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A Steel Surface Defect Recognition Algorithm Based on Improved Deep Learning Network Model Using Feature Visualization and Quality Evaluation

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ABSTRACT Steel defect detection is used to detect defects on the surface of the steel and to improve the quality of the steel surface. However, traditional image detection algorithms cannot meet the detection requirements because of small defect features and low contrast between background and features about steel surface defect datasets. A novel recognition algorithm for steel surface defects based on improved deep learning network models using feature visualization and quality evaluation is proposed in this paper. Firstly, the VGG19 is used to pre-train the steel surface defect classification task and the corresponding DVGG19 is established to extract the feature images in different layers from defects weight model. Secondly, the SSIM and decision tree are used to evaluate the feature image quality and adjust the parameters and structure of VGG19. On this basis, a new VSD network is obtained and used for the classification of steel surface defects. Comparing with ResNet and VGG19 methods, experiment results show that the proposed method markedly can improve the average accuracy of classification, and the model is able to converge quickly, which can be good for steel surface defect recognition using VSD network model of feature visualization and quality evaluation.

INDEX TERMS Deep learning, DeVGG19 network, feature visualization, steel defect recognition, VSD network.

I. INTRODUCTION

Steel quality control is a hard problem in quality management. The quality of the steel not only affects the cost of the product but also has a great impact on the subsequent processing accuracy. Therefore, steel surface defect detection is a crucial part of steel quality management. The computer image processing method is a kind of steel detection method [1], [2], by which many detection algorithms are formed. The traditional detection algorithms based on feature extraction of artificial experience can detect simple and fast, but it only can detect a single goal and use it in a specific circumstance [3]–[11]. And some traditional methods improved the accuracy of defects by adjusting the illumination [12], [13]. Compared with traditional image processing detection algorithms, deep learning algorithms can extract features from detected objects in different environments and application background. Therefore, for different detection objects and detection background, the deep learning algorithms have sufficient flexibility to achieve the detection target [14]–[20]. It could be widely used in various domains [21]–[23].

In the Deep Learning area, the convolutional neural network is a very classic structure that is inspired by the human visual perception mechanism. In 1989, LeCun *et al.* established a classic framework [24]. Then in 1990, they optimized the framework and proposed a new structure called LeNet-5 [25], which consists of a multi-layer neural network and shows excellent performance in handwritten digital classification. However, due to insufficient data and worse computer hardware, LeNet-5 did not perform well at that time. In 2006, AlexNet [26], proposed by Krizhevsky, had a

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similar but deeper structure than LeNet-5, and the classification accuracy was significantly improved compared with the previous one. Since then, deep learning has entered a stage of booming. So far, there are four representative networks, namely ZFNet, VGGNet, GoogleNet, and ResNet.

Because of the improvement of the neural network and hardware, the network structure is getting deeper and deeper. For example, ResNet [27] has a depth of 152 layers, which is equal to 8 times that of VGGNet. Although VGG19 proves that deeper structures can show better performance, it is still a linear network. To improve the problem caused by the linear structure [28], a nonlinear deep residual learning framework was introduced in ResNet and performed well in image classification tasks. Matthew D.Zeiler introduced a multi-layered deconvolutional network that could check into the feature layer and the operation of the classifier. And it also could explain why convolutional neural networks can perform so well [29]. GoogleNet designed by Szegedy *et al.* used average pooling to replace the full connect layer and the inception module to reduce the number of parameters in the network [30].

The datasets which are caught in a complex circumstance and trained by existing classification networks such as ZFNet, VGGNe, GoogleNet, ResNet, MobileNet [31] are including heavy target information, background information, and color information. And the capacity of the dataset is also larger and larger. More background detection and feature extraction processes are used to extract the underlying information of the target image from the complex backgrounds. Therefore, the structure of the neural network model is gradually deeper, non-linear, multi-group, and multi-modular, which helps over-fitting could be avoided and features are extracted at the same time. However, the images collected in the industrial background are very simple in the background and contain littler pixels than the normal dataset. Especially in the steel surface defect images, the feature information is scarce, and the picture color usually is black, grey and white. So, the current convolutional neural network models for the image classification task in the steel background are too complicated and redundant.

