Intelligent recognition of surface defects of parts by Resnet

Fushuai Wang¹, Jiyuan Qiu², Zhefeng Wang* and Wenrui Li*

¹Faculty of Materials and Engineering, Shenyang Aerospace University, Shenyang, Liaoning, 110136, China
²Aerospace Academy, Shenyang Aerospace University, Shenyang, Liaoning, 110136, China
*Corresponding author’s e-mail: zhefeng_w@126.com

Abstract. Nowadays, Automatic metal surface defect recognition is an important research direction in the field of surface defect recognition, and more convolution neural network algorithms are applied in this field. However, with the deepening of network layers, network degradation will occur. We propose a ResNet method for classifying metal surface defects. After experimental testing, we use ResNet34 to build an identification network. After training 300 epoch of the network using the NEU surface defect data set, the convergence of the network is very good. The accuracy of test set verification is 93.67% and higher than that of other surface defect recognition algorithms. Also, we can deepen the number of layers ResNet the network without worrying about network degradation.

1. Introduction

Metal parts are generated or used, there's always a lot of damage, these will affect the performance of metal parts. For producers or defenders, the detection and classification of metal surface damage is helpful for the production and maintenance of metal parts. Early surface defects were mainly manually detected, high cost and low efficiency [1] this method. In recent years, automatic detection is becoming a hot topic, it can improve the efficiency of metal surface damage detection, reduce cost [2]. In previous studies, machine learning (ML) is one of the conventional defect recognition methods. Traditional machine learning methods such as k nearest neighbor [3], SVM [4], Learning vector quantization [5] and artificial neural network [6] are excellent defect recognition performance, but these methods all require feature extraction. With the rise of artificial intelligence, convolutional neural network (CNN) can automatically extract features by convolution kernel, have been applied in other recognition fields [7-10]. J Masci et al [11] proposed a maximum pool convolutional neural network method for monitoring defect classification for defect detection, the recognition accuracy is 93%. Yiping G [12] et al [13] proposed a semi-supervised convolutional neural network for steel surface defect recognition, the recognition accuracy is 90.7%.

On the study of convolutional neural networks to identify surface defects, most are improved studies using LeNet-5 neural networks. And this network is simple, but with few parameters, learning ability is weak. LeNet-5 [13] is the CNN architecture LeCun designed in 1998, are the most representative architectures in the early CNN. In 2012, Krizhevsky and other [14] propose a large deep convolution neural network - AlexNet. VGGNet is the [15] proposed by the Oxford University VGG Group. VGGNet use 33 convolution kernels and 22 maximum pool kernels to improve performance by deepening the network structure. And its small convolution kernel is better than the large convolution kernel, because multilayer nonlinear layers can increase the depth of the network to ensure more
complex patterns, which the required parameters are relatively small. And as the network deepens, there's a drop in training set accuracy, the rise in error rates, Is the so-called "degradation" problem. On this issue, ResNet [16]. HE K et al . 2015.

In order to improve the learning ability of defect recognition neural network and improve the recognition accuracy, we choose to use a more mature ResNet network to identify the process defects on the surface of the parts.

2. INTRODUCTION TO RESNET
Residual Net (ResNet) was proposed by HE K et al . [16] in the 2015 ILSVRC contest, won the championship in the five competitions of ImageNet classification, ImageNet detection, ImageNet positioning, COCO detection and COCO segmentation in 2015, and affected the development direction of the field of deep learning since then. ResNet proposal solves the problem that as the network depth increases, gradient parameters disappear, the convergence effect of the network is not ideal, accuracy to saturation [17], this phenomenon is called neural network degradation. ResNet is improved by plain net. And in the RestNet, address degradation by introducing a deep learning framework. The network connection is compared as follows:

![Figure 1. Blocks of CNN, plain net on the left, ResNet on the right.](image)

The stacked layers are layer called a block, and for the block, in the ResNet, in addition to the output from the convolution layer, there is a branch that connects the input directly to the output. The output of the block is $H(x)$. The output of the ResNet block becomes $H(x) = F(x) + x$. For input $x$, for the output $F(x)$ obtained through the convolution layer. when the convolution layer output is 0, then we can get $H(x) = x$ for identity mapping, the residual learning structure artificially adds identity mapping, the network performance will not be worse and worse because of the increase of depth. With the increase of training times, on the basis of identity mapping, the convolution layer can constantly update the weight and iterate in the direction of gradient descent.

ResNet is a subversive network structure, from a new perspective to improve the performance of the network, so that the network depth can reach more than 100 layers.

