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Research Article

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Neural network big data fusion in remote sensing image processing technology

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Abstract: Remote sensing (RS) image processing has made significant progress in the past few years, but it still faces some problems such as the difficulty in processing large-scale RS image data, difficulty in recognizing complex background, and low accuracy and efficiency of processing. In order to improve the existing problems in RS image processing, this study dealt with ConvNext-convolutional neural network (CNN) and big data (BD) in parallel. Moreover, it combined the existing RS image processing with the high dimensional analysis of data and other technologies. In this process, the parallel processing of large data and high-dimensional data analysis technology improves the difficulty and low efficiency of large-scale RS image data processing in the preprocessing stage. The ConvNext-CNN optimizes the two modules of feature extraction and object detection in RS image processing, which improves the difficult problem of complex background recognition and improves the accuracy of RS image processing. At the same time, the performance of RS image processing technology after neural networks (NNs) and BD fusion and traditional RS image processing technology in many aspects are analyzed by experiments. In this study, traditional RS image processing and RS image processing combined with NN and BD were used to process 2,328 sample datasets. The image processing accuracy and recall rate of traditional RS image processing technology were 81 and 82%, respectively, and the $F1$ score was about 0.81 ($F1$ value is the reconciled average of accuracy and recall, a metric that combines accuracy and recall to evaluate the quality of the results, a higher $F1$ value indicates a better overall performance of the retrieval system). The accuracy rate and recall rate of RS image processing technology, which integrates NN and BD, were 97 and 98%, respectively, and its $F1$ score was about 0.97. After analyzing the process of these experiments and the final output results, it can be determined that the RS image processing technology combined with NN and BD can improve the problems of large-scale data processing difficulty, recognition difficulty under complex background, low processing accuracy and efficiency. In this study, the RS image processing technology combined with NN and BD has stronger adaptability with the help of NN and BD technology, and can adjust parameters and can be applied in more tasks.

Keywords: remote sensing image, image processing, neural networks, big data, high dimensional data analysis

1 Introduction

At present, remote sensing (RS) technology has been deeply applied in many fields such as military, agriculture, meteorological observation, and environmental analysis. Professionals in related fields use RS technology to process a variety of signals reflected or scattered by the observed target to complete the identification and detection of the observed target. However, RS image processing technology is still faced with problems such as big data (BD) processing difficulties, low classification and recognition accuracy of objects in images, low accuracy and efficiency of image processing, etc. These problems force the current traditional RS image

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processing technology to be more or less problematic in many industries. This study verifies the feasibility and reliability of a new RS image processing technology based on the fusion of neural networks (NN) and BD, and conducts experimental analysis on the role of the fusion of NN and BD in RS image processing technology.

At present, RS image processing technology has been widely used in many industries, so some researchers in related fields have analyzed the application status of RS image processing technology in various industries. Among them, Hamida et al. studied the classification methods of RS images in the field of RS image processing. During the research, they determined that the current RS image processing was still limited by the insufficient content of large datasets, so they proposed the deep learning (DL) method to complete the classification of RS images. This RS image classification combined with DL technology can help people better detect and classify objects in RS images [1]. Ye et al. studied the multi-modal RS image processing mode in RS image processing, and analyzed some shortcomings of RS image processing technology in the current society. At the same time, he proposed a multi-modal RS image classification method that can be matched quickly and accurately, and this RS image classification method can identify and match the same target in different RS images [2]. Yuan et al. analyzed the panchromatic sharpening of RS images in the domain of RS image processing. RS image processing technology is applied in many fields at present. Panchromatic sharpening has always been the basic task of RS image processing, which determines that RS images with high resolution cannot be obtained due to the insufficient performance of panchromatic sharpening in existing RS image processing technologies [3]. These studies analyze some problems in the existing RS image processing technology, and put forward some preliminary solutions. However, they did not completely solve these problems.

Other researchers have also analyzed the application status of RS image processing technology in various industries. Cai et al. analyzed the hyperspectral RS image analysis mode. He determined that the detection and classification of hyperspectral RS images in the current society have deep applications in many fields such as geological exploration and marine RS. At the same time, the performance of the existing hyperspectral RS image analysis in terms of feature extraction and mining cannot meet some requirements in these fields, so they combined the multi-attention residual fusion network to study the feature extraction and mining of hyperspectral RS images [4]. Shao and Cai analyzed the application mode of RS image fusion in the field of RS image processing in society, and determined that RS image fusion can assist environmental monitoring. At present, RS image fusion still has many shortcomings. He proposed to use NN technology to optimize RS image fusion [5]. Song et al. mainly studied a classification model of RS images, which has been applied in many industries. However, the effectiveness of this kind of RS image classification is often not guaranteed, so it is necessary to study the working mode of RS image classification and optimize the classification of RS image with the help of NN and other technologies [6]. Huang et al. analyzed the application of RS images in agriculture, and determined that RS images can help people analyze field data in agriculture through the investigation of a large number of relevant literature. With the development of various information technologies, the current RS image processing can no longer meet the needs of agricultural field exploration, and further optimization and improvement are needed [7]. These scholars' research on the application of RS image processing technology can provide a certain application basis for this study, and can also provide more ideas and methods for this study. However, due to their focus on application results rather than focusing on exploring the problems of RS image processing technology in data processing difficulties, recognition difficulties, and low recognition accuracy and efficiency, the research results do not have much reference value, and have difficulty in meeting the actual needs of current BD fusion. Through the analysis of literature on RS image, this study confirms that RS image processing technology has occupied an important position in many industries, but there are still problems such as data processing difficulties, recognition difficulties, and low recognition accuracy and efficiency, and hence further optimization is needed.