II. RELATED THEORY ANALYSIS

Industrial applications gradually adopt deep learning methods to detect industrial products. Due to the smaller number of defect datasets on hot-rolled steel surfaces, some papers used semi-supervised methods to augment datasets [32]–[34]. For example, Yiping Gao *et al.* raised a method, which used the semi-supervised framework to generate fake labels to satisfied the label's requirement. The experiment got good performances with limited labeled data and fake labeled data, which achieves an accuracy of 90.7% with 17.53% improvement [33]. Yu He *et al.* showed that a categorized generative adversarial network (GAN) is used to generate a large amount of unmarked data against the network, and then the residual network is used for classification. The final classification accuracy rate is 99.56% [34]. In order to improve the detection accuracy, He, D *et al.* used combined networks to detect surface defects, in which multi-group convolutional neural network (MG-CNN) was used to pre-classification; and then different types of extracted defect features were input into another Yolo-based neural network for detection and recognition. The defect-recognition accuracy is 94% by the method [35]. Besides, in the medical field, Bhandary, A. *et al.* adopted an approach by combining two different deep learning techniques to access the diagnosis problem of lung abnormalities. They used the modified AlexNet to classify the chest X-Ray images into normal and pneumonia class. The classification accuracy is attained in 97.27% successfully [36]. To extract the information efficacy, Ali *et al.* proposed a method that using multi-approaches to overcome the complex problem in social, like unsupervised machine learning, dimensionality reduction and computation classification [37].

To improve the classification accuracy of industrial hot-rolled steel surface defects, this paper introduces an algorithm that visualizes the underlying features of a defect and adjusts the network based on the quality evaluation results of the featured image. First of all, VGG19 is used as a pre-training network to pre-train the 6 kinds of steel surface defect classification tasks. Secondly, the corresponding DeVGG19 network is built according to the network structure of VGG19 and extracted the feature maps in each layer of the convolutional network; at the same time, the original images are cropped according to the receptive fields size of each layer. And then, the cropped original maps and feature map of each layer are obtained; the feature map is used as the distortion image. Next, these two kinds of pictures are elevated by the SSIM image quality evaluation algorithm, which obtains the image quality evaluation result between the featured image and the original image; the image quality evaluation results were mined by the decision tree. Finally, the VSD network is generated according to the evaluation quality result and the mining results of the decision tree and used to classify steel surface defects.

III. SPECIFIC CONTENTS

A. VGG19 NETWORK

VGGNet is a convolutional neural network designed by Karen Simonian and Andrew Zisserman, who won the runner-up in the 2014 ImageNet ILSVRC Challenge [28]. By replacing the large convolution kernels of sizes 11*11 and 5*5 with 3*3 kernel size one after another, they found in VGGNet that the small convolution kernels can increase the depth of non-linear networks and make networks more complex and able to learn more complex features. It proves that the increase in network depth can get better performance. However, deeper networks also need a huge computational requirement.

VGG19 consists of several convolution kernels that are used to compute different feature maps. As shown in Figure 1, the new steel surface defect's feature map can be obtained

TABLE 1. VGG19 network body architecture.

Type/stride	Filter shape	Input size
Conv 1_1/s1	3×3×64	224*224*3
Conv 1_2/s1	3×3×64	
Conv 2_1/s1	3×3×128	112*112*3
Conv 2_2/s1	3×3×128	
Conv 3_1/s1	3×3×256	56*56*3
Conv 3_2/s1	3×3×256	
Conv 3_3/s1	3×3×256	
Conv 3_4/s1	3×3×256	
Conv 4_1/s1	3×3×512	28*28*3
Conv 4_2/s1	3×3×512	
Conv 4_3/s1	3×3×512	
Conv 4_4/s1	3×3×512	
Conv 5_1/s1	3×3×512	14*14*3
Conv 5_2/s1	3×3×512	
Conv 5_3/s1	3×3×512	
Conv 5_4/s1	3×3×512	
Max_pool		7*7*3
Fc-4096		
Fc-4096		
Fc-1000		
SoftMax		

by many convolving the input with many learned kernels and then applying a nonlinear activation function (reul) on the convolved results. By using several different kernels, the completely new feature maps are obtained [38]. Mathematically, the single feature value V in the feature map is calculated by the formula (1):

$$V = f\left(\sum_{i=1}^{n} p_i w_i + b\right) = f\left((w_1, w_2 \ldots w_n)\begin{pmatrix} p_1 \\ p_2 \\ \cdots \\ p_n \end{pmatrix} + b\right) = f\left(W^T P + b\right) \tag{1}$$

where W and b are the weight vector and bias value respectively, and p is the input vector, and the kernel w is shared. This is a $p = (p_1, p_2 \ldots p_i \ldots p_n)$ weight sharing mechanism that can reduce the model parameters and make the network easier to train. The activation function f introduces nonlinearities to CNN, which are helped multi-layer networks to detect nonlinear features. The structure of VGG19 is shown in Table 1.

B. DeVGG19 NETWORK

According to the VGG19 network framework, deconvolution and Unpooling modules in ZFNet, this paper builds the model DeVGG19 to visualize the feature map of steel surface defects. Firstly, VGG19 is used to classify the six hot-rolled steel surface defects to obtain the weight of the pre-training model. Then, the DeVGG19 network is established by using many deconvolution modules and Unpooling modules to Unpooling, Reul and Deconvolution the different convolutional layers of the pre-training model. The features in the convolution kernel of each convolutional layer are extracted and projected into the pixel space for visualization as showed in Figure1.