3. EXPERIMENTAL RESULTS OF RESNET
ResNet34 is a type of ResNet with a weighted number of layers of 34, in this section, we train the RestNet34 using the benchmark dataset NEU and give the ResNet34 network parameters, and the training results. ResNet34 use pytorch to build, use GPU to train 300 epochs.

3.1. Interpretation of data
NEU surface defect data set is a surface defect database published by Northeast University. At Northeastern University (NEU), Six typical surface defects of hot rolled steel strip were collected, i.e.
Rolled-in Scale (RS), Patches (Pa), Crazing (Cr), Pitted Surface (PS), Inclusion (In) and Scratches (Sc), as shown in figure 2. The database includes 1800 grayscale images, 300 samples each of six different types of typical surface defects. Image is a gray image of BMP format size. Maintaining the Integrity of the Specifications.

Figure 2. Example of NEU data

From the image, we can see that different types of surface damage are more obvious, but some of the same types of defects are not familiar. In this experiment, we selected 1500 pictures from 1800 original data, 250 pictures of each kind were trained, and the remaining 300 pictures were used to detect the model. At the same time, in order to bring the picture into the network training smoothly, we use the bicubic interpolation method to change the picture from size to size.

3.2. Introduction of Resnet34
ResNet34 is a type of ResNet called ResNet34, because its weighted number of layers is 34. We used pytorch-gpu 1.2.0 to build ResNet34. In this experiment, a ResNet34 network structure is shown below:

Figure 3. ResNet34 network structure, network construction reference [16]

3.3. Results of training testing
After we bring 1500 pictures into the ResNet34 training, the learning rate is set to 0.0001. After 300 epoch of training, the training results are shown below.
Figure 4. Training results ResNet34 after 300 epoch of training

As we can see from the diagram, after 300 epoch of training, the loss convergence of the training set and the test set is good, and the accuracy reached a better level. Eventually, when epoch=300, the final results of the model, such as table 1 and table 2. The table 2 shows epoch=300, ResNet34 training set and test set loss and classification accuracy respectively. Train loss and train accuracy are training set results, test loss and test accuracy are test set results. During table 2 test set training, identification of different types of defects. The total number of pictures is 300. The training set data classification model classification is all correct.

Table 1. At epoch=300, the training results of the model

| Variable name | results     |
|---------------|-------------|
| train loss    | 0.01386     |
| test loss     | 0.34568     |
| train accuracy| 100%        |
| test accuracy | 93.67%      |

Table 2. Classification of different types of images at epoch=300

| Type of picture    | Total number | correct pictures | accuracy |
|--------------------|--------------|------------------|----------|
| Crazing            | 50           | 46               | 92%      |
| Inclusion          | 50           | 44               | 88%      |
| Patches            | 50           | 50               | 100%     |
| Pitted Surface     | 50           | 47               | 94%      |
| Rolled-in Scale    | 50           | 49               | 98%      |
| Scratches          | 50           | 45               | 90%      |
Subsequently, we compare the accuracy of our model with the traditional method of surface defect recognition. Label propagation [18], SVM [19], Safety-aware graph [20], Laplacian ELM [21], ladder network [22], PLCNN [12] and VGG16, are the traditional methods of comparison VGG16 we build and get results. The results are as follows:

| methods                      | Label propagation | S3VM | Safety-aware graph | Laplacian ELM |
|------------------------------|-------------------|------|--------------------|---------------|
| accuracy                     | 34.0%             | 42.86% | 78.7%             | 16.7%         |
| methods                      | ladder network    | PLCNN | VGG16              | ResNet34      |
| accuracy                     | 27.7%             | 90.7% | 91.33%             | 93.67%        |

From the table 3 we can see that compared with other methods. ResNet34 accuracy of image surface defect classification exceeds some methods. The accuracy rate is greatly improved compared with the VGG16, at the same time ResNet there are VGG incomparable advantages, which can deepen the number of network layers, increase the learning ability of the network without causing network degradation.

4. Conclusion
In this paper, we propose a method to identify metal surface defects based on ResNet networks. after testing, we trained the ResNet34 network using the NEU surface defect dataset. after training 300 epoch, the convergence of the network is very good. Compared with other methods, the accuracy of ResNet34 classification of different types of images is higher, and the recognition accuracy is higher than that listed in this paper, and ResNet can also increase the number of network layers without worrying about network degradation. In the future, we can improve the ResNet34 and increase the depth of the network in order to achieve better learning ability and improve the recognition accuracy. However, the defects of the network are also obvious. The work done in this paper belongs to supervised learning and depends on large-scale labeled samples for model training. In some real-world situations, it is difficult and expensive to obtain large-scale labeled samples because marking large-scale samples requires expert knowledge, and this limitation hinders the application of current work in defects. Therefore, in the future, we can consider combining semi-supervised learning or even unsupervised learning to promote the application of ResNet detection.

