50	ResNet-101
Conv1	112×112	$7\times7\times64$, stride = 2			
Conv2_x	56×56	3×3max pool, stride = 2			
		$\begin{bmatrix}3\times3\times64\\3\times3\times64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3\times64\\3\times3\times64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1\times64\\3\times3\times64\\1\times1\times256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1\times64\\3\times3\times64\\1\times1\times256\end{bmatrix}\times3$
Conv3_x	28×28	$\begin{bmatrix}3\times3\times128\\3\times3\times128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3\times128\\3\times3\times128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1\times128\\3\times3\times128\\1\times1\times512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1\times128\\3\times3\times128\\1\times1\times512\end{bmatrix}\times4$
Conv4_x	14×14	$\begin{bmatrix}3\times3\times256\\3\times3\times256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3\times256\\3\times3\times256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1\times256\\3\times3\times256\\1\times1\times1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1\times256\\3\times3\times256\\1\times1\times1024\end{bmatrix}\times23$
Conv5_x	7×7	$\begin{bmatrix}3\times3\times512\\3\times3\times512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3\times512\\3\times3\times512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1\times512\\3\times3\times512\\1\times1\times2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1\times512\\3\times3\times512\\1\times1\times2048\end{bmatrix}\times3$
	1×1	Average pool,1000-d fc, softmax			

ResNet-v2 derived model structure

According to the original residual network unit, some improvements are proposed to form a new residual network unit. In the original ResNet model, the ReLU function is used as the activation function, which requires high learning rate and is prone to “neuron death“. The improved ResNet-v2 derived model uses sigmoid function to put sigmoid activation function into ‘pre-activation’ which is regarded as weight layer instead of traditional “post-activation”. From this point of view, a new residual cell is generated, as shown in Fig. 3 below.

The new algorithm based on ResNet-v2 algorithm is as follows: firstly, convolution processing is performed on the plate defect image, the convolution core is 7 * 7 * 64, the step size is 2, and the convolution result of the previous step is maximized. Analysis of residual in ResNet. According to the parameter configuration in Tab. 1, if the ResNet-v2 network structure is 18 or 34 layers, repeat the above operation twice; if the network structure is 50 or 101 layers, repeat the above operation three operations. The data of the last convolution operation is superimposed with the data just entering BN normalization processing. According to the network layer requirements of ResNet-v2, repeat the PreActBlock. The last layer of ResNet-v2 network system is the same as the ResNet network structure. It adopts average pooling, FC full connection and sigmoid activation function to classify. The cross entropy loss function is used as the loss function, and momentum SGD is used as the optimization method.

The new algorithm based on ResNet-v2 can simplify the optimization process and reduce the loss of information in the process of information transmission. In addition, as a ‘pre-activation’ BN layer plays a role of regularization, which can effectively suppress the over fitting phenomenon. Compared with the original ResNet network structure, the new algorithm based on ResNet-v2 is easier for deep learning and has stronger generalization ability. The structure comparison diagram of ResNet and the new algorithm derived from ResNet-v2 is shown in Fig. 3.

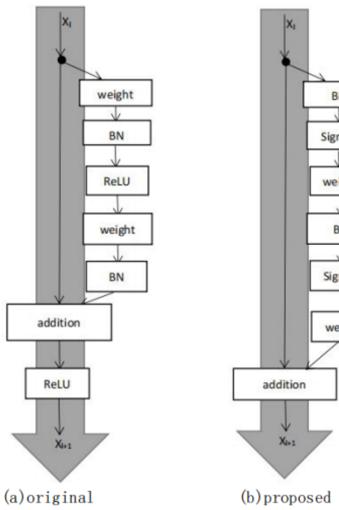

Fig. 3: Network structure of PreActBlock link.

RESULTS AND DISCUSSION

Experimental results

In this paper, we use the method of comparative experiment, put the data set into VGG-16 model, GoogLeNet model, ResNet model and ResNet-v2 model at the same time, and then compare the test accuracy of various models with other irrelevant variables, such as batch size, optimization method, loss function, etc. The experiment was completed based on inter (R) core (TM) i5-6300hq CPU@2.30GHz, memory 8.00GB, hard disk 208GB hardware environment.

VGG-16 model realizes the plate defect classification, and the highest accuracy of test set is 83.301% in the 14th iteration. The training set loss function and test set accuracy of VGG-16 model are shown in Fig. 4a. In the 16th iteration, the highest accuracy of test set is 86.648%. The training set loss function and test set accuracy of GoogLeNet model are shown in Fig. 4b.