After studying the application patterns and functions of NN and BD in image processing, the feasibility and advantages of NN and BD in image processing are determined. There are many types of image processing technologies in the current image processing field, among which the most widely used is RS image processing technology. RS image processing can help people solve problems in many industries. However, with the development of time, the performance of RS image processing technology has gradually fallen behind. Therefore, some researchers have proposed a classification method of RS hyperspectral images based on NN, which uses NN technology to achieve better classification performance of RS images [8]. Maeda et al.

analyzed the role of image processing technology in pavement damage detection and determined that image processing could not handle a large amount of pavement data well. Therefore, relevant researchers combined NN technology with image processing in smart phones to improve the performance of road injury detection and injury classification [9]. At the same time, in the field of image processing, Pelt and Sethian discussed and studied the universality of image processing models, and determined that the current image processing problems cannot be used in multiple applications. Therefore, they proposed a general image processing model combined with NN architecture, which can play a role in multiple applications [10]. At the same time, a special NN technology is also used by researchers in related fields to optimize working modes such as image denoising and image restoration in image processing, which mainly combines NN technology to improve the image denoising ability of image processing models [11]. Bayar and Stamm studied a new detection method for image processing, which found that the combination of image detection and NN technology in image processing has a higher accuracy in the detection and operation of image features. At the same time, the general image detector based on NN technology has better comprehensive performance than the traditional detector [12]. NN technology can also be combined with image classification models in the field of image processing, which can mainly reduce the amount of computational tasks in the process of image classification and improve the efficiency of image classification [13]. In addition, some researchers have analyzed the combination of image processing and BD technology, and determined the feasibility of combining the existing image processing and BD technology in the process of analysis. At the same time, they discussed the application scenarios of the image processing model based on BD and determined that BD technology has great development potential in the field of image processing [14]. Through the analysis of NN and BD technology, researchers in these literature verify that these two technologies can be combined with image processing technology and improve the data processing ability, image processing accuracy, and efficiency in the image processing process.

In this study, it is determined that NN and BD technologies can improve the cleaning, classification, and processing ability of a large number of RS image data in the traditional RS image processing technology. The improvement of data processing capability enables the RS image processing technology combined with NN and BD to process a large amount of data quickly and ensure a certain accuracy in the process of processing. In this study, ConvNext-convolutional neural network (CNN), parallel processing, and data enhancement techniques are used to improve the problems in traditional RS image processing. Among them, ConvNext-CNN is responsible for optimizing the working mode of image feature extraction and object detection in complex environments in RS image processing. BD technology, such as data enhancement and parallel processing, mainly reduces the processing complexity of RS images and improves the efficiency of data processing. Its RS image processing technology can improve the processing performance of complex RS images and improve the accuracy and efficiency of RS image processing, which integrates NN and BD technology.

2 RS image preprocessing

2.1 Dataset selection

The data is derived from the UC Merced Land Use Dataset constructed by Newsam SD, Yang Y [15]. The dataset contains images of 21 land use categories, which are manually extracted from large images sourced from the USGS National Map Urban Area Imagery collection, focusing primarily on various urban areas. In the process of analyzing RS image processing technology, this article selected 400 RS data images that meet the research requirements based on parameters such as spatial resolution, temporal resolution, and spectral resolution of RS data, including 100 RS images of buildings, 100 storage tanks, 100 parking lots, and 100 farms, and they were all in Tagged Image File Format (TIFF). The size of these 400 RS images is 256 × 256, and the resolution of RS images is 72 dpi (dots per inch). At the same time, in order to ensure the reliability of subsequent image processing and analysis of experimental results, it is necessary to evaluate the image quality of these 400 images. This article improves image quality through methods such as image enhancement, gray scale processing, noise removal, and geometric transformation. First, image gray scale processing is performed by adjusting parameters such as brightness, contrast, and color saturation to enhance the details and visual effects of the image. Then, the nearest neighbor interpolation method and bilinear interpolation method are used for image geometric transformation, and finally, median filtering, Gaussian filtering, and mean filtering are used to smooth the image. In this study, histogram analysis is chosen to evaluate the quality of RS images.

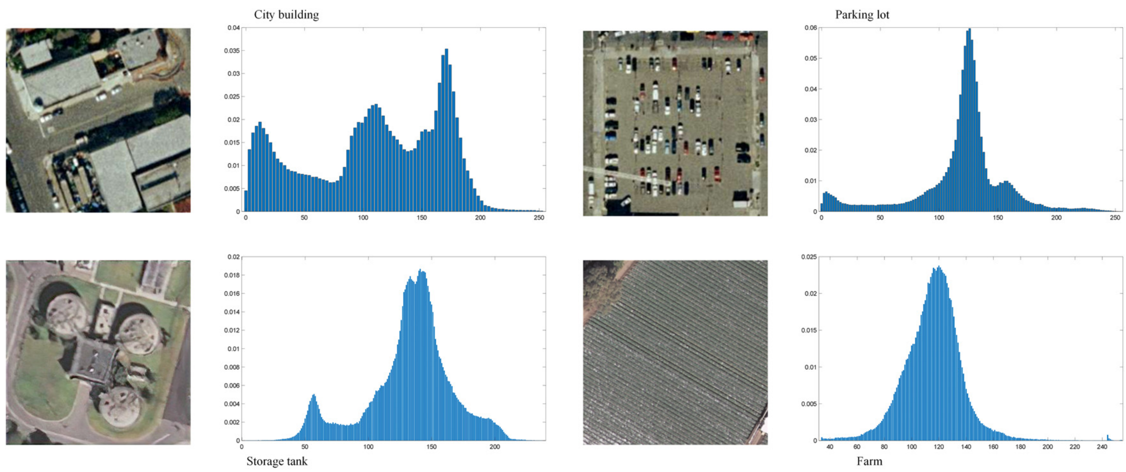

Figure 1: Presentation of histogram of category 4 RS images [15].

In the evaluation process, this study analyzes the histogram of these 400 images, and determines whether there is overexposure or color imbalance in each RS image. At the same time, a RS image was randomly selected from 400 RS images of different categories to display its histogram, as shown in Figure 1.