Acknowledgments
The authors wish to thank the reviewers and associate editor. Their comments and advice promote the paper more solid. The authors also give thanks to sponsor and support from Key Laboratory Development Projects Fund (Grant SHSYS202008).

References
[1] Vilcek I, Rehor J, Carou D, et al. Residual stresses evaluation in precision milling of hardened steel based on the deflection-electrochemical etching technique[J]. 2017, 47(oct.):112-116.
[2] Gan J, Wang J, Yu H, et al. Online Rail Surface Inspection Utilizing Spatial Consistency and Continuity[J]. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2020, 50(7):2741-2751.
[3] Dupont F, Odet C, Cartont M. Optimization of the recognition of defects in flat steel products with the cost matrices theory[J]. NDT & E International, 1997, 30(1):3-10.
[4] Muhammad K, Ahmad J, Lv Z, et al. Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications[J]. Systems, Man, and Cybernetics: Systems, IEEE Transactions on, 2018.
[5] Caleb P, Steuer M. Classification of surface defects on hot rolled steel using adaptive learning methods[C]// Knowledge-Based Intelligent Engineering Systems and Allied Technologies, 2000. Proceedings. Fourth International Conference on. IEEE, 2000.

[6] Bustillo A, Pimenov D Y, Matuszewski M, et al. Using artificial intelligence models for the prediction of surface wear based on surface isotropy levels[J]. Robotics and Computer-Integrated Manufacturing, 2018, 53:215-227.

[7] Rocha L F, Ferreira M, Santos V, et al. Object recognition and pose estimation for industrial applications: A cascade system[J]. Robotics and Computer-Integrated Manufacturing, 2014, 30(6):605-621.

[8] Aouaidja K, Bin S, Po Y, et al. Deep Convolutional Neural Networks for Human Action Recognition Using Depth Maps and Postures[J]. IEEE Transactions on Systems Man & Cybernetics Systems, 2018, PP:1-14.

[9] Krizhevsky A, Sutskever I, Hinton G. ImageNet Classification with Deep Convolutional Neural Networks[C]// NIPS. Curran Associates Inc. 2012.

[10] Muhammad K, Ahmad J, Lv Z, et al. Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications[J]. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2019, 49(7):1419-1434.

[11] J. Masci, U. Meier, D. Ciresan, J. Schmidhuber, G. Fricout, Steel defect classification with max-pooling convolutional neural networks, Proc. Int. Jt. Conf. Neural Networks, 2012, pp. 1–6, , https://doi.org/10.1109/IJCNN.2012.6252468.

[12] Yiping G, Liang G, Xinyu L, et al. A semi-supervised convolutional neural network-based method for steel surface defect recognition[J]. Robotics and Computer Integrated Manufacturing, 2020, 61(2):101825.1-101825.8.

[13] Lecun Y, Bottou L. Gradient-based learning applied to document recognition[J]. Proceedings of the IEEE, 1998, 86(11):2278-2324.

[14] Krizhevsky A, Sutskever I, Hinton G. ImageNet Classification with Deep Convolutional Neural Networks[C]// NIPS. Curran Associates Inc. 2012.

[15] Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Recognition[J]. arXiv, 2014.

[16] HE K, ZHANG X, REN S, et al. Deep Residual Learning for Image Recognition[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2016:770-778

[17] He K, Sun J. Convolutional neural networks at constrained time cost[C]// 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2015.

[18] O. Delalleau, Y. Bengio, N. Le Roux, Efficient non-parametric function induction in semi-supervised learning, Proc. Tenth Int. Work. Artif. Intell. Stat. 2005, pp.100–105

[19] Gieseke F, Airola A, Pahikkala T, et al. Fast and simple gradient-based optimization for semi-supervised support vector machines[J]. Neurocomputing, 2014, 123(jan.10):23-32.

[20] Gan H , Li Z , Wu W , et al. Safety-aware Graph-based Semi-Supervised Learning[J]. Expert Systems with Applications, 2018, 107:243-254.

[21] Shuang L, Shiji S, Yike W. Laplacian twin extreme learning machine for semi-supervised classification[J]. Neurocomputing, 2018, 321(DEC.10):17-27.

[22] A. Rasmus, M. Berglund, M. Honkula, H. Valpola, T. Raiko, Semi-supervised learning with ladder networks, Adv. Neural Inf. Process. Syst. 2015, pp. 3546–3554.