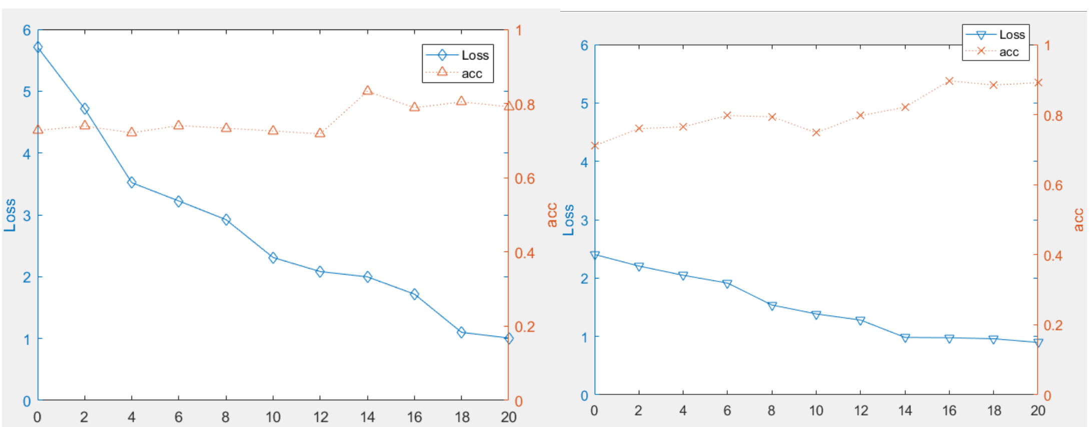

Fig. 4: Loss function and accuracy: a) VGG-16, b) GoogLeNet model.

For the ResNet model of layers 18, 34, 50 and 101, the accuracy of the test set is shown in Fig. 5a. The loss function of training set is shown in Fig. 5b. In the 71st iteration of ResNet-18 network structure, the maximum accuracy is 82.108%. In the 81st iteration of ResNet-34 network structure, the maximum accuracy is 87.745%.The maximum accuracy of ResNet-50 network structure is 98.625% in the 71st iteration. In the 81st iteration of ResNet-101 network structure, the maximum accuracy is 96.814%.

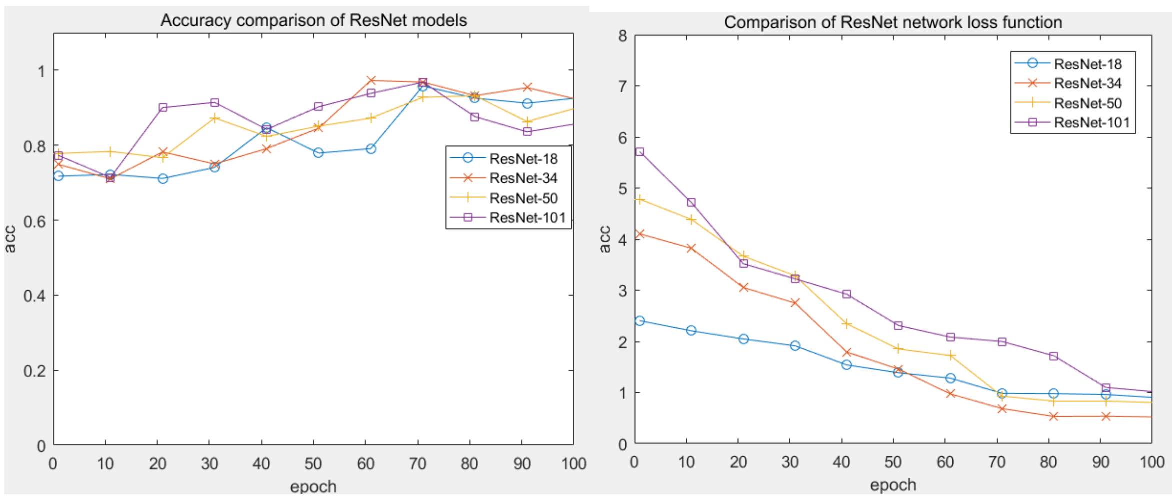

Fig. 5: a) Accuracy comparison of ResNet test set, b) loss function comparison of ResNet training set.