After analyzing Figure 1, according to the pixel distribution of the histogram, it can be seen that the brightness distribution of the two images of the parking lot and farm is not close to the left or right side, which indicates that there is no overexposure or underexposure of brightness in these two images. The gray distribution of pixels of buildings and storage tanks has a certain distribution on the leftmost side of the histogram, but it is not mainly concentrated on the leftmost or right side. This indicates that the gray scale distribution of the image is relatively uniform or there is a certain degree of gray scale shift. Generally speaking, if the gray scale distribution of an image is mainly concentrated on the leftmost side (i.e., dark area), it indicates that the image is dark and lacks brightness. On the contrary, if it is mainly concentrated on the far right (i.e., bright area), it indicates that the image is slightly brighter and lacks contrast. When the gray scale distribution has a certain distribution on the far left side of the histogram, but is not mainly concentrated on the far left or right side, there may be the following situations: first, the gray scale distribution of the image is relatively uniform, and second, the image has a certain gray scale offset. Finally, after visual detection and

Table 1: Display of image quality evaluation results in sample image dataset

	Images with visual defects	Images with luminance defects	Images with color balance deficiencies
RS images of storage tanks	0	2	3
RS images of urban buildings	0	2	0
RS image of parking lot	0	1	1
RS images of farms	2	0	1

histogram analysis of 400 RS images, color imbalance or overexposure in 400 images are determined. The quality assessment results of 400 images are shown in Table 1.

After analyzing the data in Table 1, it can be determined that among the 400 RS images, 2 RS images of storage tank have the problem of brightness overexposure or underexposure, and 3 RS images have the defect of color balance. Therefore, there are 95 RS images of storage tank that can be used in this study. Second, there are 2 RS images of urban buildings with brightness defects, so there are a total of 98 smoke sensing images of urban buildings that can be used. Then, there is 1 RS image of parking lot with brightness defect and 1 RS image with color balance defect, so there are 98 RS images of parking lot available. Finally, there are two RS images of farms with visual defects and one with color balance defects. A total of 97 RS images of the farm were therefore available.

At the same time, part of the RS image public dataset used in this study is displayed. Public RS image datasets are RS image datasets from a variety of publicly available data sources, which are usually released by government agencies, research institutions or commercial companies, etc. They usually contain various types of images, such as visible, infrared, hyperspectral, etc. These images can provide information about different aspects of the Earth's surface, such as the natural environment, human activities, and climate change. The formats of these datasets also vary, and common formats include GeoTIFF, ENVI, HDF5, etc. The sources of public RS image datasets are mainly various satellite and airborne RS platforms, including but not limited to Landsat, Sentinel-2, Google Earth Engine, Kosatellite, and so on. These platforms regularly collect and process large amounts of RS imagery data and release them for public use. In addition, some commercial companies such as DigitalGlobe and Planet Labs also provide high-resolution RS image data, which can also be used for research and applications in the fields of machine learning and computer vision. Some of the public RS image datasets are shown in Figure 2.

The first row in Figure 2 is the RS image of the storage tank, in which the boundary of the storage tank in image 2a and b is clear, so the difficulty of RS image processing is relatively low. In Figure 2c and d, the boundary of the storage tank is blurred or there are many similar objects, which can easily increase the processing difficulty of the RS image processing model. The eight RS images 2e, f, i, j, k, l, o, and p are easy to process, while the four RS images 2g, h, m, and n are difficult to process.

Then, the image processing difficulty of 388 available RS images was studied and plotted, as shown in Table 2.

Table 2 shows how many RS images are easier to process and how many are harder to process for four different types of RS images when RS image processing technology is used.

2.2 Preprocessing steps

In the process of RS image preprocessing, 388 RS images that can be used need to be converted into gray images, and the selection of gray images involves selecting different gray methods for different types of RS images. In this study, storage tank remote sensing image, urban building remote sensing image, parking lot remote sensing image and farm remote sensing image are used for gray processing. Image dimensions were converted from 300 × 300 to 250 × 250. In this study, four RS images of storage tanks, urban buildings, parking lots, and farms were randomly selected to display gray image conversion, mainly using four methods: system function operation gray, average gray, weighted average gray, and maximum gray, as shown in Figure 3.

In the process of RS image preprocessing, there are several main purposes for converting RS image to gray level image. First, gray scale images have fewer color channels than RS images. This means that the computing tasks of RS image processing are more than that of gray scale image, which requires more server computing resources. Then, the conversion of gray image can further remove the influence of color information in the process of image processing. Gray scale image conversion is a commonly used method in image processing, which can convert color images into gray scale images for further processing and analysis. In gray scale image conversion, by contrast stretching, dense gray scale areas can be transformed into a wider range, compressing the gray scale range of areas of interest. Afterwards, by using the corresponding 0/1 of each pixel to generate the image, it helps to save space occupied by the data. For images with a concentrated gray scale range on the histogram, they may appear dark or bright, resulting in a low contrast visual effect. Histogram equalization

