Retraction

Retracted: Superresolution Reconstruction Method of Software Remote Sensing Image Based on Convolutional Neural Network

Journal of Sensors

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Wang, J. Dong, B. Wang, S. Khanna, A. Singh, and S. A. Hussain, "Superresolution Reconstruction Method of Software Remote Sensing Image Based on Convolutional Neural Network," *Journal of Sensors*, vol. 2022, Article ID 1777112, 7 pages, 2022.

Research Article

Superresolution Reconstruction Method of Software Remote Sensing Image Based on Convolutional Neural Network

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In order to solve the problem of long training time for remote sensing image super-resolution reconstruction algorithm, a method for remote sensing image superresolution reconstruction based on convolutional neural network is proposed, which combines dense convolutional network, parallel CNN structure, and subpixel convolution. The features of low-resolution images are extracted using dense convolutional networks, parallel CNNs are used to reduce network parameters, and subpixel convolutions are used to complete feature reconstruction. The results show that the final PSNR value of the black curve with the number of iterations of the three methods in the training process is the highest 27.3, followed by the middle curve, and the worst curve is 27.0. It is proved that the method extracts more features, retains more image details, and improves the reconstruction effect of the image; it greatly reduces the parameters in the network and avoids the phenomenon of overfitting in the deep network.

1. Introduction

With the rapid development of modern aerospace technology, remote sensing images are more and more widely used in various fields, and the requirements for its resolution are getting higher and higher [1]. In the process of acquiring remote sensing images, atmospheric disturbances and frequency aliasing, and many factors such as imaging and transmission will cause the resolution to drop [2]. Due to the limitation of manufacturing process and production cost in terms of hardware, therefore, many researchers use software methods to improve the resolution of images, this method is called superresolution image reconstruction [3]. Due to the limitations of sensor technology, the image data returned by Earth observation satellites are usually high-resolution panchromatic images and low-resolution multi-

spectral images. For example, the image collection of the QuickBird satellite and the Geoeye satellite, the single-channel high-resolution panchromatic image has very rich features of surface details, however, due to the lack of spectral information, it is difficult to accurately identify and classify them; although the corresponding low-resolution multispectral image has low definition, but it has more spectral information [4]. Therefore, in the actual application of remote sensing images, usually the high-resolution panchromatic image and the multispectral image with rich spectral information are fused, to obtain high-resolution multispectral images, so as to provide high-quality image data for the later processing of target monitoring and recognition [5]. Convolutional neural networks (CNN) are a kind of feed-forward neural network containing convolutional computing and deep structure. It is one of the representative

algorithms of deep learning. Convolutional neural networks have representational learning ability to translation invariant classify input information by their class structure and are therefore also known as "translation invariant artificial neural networks." Neural network algorithm (neural network) is a very, very important algorithm in machine learning. Inspired by the neural network in the human brain, it is the core algorithm for the whole deep learning. Deep learning is an extension of the neural network algorithm.

Superresolution reconstruction technology is a very effective method to solve this problem. Currently, superresolution reconstruction algorithms are roughly divided into three categories: interpolation-based methods, reconstruction-based methods, and learning-based methods. Among them, the method based on interpolation is to estimate the intermediate unknown pixel according to the neighborhood pixel value, simple and easy to implement, low complexity, but high-frequency detail recovery is not obvious, and the edge details of the reconstructed image are easy to blur. The reconstruction-based method utilizes prior knowledge, constrain the super-resolution reconstruction process, the reconstruction effect is better, and the restoration of details is more obvious, but the general complexity is high, the calculation time is long, and the convergence is difficult. Learning-based methods are the main research direction in recent years, use the mapping relationship between high and low-resolution images to guide the superresolution reconstruction of the image, prior knowledge can also be added to the learning process, the effect of reconstruction is generally better than interpolation and reconstruction methods [6]. Lu et al. based on sparse representation reconstruction method, through the low-resolution image block dictionary and high-resolution block dictionary joint training, strengthen the similarity between the corresponding dictionary sparse representation, from the sparse relationship between low-resolution image block and high-resolution image super complete dictionary, reconstruction effect is good, but there are slow reconstruction speed, super complete dictionary selection requires high, poor universality [7]. At present, convolutional neural network is a research hotspot of superresolution reconstruction method based on learning and achieved good results. Convolutional neural networks refer to those neural networks that use convolution operations in at least one layer of the network to replace general matrix multiplication operations and can be used to specifically process data with a grid-like structure, for example, time series data and image data. The self-convolutional neural network was proposed and has been widely used in many research fields. In terms of image superresolution reconstruction, convolutional neural networks achieve the purpose of improving resolution by directly learning the mapping from low-resolution images to high-resolution images. He et al. study new image superresolution methods based on deep and deep cascade convolutional neural networks to reconstruct clear high-resolution (HR) remote sensing image input from low resolution. The method directly learns the residual and mapping between simulated LR based on deep and shallow end-to-end convolutional networks and their corresponding HR remote sensing images rather than assuming any specific recovery model. Additional maximum pools and