DeVGG19 is a deconvolution neural network with the same structure from the VGG19 network. The important operations in the network are as follows:

1) *Unpooling:* It is impossible to really flip the operation of the convolutional network, but it is possible to select the appropriate position in the convolution value area in the maximum pooling operation. In a DeVGG19 network, Unpooling is used to find the proper location for the changed variables from the upper layer, to form a refining steel surface defect result and maintain structural activation.

2) *Rectification:* no matter in convent or DeVGG19, the relu non-linearities can still positive the feature map. Therefore, using the same relu function to make the feature map be positive and obtain the defect feature reconstructions at each layer.

3) *Filtering:* The learned filter in the VGG19 network is used to convolve the steel surface defect feature maps of the previous layer. To reverse this step, the same transpose filter in DeVGG19 is used only for the modified feature map, instead of the output of the lower layer. This operation means flipping each filter horizontally and vertically.

By the main three steps, this new feature images of convolution layers are mapped back to the input pixel space. And show the result of the steel surface defect feature image at last.

C. IMAGE QUALITY EVALUATION–SSIM

To find the steel surface defect regulation between the original image and feature image in a different layer, the approach uses the SSIM [39] function to evaluate the quality of the steel defect feature image. A variety of experimental results have demonstrated that neural networks are the criteria for classification by learning the lowest level features of images. The underlying feature image extracted by the deconv module is the edge contour information of the image feature and it is also a kind of structural image. Therefore, the quality between the steel surface defect feature image and the cropped image can be evaluated by SSIM. And as a basis to judge the effect of each layer of convolution layer feature extraction.

To emphasize structural differences, an alternative complementary framework for quality assessment based on the degradation of structural information is introduced in SSIM. The probability calculation of SSIM is given as follow:

$$SSIM(x, y) = [l(x, y)]^{\alpha} [c(x, y)]^{\beta} [s(x, y)]^{\gamma} \tag{2}$$

$$l(x, y) = \frac{2\mu_x \mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \tag{3}$$

$$c(x, y) = \frac{2\sigma_{xy} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \tag{4}$$

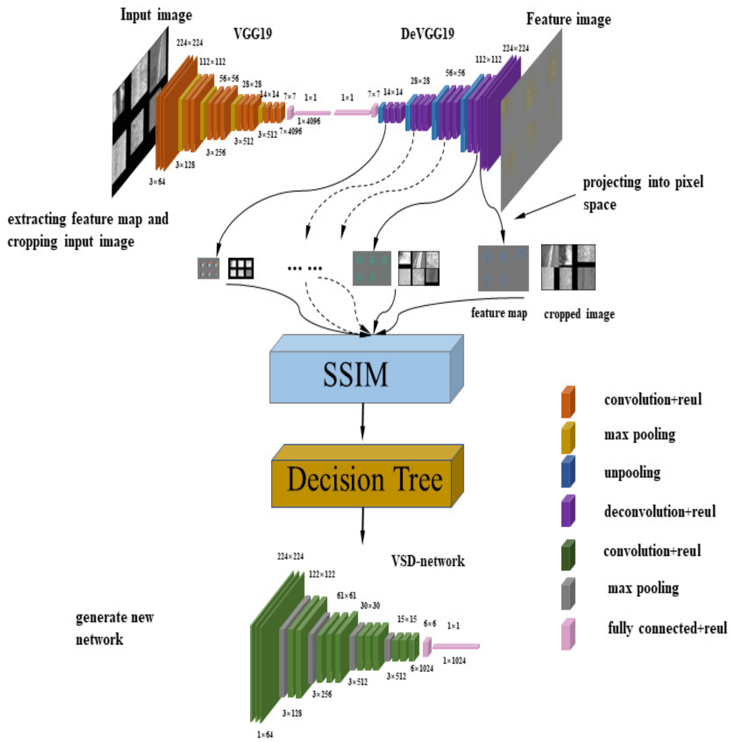


FIGURE 1. Model structure based on deep learning classification of steel surface defects.

TABLE 2. Decision tree results.