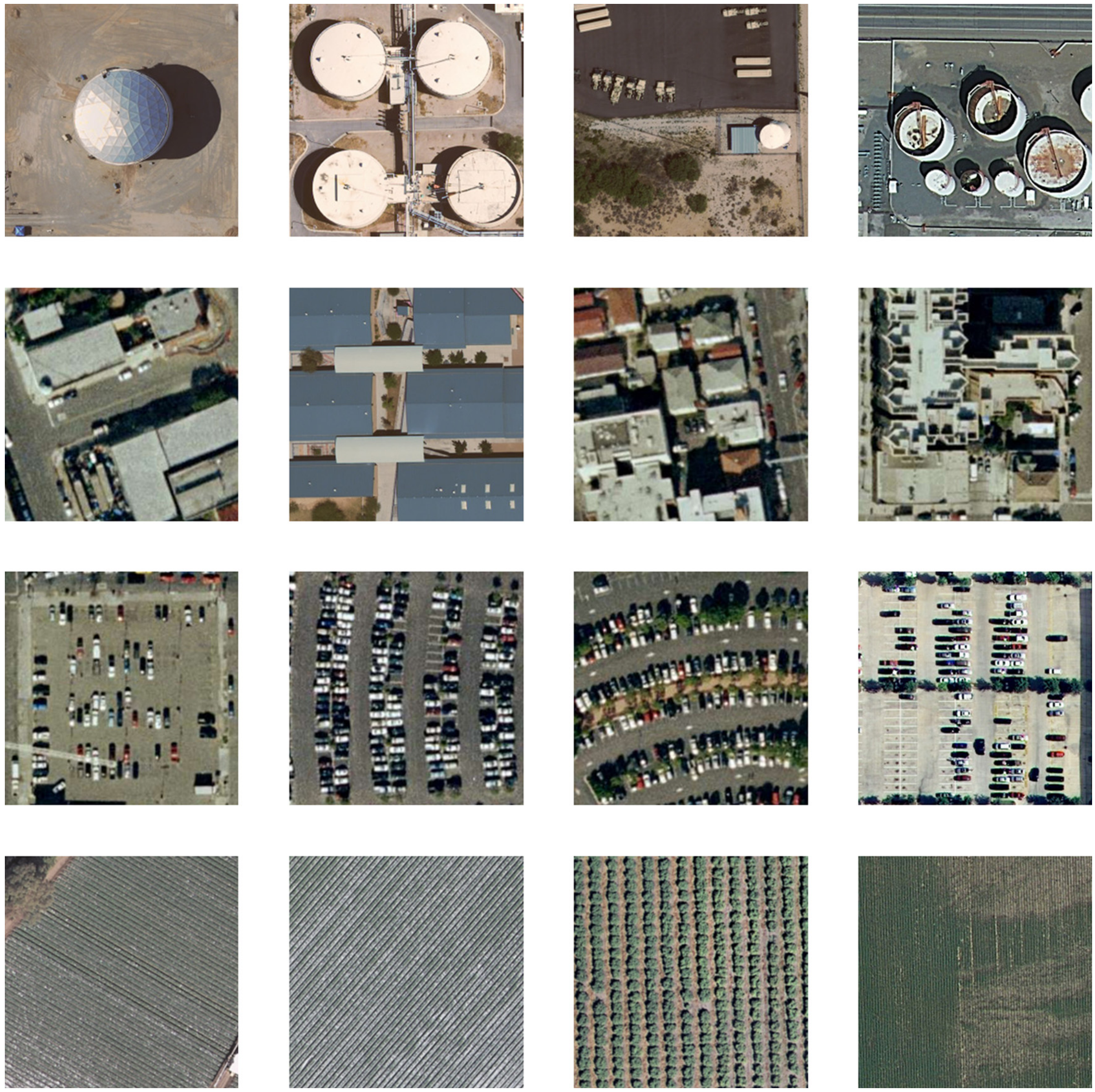

Figure 2: Image display in the public dataset of RS images [15].

Table 2: Image processing difficulty of 388 RS images

	RS images that are easier to process	RS images that are difficult to process
RS images of storage tanks	53	42
RS images of urban buildings	49	49
RS image of parking lot	47	51
RS images of farms	72	25

can be performed to enhance the contrast. Second, after the image is converted from RS image to gray scale image, the feature dimension of the image would be reduced to a certain extent, which can improve the accuracy of image classification and detection of image processing technology. Finally, gray scale images have only one color channel, so the same number of gray scale images occupy less storage space than RS images in the system.