upsampling are used to achieve multiscale space by connecting low-level and high-level feature maps and to generate HR images by combining LR inputs and remaining images. The model ensures a strong response to spatially local input patterns by using large filters and cascading small filters. The results show that the model greatly improves remote sensing images in spatial detail and spectral fidelity and outperforms state-of-the-art SR methods in terms of peak signal-to-noise ratio, structural similarity, and visual assessment [8]. Tian et al. use the Qt5 interface library to realize the user interface of the remote sensing images superresolution software platform and use the intermediate layer convolutional neural network and the superresolution reconstruction algorithm proposed for remote sensing images. When the training of epoch reaches 35 times, the network has converged. At this time, the loss function converges to 0.017, with a cumulative time of about 8 hours. This study helps to improve the visual effect of remote sensing images [9].

For the long training time of convolutional neural network, we study a convolutional neural network. Methods combining dense convolutional networks, parallel CNN structures, and subpixel convolution use dense convolutional networks to extract features of low-resolution images, and CNN reduces parallel network parameters and subpixel convolution to complete feature reconstruction. Results show that this method extracts more features and retains more image details and improves the image reconstruction effect; greatly reduces the parameters in the network and avoids the phenomenon of over-fitting in the deep network. Results show that the method is faster in training and has improved subjective quality and objective evaluation indicators.

2. Research Methods

2.1. Basic Principles. In shortcoming in the past SISR algorithm, considering that remote sensing images have rich spectral characteristics and texture characteristics. The introduction of intensive connection improves the transmission of feature information in the network, the problem of alleviating gradient disappearance. In addition, it allows you to reuse feature mappings from the previous layer and avoid repeated learning redundancy characteristics. In addition, use the hopping connection, combining low-level features and high-level features, provide extensive information for SISR, fusion subpixel volume layer, restore image details, and speed up the reconstruction process.

2.2. Densus Convolution Neural Network. Learn common models in deep learning, convolutional neural networks, CNNs, with its high degree of deformation such as translation, zoom, and tilt; the advantages of weight sharing characteristics and high efficiency are widely used. Convolutional neural networks are typically composed of 3 portions of the input layer, a convolution layer, and an output layer [10]. Shallow features can be abstracted into high-order features by multiple convolution operations; therefore, the deep network contributes to the extraction of network features. Unlike previously deepened or widened network structures,

DensNet is a convolutional neural network with intensive connections, this structure enhances the propagation and reuse of features, simplifies the parameters of the model, and better results can be obtained [11]. Densenet is generally composed of multiple Denseblock and TransitionLayer.

2.2.1. Reverse Propagation Algorithm. Convolutional neural networks optimize the regression target function by using a reverse propagated gradient method during the training. The predicted value is inevitable between the real value, reverse communication is to return this error information to each layer, and let these layers modify their weights, making convolutional neural networks more accurate [12].

$$W_{\text{new}}^l = W_{\text{old}}^l - \eta \frac{\partial E}{\partial W_{\text{old}}^l}, \tag{1}$$

$$b_{\text{new}}^l = b_{\text{old}}^l - \eta \frac{\partial E}{\partial W_{\text{old}}^l}, \tag{2}$$

where η is the loss of gradient decline; W_{new}^l is the weight of the updated Layer; b_{new}^l is the deviation of the term L layer; E is the cost of the error. The so-called error in the BP network is the sensitivity of each neuron of each layer, and this sensitivity can be expressed as

$$\frac{\partial E}{\partial b} = \frac{\partial E}{\partial u} \frac{\partial u}{\partial b} = \delta. \tag{3}$$