For the ResNet-v2 derived model based on layers 18, 34, 50 and 101, the accuracy of the test set is shown in Fig. 6a.The loss function of training set is shown in Fig. 6b. In the 81st iteration of the 18 layer network structure, the maximum accuracy is 95.801%. In the 71st iteration, the maximum accuracy is 97.266%. In the 81st iteration, the maximum accuracy of 50 layer network structure is 93.203%. In the 71st iteration, the maximum accuracy of 101 layer network is 91.814%.

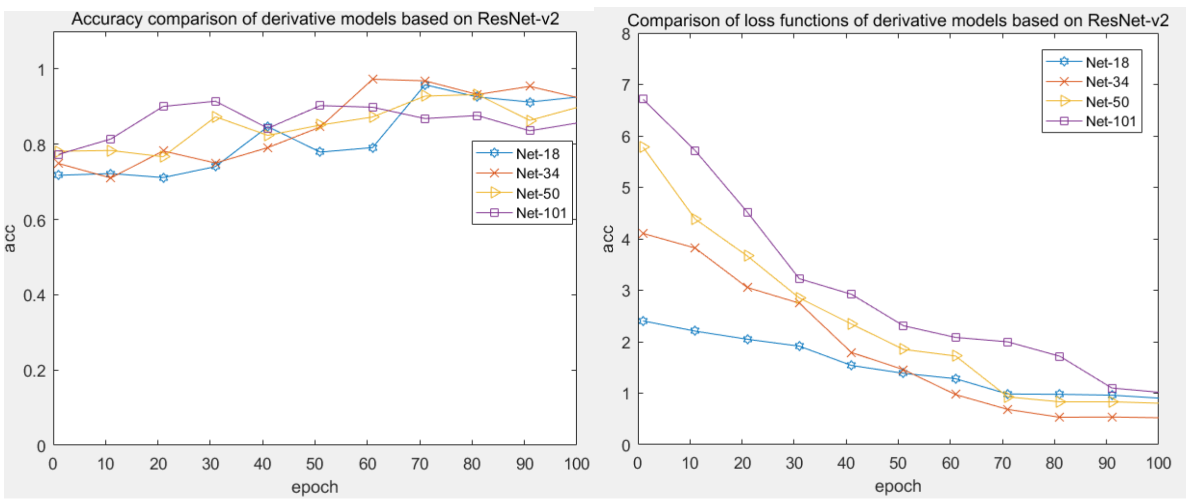

Fig. 6: a) Accuracy comparison of derived model test set based on ResNet-v2, b) comparison of training set loss function based on resnet-v2 derivative model.

The accuracy of ResNet model and derived model test set based on ResNet-v2 is shown in Tab. 2, and the classification accuracy of three types of defects is shown in Tab. 3.

Tab. 2: Classification accuracy of test set.

	18	**34**	**50**	**101**
ResNet	82.108%	87.745%	98.625%	96.814%
ResNet-v2 derived model	95.801%	97.266%	93.203%	91.422%

Tab. 3: Defect accuracy of ResNet-v2 derived model.

	Wormhole	**Dead joint**	**Live joint**
Derived model-18	94.172%	93.834%	98.638%
Derived model-34	92.824%	99.401%	97.343%
Derived model-50	93.900%	95.412%	91.629%
Derived model-101	89.159%	95.928%	90.033%

VGG model, GoogLeNet model, ResNet model and the derived model of ResNet-v2 are compared for the recognition accuracy of plate defects, as shown in Tab. 4.

Tab. 4: Comparison of accuracy of four models.

	VGG	**GoogLeNet**	**ResNet**	**ResNet-v2 derived model**
Accuracy	83.301%	86.648%	98.625%	97.266%

CONCLUSIONS

In this paper, VGG-16 model, GoogLeNet model, ResNet model, and the derived model based on ResNet-v2 are constructed to identify wood defects. The images of wood defects are put into each model for deep learning. By comparing the data results of the four models, it is found that the derived model of ResNet-v2 can well distinguish the types of sample defects, and has high accuracy and good performance By controlling the learning rate, the speed of data learning can be accelerated, and the phenomenon of gradient explosion and gradient dispersion can be effectively avoided. However, with the increase of convolution layers, the classification accuracy of ResNet-v2 system is not as good as that of ResNet system, which is also the deficiency of this study. It is hoped that further improvement can be made in future research.

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