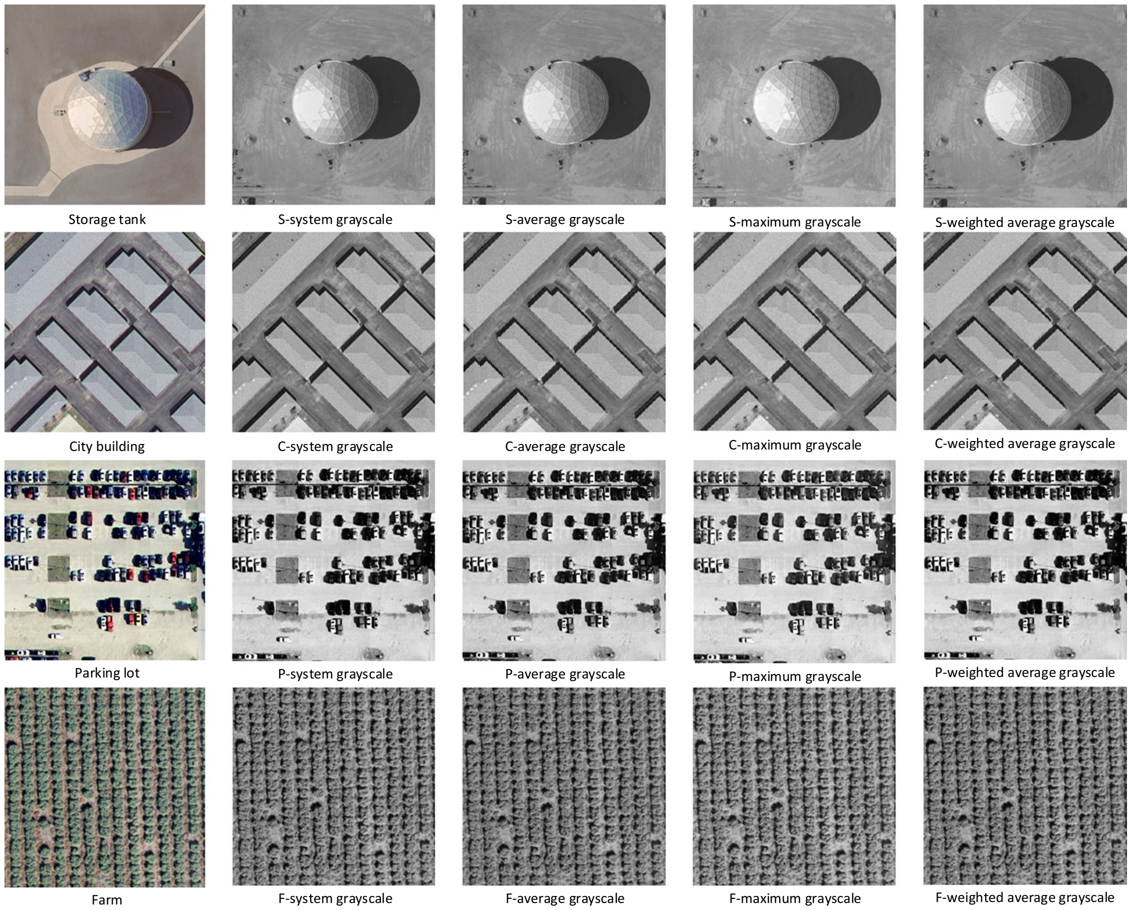

Figure 3: Grayscale display of the RS images of storage tanks, city buildings, parking lots, and farms [15]

In this study, 388 RS images are gray-processed by using these four methods. In the process of gray-processing, a gray scale image that is most conducive to image processing would be selected from the gray scale images constructed by the four gray scale methods and put into the gray scale image sample dataset. A sample dataset with 388 gray scale RS images is presented.

This method of selecting the gray scale image that is most conducive to image processing is mainly obtained by comparing the contour similarity between the image and the original image. In this study, the image of the parking lot is used to illustrate. First, the original image of the parking lot and the target edge contour of the four gray scale methods need to be obtained. In the edge detection, the Prewitt edge detection operator is used. This is because the Prewitt operator utilizes the pixel averaging method when detecting edges, which can effectively reduce the impact of noise on edge detection results. In contrast, some other edge detection operators, such as the Roberts operator, have lower noise suppression performance than the Prewitt operator. At the same time, the Prewitt operator utilizes two directional templates to perform neighborhood convolution with the image in the image space to complete edge detection. These two directional templates detect horizontal edges and vertical edges. This method helps to detect edge information in images more comprehensively, as shown in Figure 4.

Figure 4 shows the effect of the original RS image [15], system function gray level image, average gray level image, maximum gray level image, and weighted average gray level image after using the Prewitt edge detection operator to continue edge detection, and the contours of the five images have little difference in intuitive visual performance. Therefore, this study introduces the Structural Similarity Index measure (SSIM) to calculate which of the four gray scale images has the better SSIM with the original image, so as to complete the selection of gray scale method.

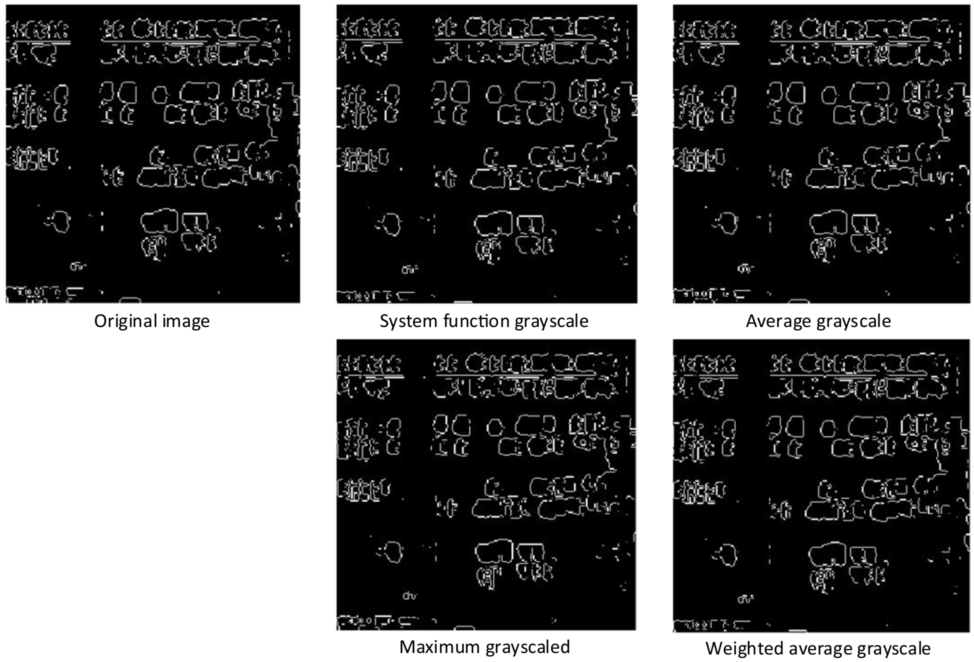

Figure 4: Prewitt edge detection display of the parking lot and four gray scale methods [15].

In SSIM, it is proposed to extract the features of brightness, contrast, and structure from the image for comparison. Therefore, compared with traditional image error comparison methods, SSIM is a more suitable image similarity assessment method for human vision. The main formula used is shown in formula (1).

$$\mathrm{SSIM}(a, b) = \frac{(2u_a u_b + C1)(2\gamma_{ab} + C2)}{({u_a}^2 + {u_b}^2 + C1)({\gamma_a}^2 + {\gamma_b}^2 + C2)}, \tag{1}$$

where a and b usually represent the original image and the contrast image in two 8 × 8 or 11 × 11 windows, u_a and u_b represent the average of a and b, ${u_a}^2$ and ${u_b}^2$ represent the variance of a and b, and γ_{ab} is the covariance of a and b. At the same time, in the evaluation of SSIM calculation results, the closer the value is to 1, the two images are very similar, and the closer the value is to 0, the two images are very different.