The U is $\delta^l = \partial E / \partial b^l = f(u^l) \circ (y^n - l^n)$. Due to formula (3), $\delta^l = \partial E / \partial b^l = f(u^l) \circ (y^n - l^n)$; therefore, the sensitivity is equal to the deviation of the derivative of the input neurons. The sensitivity formula in the last layer is different from the above, which can be expressed as

$$\delta^l = \frac{\partial E}{\partial b^l} = f\left(u^l\right) \circ (y^n - l^n). \tag{4}$$

The "∘" represents a point multiplication and uses the formula (5) and can realize the reverse propagation of the network from output to the input:

$$\delta^l = \left(w^{l+1}\right)^T \delta^{l+1} \circ f\left(u^l\right). \tag{5}$$

2.2.2. Adjustable Gradient Crop. Gradient decline based on reverse propagation algorithm is applied to training convolutional neural network, and parameter update formula is

$$\Delta_{i+1} = m \cdot \Delta_i + \eta \frac{\partial \text{loss}}{\partial W_i^l}, \tag{6}$$

$$W_{i+1}^3 = W_i^l \Delta_{i+1}, \tag{7}$$

where M represents momentum parameters, the value is 0.9; η is a learning rate; $\partial \text{loss} / \partial W_i^l$ represents a gradient.

When training is used, high learning rates are used and can improve the convergence of training more faster; how-
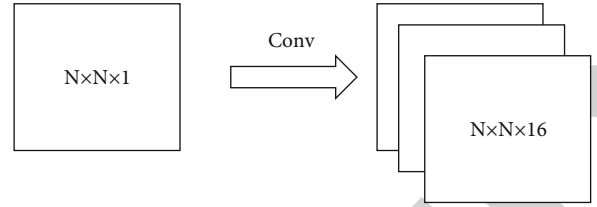

Figure 1: Shallow feature extraction.

Table 1: Environment.

	Environmental configuration
System	Ubuntu 16.04,Windows 10
CPU	Intel (R) Core (TM) i7-6700HQ
RAM	16 GB
GPU	NVIDIA GeForce GTX1060
Simulation program	MATLAB R2014a,Python3.5,Tensorflow2.0

ever, it will also cause blasting in the gradient. Therefore, the gradient crop is used to limit the maximum gradient. Gradient value $\partial \text{loss} / \partial W_i^l = \sqrt{W_1^2 + W_2^2 + \cdots + W_n^2}$, when the gradient value $\partial \text{loss} / \partial W_i^l$ reaches the threshold 10, reduce gradient to $[-\tau/\eta, \tau/\eta]$, and τ is a constant. Experiments found that adjustable gradient cutting makes the network's convergence speed is very fast, 20-layer network training is completed within 4 hours, while 3-layer SRCNN takes 240 hours of training.

During the network training process, optimize the regression target function using a gradient method based on reverse propagation, and training is regularization by weight attenuation [13, 14]. This experiment is set to 0.9, the maximum number of iterations is 93,5840 times, the basic learning rate is 0.1, each test 500 times is tested, each iterates 100 times to show a training, attenuation value is 0.0001, and the arithmetic processor is set to the GPU mode.

2.3. Depth Network. Convolutional neural network utilizes the convolutional operation of each hidden layer to learn the correlation between neighborhood space; therefore, all the hidden can be seen as a subset of the last layer unit, and this forms a spatial continuous feeling. However, the information of pixels outside the field cannot be utilized; therefore, the perceptual field of expanding the network can effectively improve the reconstruction quality of infrared remote sensing images [15]. In the SRCNN and ESPCN networks, on three-layer convolutional network, there is less information on the neighborhood information available in each pixel during the reconstruction process, therefore, by deepening the network, increasing the number of hidden layers to expand the perception field, thereby adding the neighboring pixel information that can be utilized to improve the quality of reconstruction. For the D layer network, if each layer is 3×3, then, the inferior size is $(2D + 1) \times (2D + 1)$. At the same time, multiple small volume cores have also been used instead of large volume nucleus commonly used in the above network and enable the network