Evaluation results (S) / Convolution layer	S<0.1	S<0.2	S<0.3	S≥0.3
	Conv1_2 Conv 2_2	Conv 1_1 Conv 2_1 Conv 3_1 Conv 3_2	Conv 3_3 Conv 3_4 Conv 4_1 Conv 5_2 Conv 5_4	Conv 4_2 Conv 4_3 Conv 4_4 Conv 5_1 Conv 5_3

$$s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x \sigma_y + c_3} \tag{5}$$

where $\alpha > 0, \beta > 0$ and $\gamma > 0$, $l(x, y)$ is brightness comparison; $c(x, y)$ is contrast comparison, and $s(x, y)$ is structural comparison; μ_x and μ_y represent the average of x, y, respectively; σ_x and σ_y represent the covariance of x and y; σ_{xy} represents the standard deviation of x, y, respectively; c_1, c_2 and c_3 are constant to avoid system errors caused by the denominator being zero.

D. DECISION TREE

In order to make the VGG19 structure more suitable for steel surface defect objects, the SSIM algorithm is used to calculate the steel surface defect feature map that is extracted from 16 layers convolution network filters and the input map after cutting. And then, the steel surface defect feature image quality evaluation results of each layer in the convolution network are obtained. As shown in Figure 1, the two-class decision tree is established by evaluating the quality to judge the effect of feature extraction of each layer of the network convolution kernel in this algorithm. And the details of the two-class decision tree are shown in Figure 2.

S means the steel surface defect quality result of SSIM function, and $0 \leq S \leq 1$; C is the group number of convolution layers. All layers are separated by 4 groups: group 1 includes Conv1_1 and Conv1_2; group 2 includes Conv2_1 and Conv2_2; group 3 includes Conv3_1, Conv3_2, Conv3_3 and Conv3_4; group 4 includes Conv4_1, Conv 4_2, Conv4_3 and Conv4_4. The result of the decision tree is shown in Table 2.

In all convolution layers, there are four convolution layers: Conv1_1, Conv1_2, Conv2_1, and Conv2_2. These layers not only belong to the first two groups but also the evaluation results are S<0.2, the quality of which is not very well. In order to extract more information from the steel defect pictures, the parameters of the convolution kernel in these

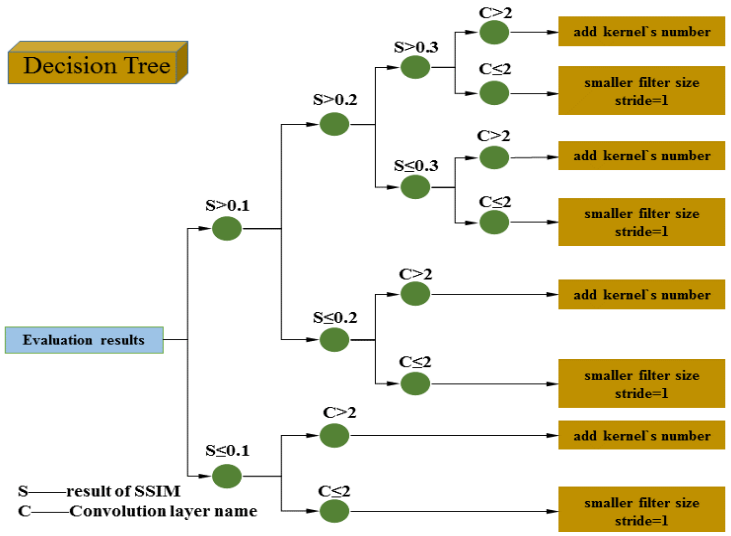


FIGURE 2. Decision tree.

4 layers are changed from 3*3 to 1*1. The convolution kernel of 1*1 not only can reduce the calculation parameters but also completely inputs the picture into the network, and it also can contain more feature information of the convolution layer of Conv1_1, Conv1_2, Conv2_1, and Conv2_2 for the extraction of subsequent network features. However, as shown in Table 1, the stride length 1 of VGG19 does not need to be changed. As for the other group of convolution layers with group number C>2 in Table 2, the number of convolution kernels is up to 256 and 512, so the number of kernels remains the same to reduce the number of parameters.

E. VSD NETWORK GENERATION

As shown in Figure 1, the new VSD network model which was be modified to detect the steel surface defect was built to the evaluation results in Table 2 and the decision-making tree in Figure 2.

The modification of the previous convolution kernel results in the mismatch between the output of the last convolution layer and the input dimension of the last fully connected layer, so the size of pool5 is modified from 2*2 to 4*4 for the final output. And then, the final output image is changed to 6*6*3. In addition, the number of neurons in the full connect layer is cut from 4096 to 1024 to reduce the computational parameters. The VSD network is formed in the end. The VSD network body architecture is shown in Table 3.

IV. RESULT AND ANALYSIS

In this section, the proposed method is tested on the hot steel surface defect dataset to prove the improvement. The SSIM algorithm is used to evaluate the steel surface defect feature image values in the VGG19, and generated the VSD network according to the evaluation results, whether it is the speed of model convergence or the classification and recognition accuracy of the model is better than before.