Finally, by comparing the SSIM of the four gray scale images and the original image, the maximum gray scale image is more similar to the original image in the parking lot gray scale method. Therefore, the maximum gray image is selected from the four gray scale images of the parking lot to be added to the sample dataset.

In this study, the data of sample dataset is expanded with the help of image geometric transformation, which mainly enhances the generalization ability of image processing model, and also helps the image processing model to alleviate overfitting and improve the robustness of the model. In this study, one of the 95 RS gray scale images of storage tanks is randomly selected to show its geometric change results, as shown in Figure 5 [15].

In the RS gray image sample dataset, one RS gray image can be expanded to five RS gray images by geometric transformation. Two interpolation methods are used in this process, namely, nearest neighbor interpolation method and bilinear interpolation method. First, the original gray scale image is rotated 20° counterclockwise with the center as the origin, and a complete rotating image is generated by using the nearest neighbor interpolation method. Then, the center of the image is rotated 20° clockwise, and the full image is generated using the same nearest neighbor interpolation method. Next the image is rotated 20° counterclockwise with the center as the origin, and the complete image is generated using bilinear interpolation. The fourth image is rotated 20° counterclockwise from the center as the origin, and the nearest neighbor interpolation method is used to generate an image of the same size as the original image. The final fifth image

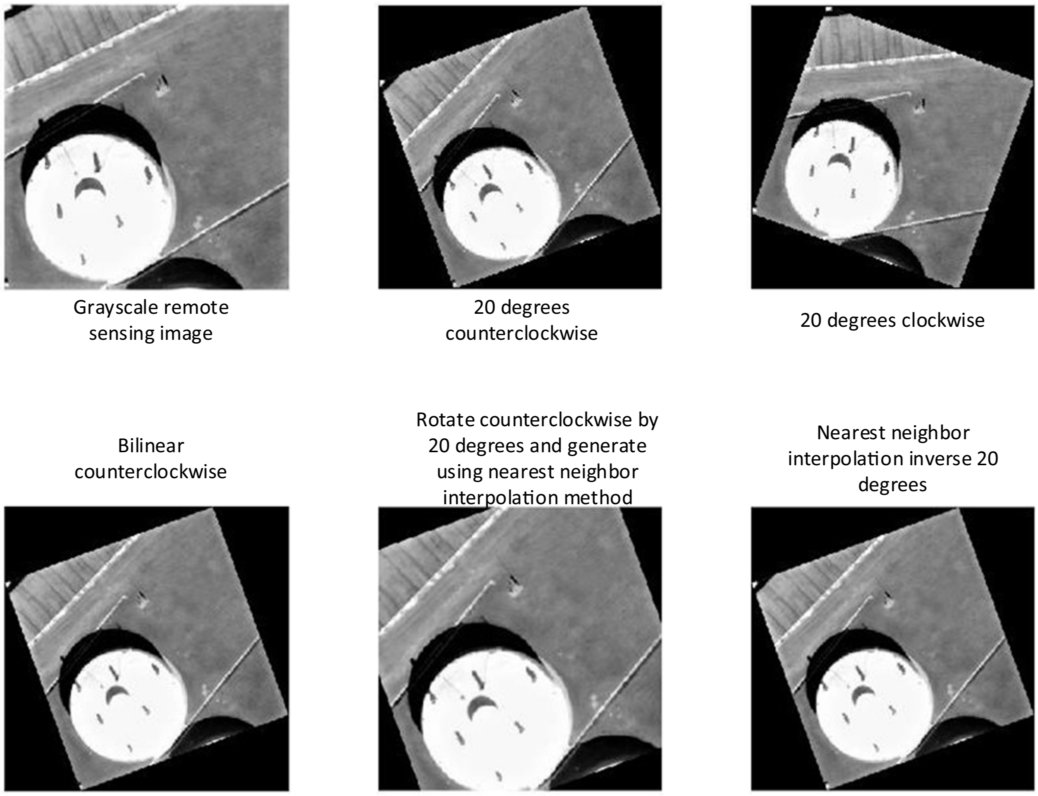

Figure 5: Geometric transformation of the image [15].

is similarly rotated 20° counterclockwise, using nearest neighbor interpolation to produce a fully rotated gray scale image.

At the same time, image denoising is also required in the preprocessing stage of RS images. In this study, a RS gray image of a storage tank is selected to demonstrate the denoising effect of different Gaussian noise methods, as shown in Figure 6 [15].

Figure 6 shows the effect of median filtering, Gaussian filtering, and mean filtering on the noise removal of gray scale images containing Gaussian noise. Median filtering is a nonlinear filtering method, which can better preserve the edges and details of the image. Gaussian filtering is a linear filtering method, which can effectively reduce the high-frequency noise in the image, but would cause the loss of image details while processing [16]. Finally, the mean filtering is a relatively simple linear filtering method. Although it can remove noise from the image, it also makes the edges of the image more blurred.

In the image preprocessing stage, the last step is histogram equalization of gray level image. This study also selects a gray scale image for histogram equalization processing and display, as shown in Figure 7.

Figure 7 shows the histogram equalization operation of RS images [15] in the preprocessing stage of this study, where the horizontal coordinate generally ranges from 0 to 255, representing the brightness range of the image. The ordinate represents the normalized pixel frequency of the RS gray image, representing the proportion or frequency of pixels with a specific brightness value in the entire image. This histogram can also be called normalized histogram, which can reduce the impact of image size and the total number of image pixels, and help researchers observe the pixel distribution of the image.