Image	Scale	Bicubic	SRCNN	ESPCN	VDSR	Ours
Buildings	×2	27.25/0.9192	29.11/0.9376	29.88/0.9397	31.05/0.9567	32.57/0.9664
	×3	23.32/0.8293	24.85/0.8326	26.12/0.8606	26.52/0.8821	27.81/0.9095
	×4	22.25/0.7716	23.11/0.7522	23.55/0.7537	22.72/0.7983	25.48/0.8274
Denseresidential	×2	27.89/0.9176	30.22/0.9349	30.70/0.9380	30.77/0.9456	32.54/0.9566
	×3	23.61/0.8246	25.54/0.8403	26.86/0.8609	26.85/0.8759	28.33/0.9012
	×4	22.91/0.7761	23.42/0.7247	24.68/0.7659	24.57/0.7862	25.64/0.8421
Airplane	×2	30.83/0.9547	32.17/0.9615	32.31/0.9617	31.93/0.9657	34.73/0.9740
	×3	27.09/0.8732	27.98/0.8844	29.49/0.8978	30.16/0.9111	31.55/0.9248
	×4	25.39/0.8323	26.05/0.8366	27.17/0.8456	27.64/0.8659	28.83/0.8852

to enhance the reconstruction effect of convolutional neural networks to a certain extent in the absence of the field. Using 3×3 convolution nuclear than the two-layer convolution network and 5×5 convolutionary core compared to a layer of convolution network has the same 5×5 size percent. On the other hand, in terms of network parameters, a plurality of small volume nucleus having the same feelings are more advantageous than a large volume. For example, for a 5×5 convolutionary core, the number of parameters is $5 \times 5 \times 1 = 25$, and two 3×3 convolutionary cores, the number of parameters is $3 \times 3 \times 2 = 18$. So the number of parameters of the network using multiple small volume copies is smaller, and for deepening convolutional neural networks, the number of parameters can be greatly reduced, thereby remarkably reduce the amount of calculation, improve training efficiency, and significantly reduce the demand for storage space, the superresolution reconstruction of the infrared remote sensing image has actual application value [16, 17].

It can be expressed as the depth convolution network consisting of the L layer hidden layer.

$$f^l(I^{LR}; W_1, b_1) = \Phi(W_1 * I^{LR} + b_1),$$
$$f^l(I^{LR}; W_{1:l}, b_{1:l}) = \Phi(W_1 * f^{l-1}(I^{LR}) + b_1), \quad (8)$$

where W_l, b_l is the weight and bias of each layer of the network; W_l is 2-dimensional volume tension, size is $n_{l-1} \times n_l \times k_l \times k_l$; n_l and k_l are the characteristics and filters of the layer; b_l is vector of length n_l; Φ is the activation function.

2.4. This Article Network Structure. The structure of the depth-intensive convolution network proposed for remote sensing image superresolution reconstruction, featureEx-TractionNetwork in the network represents the feature extraction module, this module consists of a CNN and a DENSENET network, the CNN is used to extract the shallow features of the image, and the DENSENT is used to extract the high layer characteristics of the image. The structure of the feature extraction module is shown in Figure 1.

In the network, the shallow features extracted from the network are needed to fuse the high-level features, in order to facilitate the size of the control characteristics, the net-

work uses the SAME convolution. Figure 1 represents a single-channel low-resolution image to the input size is $N \times N \times 1$, and the shallow characteristics is extracted, features size of $N \times N \times K$, specific operation, as in the following formula:

$$F_1 = \max(0, W \times Y + B). \quad (9)$$

Extract the shallow feature to extract the network to the characteristics of Densenet, represents a change in a Denseblock feature, if there is a n_2 volume layer in a Denseblock, the dimension of each volume output feature is k, adding the characteristics of each layer, a DenseBlock output is characterized by $n \times k$. In order to avoid the growth of network parameters, it is too large, set the number n_1 of Denseblock to 4, the number n_2 of the convolution layer in each Denseblock is set to 5, the growth rate of the network is set to 16. ReconstructionNetwork represents rebuild modules in the network, two parallel 1×1 cnn structures have been proposed, 1×1cnn can not only reduce the size of the front layer characteristics, accelerate the speed of calculation, it also reduces the loss of information, adding more nonlinearity, to enhance the potential expression of the network. In this discipline, the number of convolutionary cores of A1 is set to 64, and the number of convolutionary cores of A2 is set to 32.