A. TRAIN SET DATASET

The model was trained on a surface defect dataset, which was obtained from related laboratories of NEU(Northeast University). All the steel surface images were deal with pre-processed into200 $\times$ 200 pixels before training. In this dataset, six kinds of typical surface defects of the hot-rolled steel are collected, such as rolled-in scale (Rs), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In), and scratches (Sc). And the six kinds of defect images are shown in Figure 3. The datasets total included 1800 grayscale images: 300 samples each of six different kinds of typical surface defects. Each grayscale image was preprocessed by resizing from 200*200 pixels to the bigger dimension 224*224 pixels region. And the classified training dataset and the training label file were used to make the train.tf.records file as the input to the ResNet, VGG19 and the VSD. For making the train. records file, there would be a conditional judgment statement in the code to read the image data and to determine whether the input images are grayscale images. If the input image was a grayscale image, it would be converted into an RGB image by the cv2.cvtColor function. Then divide the converted RGB picture by 255.0 to achieve the normalization result. Finally, the images would be input to the network by RGB form. Others, stochastic gradient descent with a mini-batch size of 8 was used to update the parameters, starting with a learning rate = 0.001, and dropout was used in the fully connected layers with a rate of 0.5.

B. EXPERIMENTAL CONDITION

This test was trained in a Lenovo desktop which is offered by Xi'an key Laboratory of modern intelligent textile equipment, and the details about this computer are shown in Table 4.

C. EXPERIMENTAL RESULT

In this section, the first part shows the partial visualization results extracted by DeVGG19; the second part shows

TABLE 3. VSD network body architecture.

Layer	Filter shape	Input size	Parameters
Conv 1_1	1×1×64	224*224*3	224*224*64
Conv 1_2	1×1×64		224*224*64
Pool1	2×2		122*122*64
Conv 2_1	3×3×128	122*122*3	122*122*128
Conv 2_2	3×3×128		122*122*128
Pool2	2×2		61*61*128
Conv 3_1	3×3×256	61*61*3	61*61*256
Conv 3_2	3×3×256		61*61*256
Conv 3_3	3×3×256		61*61*256
Conv 3_4	3×3×256		61*61*256
Pool3	2×2		30*30*256
Conv 4_1	3×3×512	30*30*3	30*30*512
Conv 4_2	3×3×512		30*30*512
Conv 4_3	3×3×512		30*30*512
Conv 4_4	3×3×512		30*30*512
Pool4	2×2		15*15*512
Conv 5_1	3×3×512	15*15*3	15*15*512
Conv 5_2	3×3×512		15*15*512
Conv 5_3	3×3×512		15*15*512
Conv 5_4	3×3×512		15*15*512
Pool5	4*4	6*6*3	6*6*512
Fc-1024			1*1*1024
Fc-1024			1*1*1024
Fc-1000 SoftMax			

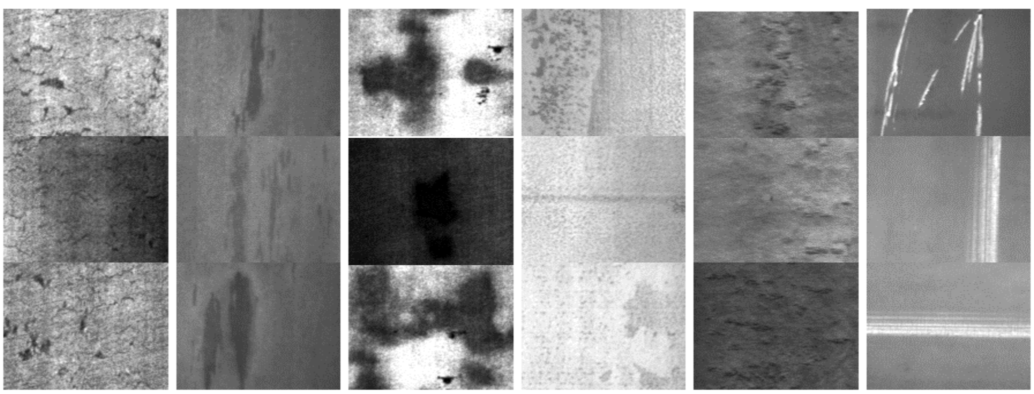


FIGURE 3. NEU surface defect database.

TABLE 4. Experimental equipment parameters.

Parameters	Lenovo desktop
Hardware	Lenovo i7-9700K/GeForce, RTX 2060
Software	Ubuntu16.04
Development Environment	Anaconda3, Spyder
Development Platform	TensorFlow-GPU, Tensorcv

the image quality evaluation results for the 16 layers convolutional network; the third part shows the accuracy and convergent speed contrast between the two representative classic networks and the network (VSD) generated by the new algorithm. And the fourth part assesses the VSD model by a confusion matrix.