In the preprocessing stage, atmospheric correction, geometric correction, and image clipping are carried out to further eliminate some factors affecting the image processing process. Atmospheric correction is usually performed using specialized software such as The Environment for Visualizing Images (ENVI) to analyze and manipulate RS images. ENVI is a complete RS image processing platform that integrates software processing technologies that cover input/output of image data, image calibration, image enhancement, correction, ortho

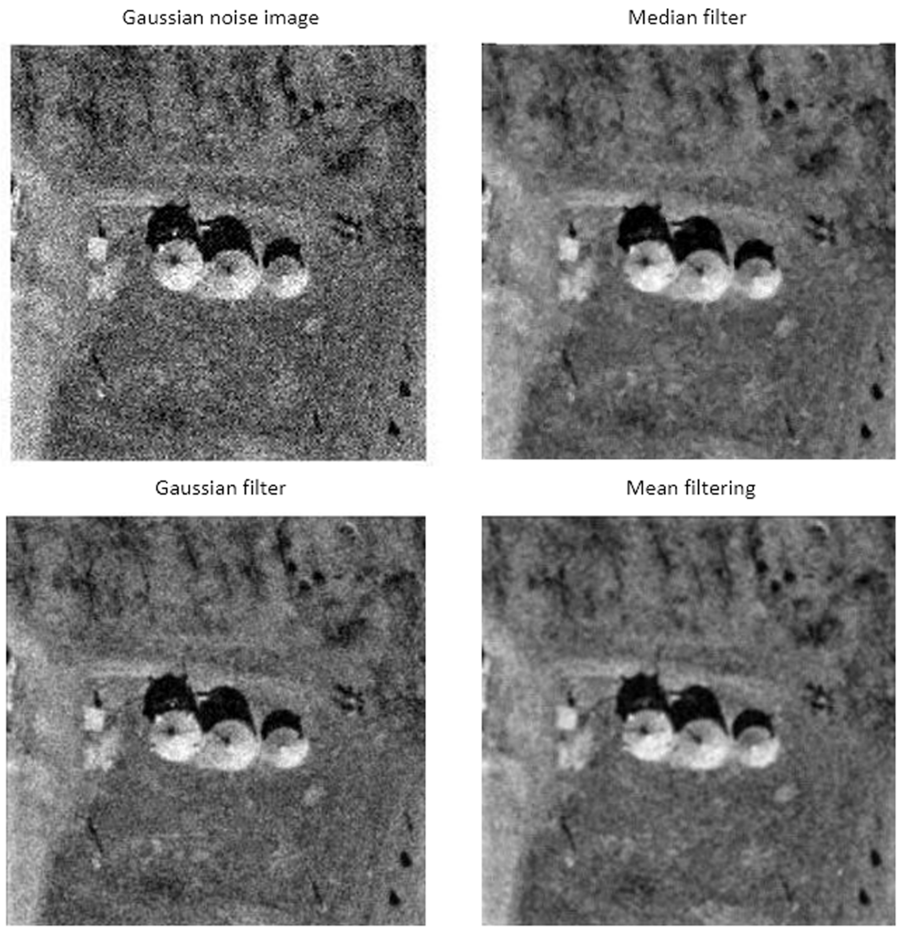

Figure 6: Gaussian noise denoising display of the image [15].

correction, embedding, data fusion, as well as various transformations, information extraction, image classification, knowledge-based decision tree classification, integration with GIS, DEM and terrain information extraction, radar data processing, and 3D display analysis.

3 RS image processing technology combined with ConvNext-CNN and BD

RS image, as a basic means to help people deepen their understanding of the earth environment and geology, has accumulated a large amount of observation data after a long period of development [17,18]. At the same time, with the development of various information technologies in modern society, the sources of a large number of RS image data collected are not limited to a class of platforms, but involve multiple types of platforms and sensors [19,20]. On the one hand, the integration of these multi-modal RS data enriches the dataset of RS image processing and improves the accuracy of RS image analysis. On the other hand, it also brings strong image data processing pressure to the existing traditional RS image processing technology. At the same time, the data processing capability of RS image processing technology in this period has not been optimized, so the existing traditional RS image processing technology is increasingly unable to complete the RS image detection work in related fields. This study analyzes and optimizes the RS image processing technology based on NN and BD. This optimization is mainly aimed at the four shortcomings of traditional RS