2.5. Data Processing and Environmental Configuration. The data is selected from the resolution of 0.3 m. Remote sensing image public data set, these include neutral remote sensing images, and the image size is 256×256. Program development build data set based on the Python platform. Select the top 5 image data creation data set for the highest average standard deviation: Harbor, Buildings, MobileHomePark, Densresidential, and Parkinglot. From the above type 5 types of images, 85 images were randomly selected as training sets; from Buildings, Denseresidential, and AirPlane class, 5 images are randomly selected as test sets. In order to verify the performance of the network, the environment for program development and model training is shown in Table 1.

According to many experiments and predecessors, set the network's BatchSize to 48, MSE is used as the loss function of the network, optimizer select the ADAM optimizer, the initial learning rate is 0.002, the learning attenuation rate

is 0.4, and the period of learning rate is 9 EPOCH, which stops training when the learning rate is below 2×10^{-5}.

3. Result Analysis

Select the visual subjective evaluation, PeaksignaltonoiseRatio, PSNR, and structural SimilarityindexMeasurement, SSIMs are as an evaluation indicator. PSNR is an objective standard for measuring image distortion or noise level, the greater the value of PSNR, the closer the image, the closer to the original high-resolution image, the formula is as in the following formulas:

$$MSE = \frac{1}{HW} \sum_{i=0}^{H-1} \sum_{j=0}^{H-1} \left[I^{SR}(i,j) - X(i,j) \right]^2, \quad (10)$$

$$PSNR = 10 \log_{10} \left(\frac{MAX^2}{MSE} \right). \quad (11)$$

SSIM is an indicator that measures the degree of image between images, as in the following formula:

$$SSIM\left(X, I^{SR}\right) = \frac{(2u_X u_{I^{SR}} + C_1)(2\sigma_{XI^{SR}} + C_2)}{(u_X{}^2 + u_{I^{SR}}{}^2 + C_1)(\sigma_X{}^2 + \sigma_{I^{SR}}{}^2 + C_2)}. \quad (12)$$

Methods and Bicubic, SrCNN, ESPCN, and VDSR methods, the quantitative assessment results of the test set buildings, Densresidential, and AirPlane are shown in Table 2.

The bold font represents the optimal value for PSNR and SSIM, while the light font represents the second best value. As can be seen from Table 2, the method presented in this paper is the best in terms of 2×, 3×, and 4× magnified recovery results in the above three test sets for PSNR and SSIM compared to other methods. When the magnification is 2, the method is compared with the secondary method, PSNR and SSIM have an average of 1.90 dB and 0.009, respectively; when the magnification is 3, PSNR and SSIM have increased 1.38 dB and 0.029, respectively; when the magnification is 4, PSNR and SSIM increase the average of 1.36 dB and 0.034, respectively. When various methods described above are 2, the qualitative assessment of AirPlane82 is obtained, by amplifying the image details, people can intuitively evaluate the quality of the reconstruction of the image from the visual effects [18]. Figure 2 is a flowchart of the remote sensing image fusion algorithm based on the convolutional neural network.

As can be seen from the above, in addition to the VDSR and this method, the reconstruction results of other methods have experienced varying degrees of image distortion and edge blurring, the image detail of the reconstruction is rich, the airplane wings are clear, target shadows and corner outline details are restored closer to the original image, and compared with the previous method, the method has a substantial increase [19]. The relationship between the average operating time and the average PSNR value of the Densresi-Dential test set is shown in Figure 3 when the abovementioned reconstruction method is 3. Observing
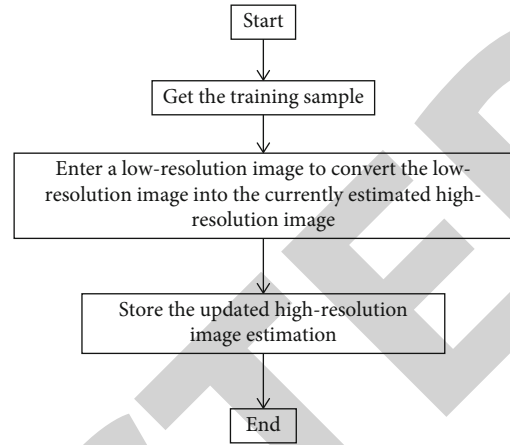