1) VISUALIZATION RESULT OF DeVGG19

Figure 4 includes five groups of steel surface defects and the cropped original images. The feature map is in the top of the cropped original image, and the biggest feature map and a cropped original image are a group images Conv5_4.

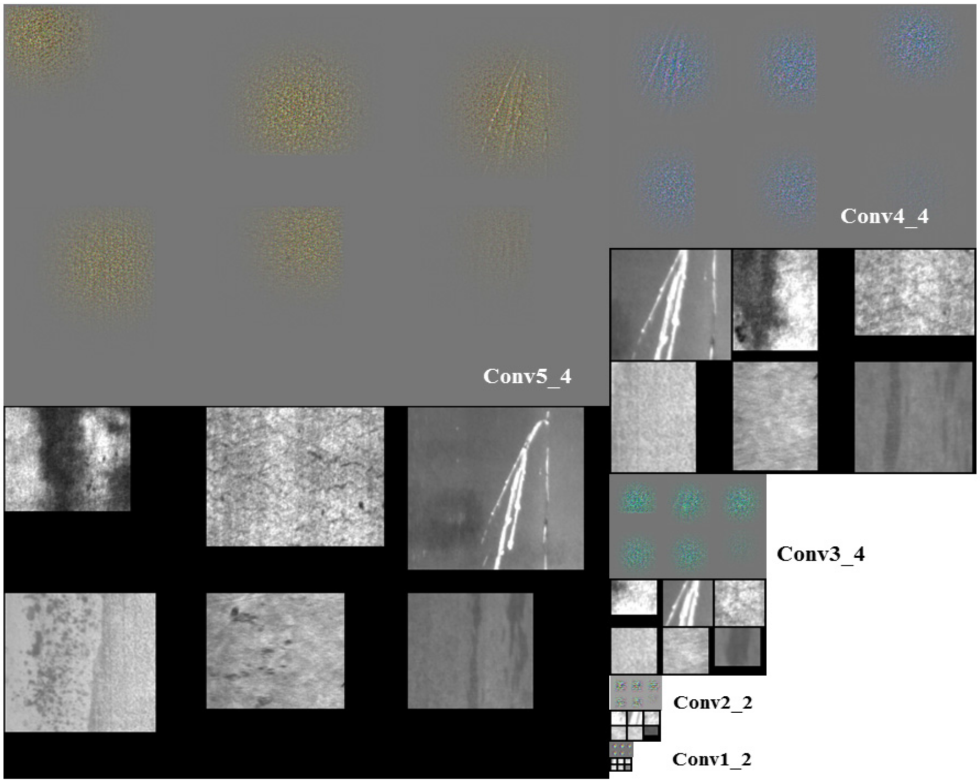


FIGURE 4. Partial visualization result.

TABLE 5. The VGG19 result of SSIM.

Layer name	Conv1_1	Conv 1_2	Conv2_1	Conv 2_2	Conv3_1	Conv3_2	Conv3_3	Conv3_4
value	0.100174	0.0768203	0.122053	0.0131082	0.185756	0.154288	0.292055	0.255701
Layer name	Conv4_1	Conv 4_2	Conv4_3	Conv 4_4	Conv5_1	Conv5_2	Conv5_3	Conv5_4
value	0.296052	0.357747	0.34785	0.370961	0.334999	0.256292	0.369427	0.260721

The couple of images Conv4_4 are on the top right of Figure 4, and another three groups are settled at the bottom right of Figure 4. Due to the large gap between the features and the background of the Scratch (Sc), the feature edge of the Scratch (Sc) is the most obvious one showed in Figure 4. And for crazing(Cr), catches(Pa), pitted surface(PS) and rolled-in scale(Rs), the feature edges of those four type defects are obvious than Inclusion(In). Therefore, the DeVGG19 neural network could extract the useful feature edge.

2) IMAGE QUALITY EVALUATION RESULT

The steel surface defect feature map extracted from the convolution kernel is used as the distortion image, and the cropped original image according to the feature map size is taken as the original image. Although these two images are the same size, the size of the images is changed during the convolution process. Therefore, the images between the layers cannot be evaluated as each other. The feature map extracted in each layer of the network is the underlying feature map after multiple convolution filtering, and the pixel loss is very large, for this reason, the result obtained by the image quality evaluation method only can be adjusted to the standard as a network structure parameter.

After the calculation of the SSIM algorithm, 16 results are obtained for different network layers, and the results are shown in Table 5.

3) CONVERGENT SPEED AND THE ACCURACY COMPARISON RESULT

Using the steel surface defect predict datasets to test the accuracy, the different convergent accuracy values of train and validation from three nets (ResNet, VGG19, and VSD) are shown in Table 6, which are collected during the training process. And the Comparison results of prediction accuracy of six surface defects and time in three nets are shown in Table 7. The defect types are rolled-in scale (Rs), patches (Pa),

TABLE 6. The comparison of train datasets and validation datasets convergent accuracy values.

net	accuracy		steps
	train	validation	
ResNet	1	87.84%	37000
VGG19	1	61.842%	14500
VSD	1	89.86%	23000

TABLE 7. Steel defects prediction accuracy in the different net.

Defect type	ResNet	VGG19	VSD network
Rs	90.92%	76.66%	90.37%
Pa	98.10%	99.82%	99.97%
Cr	88.71%	88.33%	95.58%
PS	87.02%	80.19%	82.01%
In	13.03%	89.55%	89.06%
Sc	78.52%	84.99%	92.98%

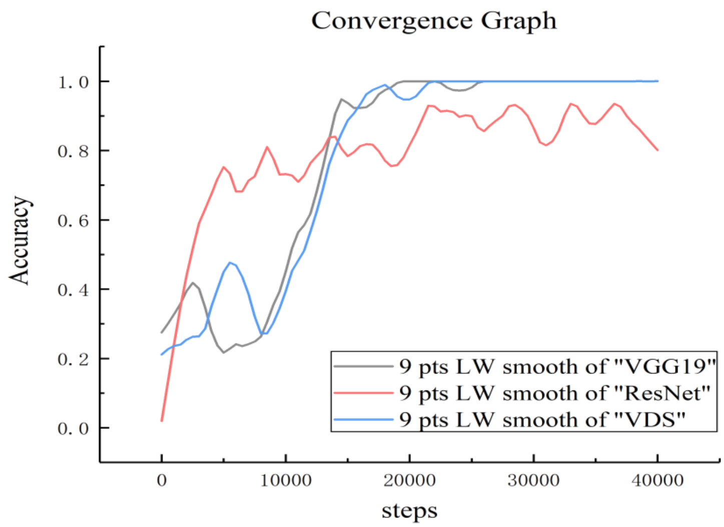


FIGURE 5. Convergence graph of VSD.

crazing (Cr), pitted surface (PS), inclusion (In), and scratches (Sc).

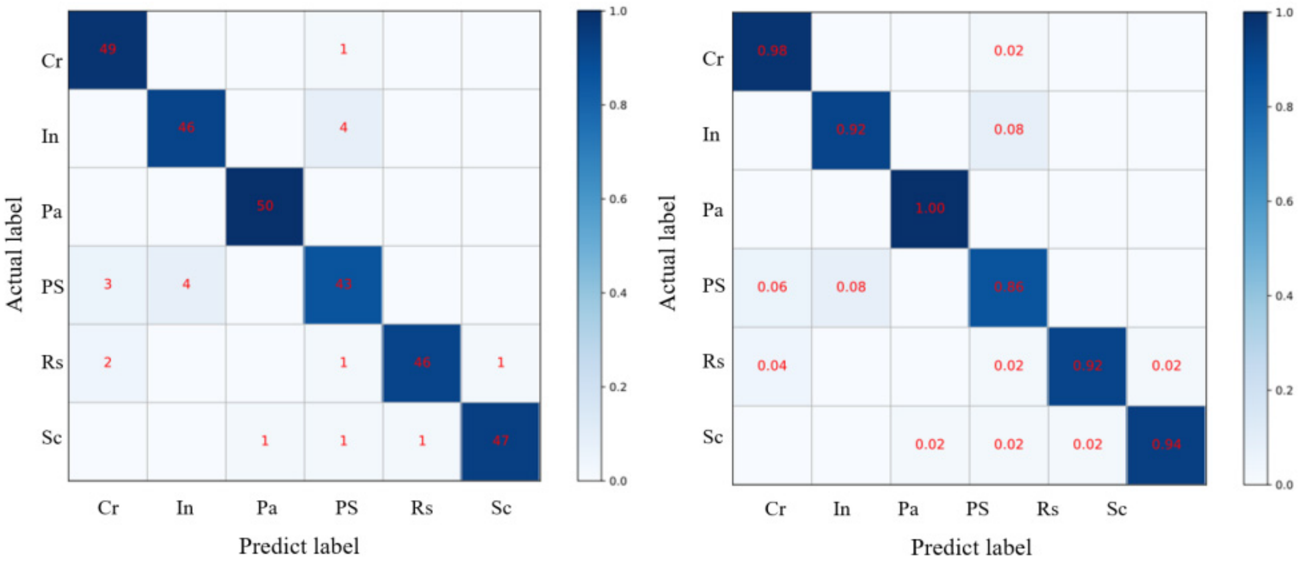
Besides, to compare the different convergence speeds of three nets (ResNet, VGG19, and VSD), all the training statistics are shown in Figure 5.