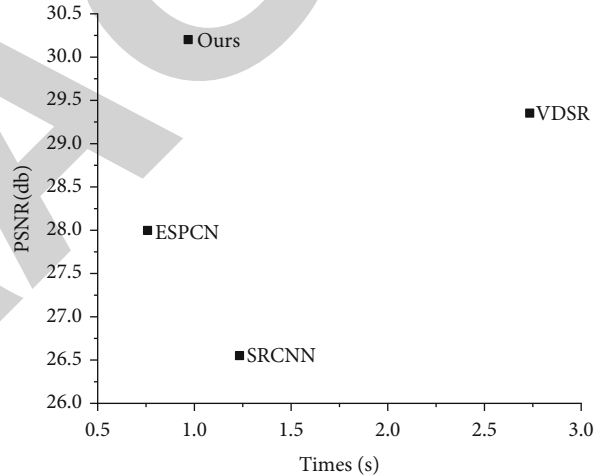FIGURE 2: Flow chart of remote sensing image fusion algorithm based on convolutional neural network.

FIGURE 3: Relationship between PSNR and calculation time in the test set at three times.

Figure 3, I know that the method of operation is second only to ESPCN, but the PSNR value is far higher than other methods. In order to further verify the effectiveness of this method, in the training set, 3 groups of comparative experiments were set in the training set when the magnification was 3; Ours_1 is the network used herein; OURS_2 is a conventional reinviller resemble subpixel consolidation based on Ours_1; the OURS_3 represents the structure of parallel CNN on the basis of Ours_2. The results are shown in Figure 4.

Observing Figure 4, it can be seen that the final PSNR value of the black curve is up to 27.3, intermediate curve, the bottom curve is the worst 27.0. It can be seen that the network used in parallel CNN structure relative to the network that does not use this structure, a substantially reduced network parameters, accelerate the convergence speed of the network, and the reconstruction effect is better [20]. The feature reconstruction is replaced by subpixel volume layer, the
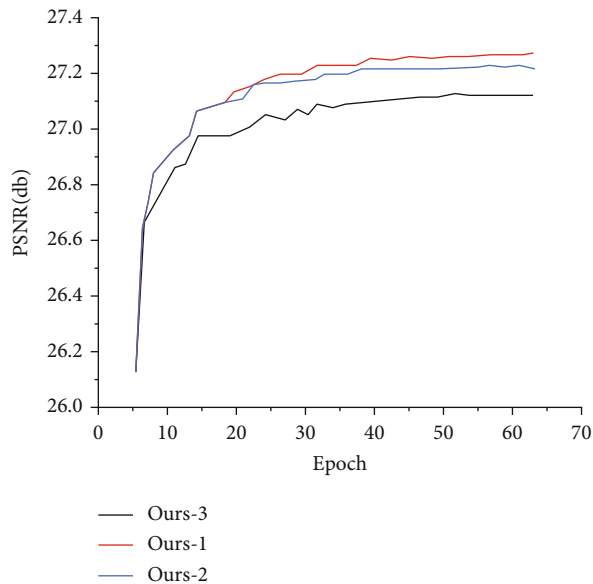
Figure 4: Three ways in the training process and the relationship between PSNR.

reconstruction accuracy will be higher, and the training effect will be better [21]. The analysis and comparison of experimental results prove that the method is faster, the quality evaluation index is significantly improved, and achieve good results in superresolution reconstruction of remote sensing images.

4. Conclusion

This paper proposes a method of superconducting remote sensing images based on the neural network of disturbances. Low-density remote sensing images are used as the first input to the network, and images are used as high-order images. Learned through a tightly folded neural network to obtain a more expressive and deeper image. The results show that the method extracts more features, retains more image detail features, and improves the reconstruction effect of the image; it greatly reduces the parameters in the network and avoids the phenomenon of overfitting in the deep network. Later, we will further study how to use multiscale convolution to extract image features and to design a more compact network structure, to further improve the network reconstruction effect.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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