As we all know, the accuracy of validation always uses to modify the parameters from the VSD model during the training process. After many processes of parameter modification, the best VSD model which has the highest accuracies of train and validation was recorded in Table 6, and the accuracies of the other two networks were compared in Table 6.

In Table 6, the VSD train dataset is fully converged in 23000 steps when the train dataset accuracy is 1 for the first time, and the validation dataset accuracy was 89.86% at the same time. For the ResNet, the training dataset is fully converged in 3700 steps, and the validation dataset accuracy is 87.84% at the same time. Obviously, the convergent accuracy of the VSD network is better than ResNet in train and validation. Compare with VGG19, although the training dataset of VGG19 converges faster than the VSD network, the accuracy of the validation dataset is indeed the lowest of the three networks at 61.842%. It can be seen that VSD only spends a little more training time and improve the validation dataset accuracy greatly.

As a matter of fact, the steel surface defect detection algorithm VSD network will apply to the industrial, the predicted accuracy should be higher to realize real-time online detection. Therefore, the accuracy of the prediction of the three networks is compared (ResNet, VGG19, and VSD network). The comparison results are shown in Table 7.

The data clearly shows that VSD network not only has a marked increase in the prediction experiment accuracy than VGG19, Rs 13.7%, Pa 0.15%, Cr 7.52%, PS 1.82%, Sc 7.99% but also better than ResNet in Pa 1.87%, Cr 6.87%, In 76.03%, Sc 14.46%. However, in some defects, the accuracy of the VSD network is lower than the other two networks, for example, Rs −0.55% and PS-5.01% are lower than the results of ResNet, and In −0.49% is lower than the result



(a)VSD Confusion Matrix

(b)VSD Normalized Confusion Matrix

FIGURE 6. **VSD confusion matrix and normalized confusion.**

of VGG19. On the whole, it can be seen from the data in Table 6 that steel defects prediction accuracy of the VSD network is better than the other two networks.

Finally, in Figure 5, all the data extracted from the trained process was smoothed by the LOWESS function. It‘s obvious that the accuracy data of ResNet show an obvious wave when ResNet was trained by a steel defection database. By contrast, the VGG19 and VSD have a narrow range fluctuation, and the accuracy data of VSD were stable extended to 1 in 23000 steps, which are more quickly than the data of VGG19. All this data proved that the change of the full connection layer in the VSD model was reduced the parameters of the VSD network and the amount of calculation. Hence, the convergence speed in the VSD network is improved.

4) CONFUSION MATRIX OF VSD

In the area of deep learning, the confusion matrix is used for the statistical classification models. It is used to evaluate the performance of the classification model. It is also one of the indicators of classification models. VSD is a model designed for steel defects classification, hence VSD is a kind of classifier. In order to evaluate VSD models, a confusion matrix was used to evaluate the performance of the VSD model. The predict database consists of 6 kinds of steel defects and each steel defect has 50 images. All the predict results were summarized by the confusion matrix and showed in Figure 6. The VSD confusion matrix is in the (a) of Figure 6, the true positive result of six steel defects are Cr 49, In 46, Pa 50, PS 43, Rs 46, Sc 47 respectively, and the accuracy of six steel defects Cr 0.98, In 0.92, Pa 1, PS 0.86, Rs 0.92, Sc 0.94 respectively in the (b) of Figure 6.

It can be seen that the total accuracy of the VSD model is 0.937, which is the average of six accuracies of steel defects. At the same time, the higher evaluation value of the VSD model is proved that the advantages of the VSD Network.

V. CONCLUSION

Due to the fewer amounts of pixels in the picture of the industrial steel defect dataset and the lower contrast between features and background, it is difficult for traditional deep learning methods to have excellent cores on the steel defect dataset. In the paper, the algorithm of an improved deep learning network model based on feature visualization and quality evaluation is used for the classification of steel surface defects. Because the algorithm can adjust accurately the network model by visualizing the underlying features of the steel defects and performing image quality evaluation on the underlying feature information of the steel defects, the proposed steel surface defect classification algorithm shows better prediction accuracy and speed than based on VGG19 and ResNet.

Although this paper has verified that the recognition effect of six kinds of common steel surface defects have better recognition accuracy, as all known, there are many kinds of steel surface defects, such as PS discrete defects, etc., how to realize the detection of unusual defects under the condition of small sample needs further in-depth study. In addition, deep learning algorithm requires the high performance of hardware, which inevitably increase the cost of industrial application, so it is suitable for the hardware design and research of deep learning need to be further explored. In the next step, research work will be the focus on the practical application of industrial steel surface defect recognition.

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