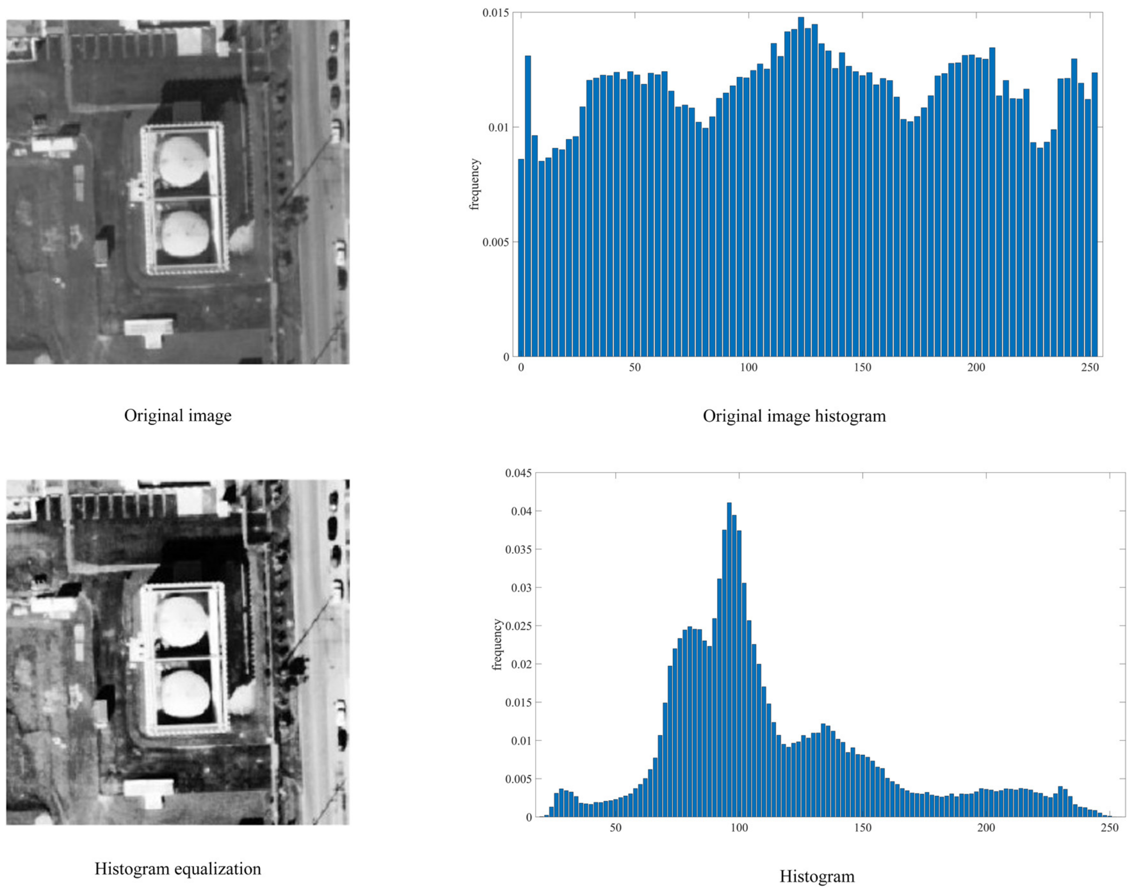

Figure 7: Histogram balanced display of gray image [15].

image processing technology, namely, the ability to analyze and process a large amount of image data, the ability to recognize objects under complex image background, and the low accuracy and efficiency of RS image processing.

In the process of analysis, the operation flow of traditional RS image processing technology is defined, and the operation flow of RS image processing technology combined with NN and BD is summarized according to its related shortcomings, as shown in Figure 8.

Traditional RS image processing technology directly carries out image classification and target recognition after image preprocessing. In this process, a large number of RS image classification and target recognition tasks would be piled up, thus reducing the overall efficiency of traditional RS image processing technology. Then, the image segmentation and information extraction are carried out. NN technology is not used in traditional RS image processing technology. Therefore, in the process of processing RS images with complex background, the target recognition ability is often weak.

The flow chart in Figure 8 shows the operation flow of RS image [15] processing technology combined with NN and BD. After image preprocessing, this RS image processing technology is processed by the RS image after the preprocessing of BD responsibility. This kind of RS image analysis and processing assisted by BD can greatly improve the analysis and processing efficiency of RS image. At the same time, the RS image processed by BD can further enrich the RS image sample dataset through image enhancement operations, and further reduce the impact of possible errors in the data processing. Then, the feature extraction of RS images is carried out. In this process, multi-dimensional features of RS images are extracted mainly by ConvNext-CNN. At the same time, the back propagation algorithm can be used to optimize the RS image feature extraction algorithm model based on ConvNext-CNN. At last, different categories of RS images are classified and then the data output and display are completed, which is the workflow of RS image processing.

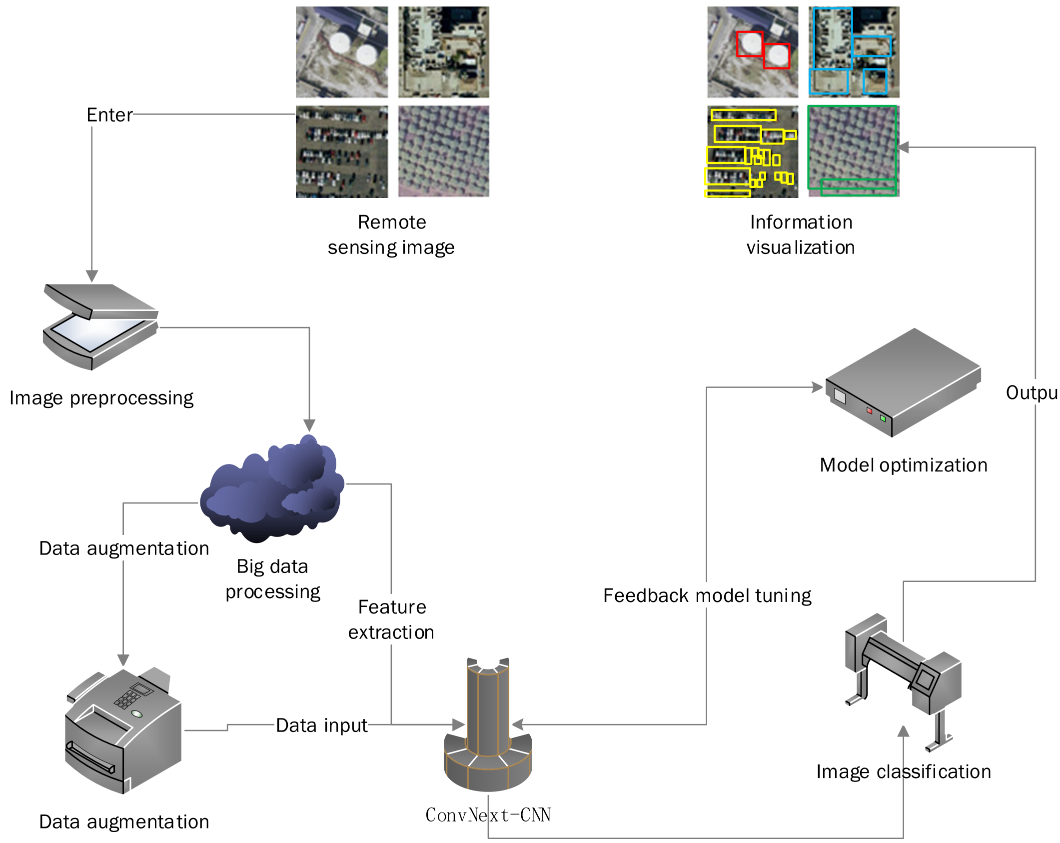

Figure 8: Display of the operation flow of RS image processing technology combined with NN and BD.

3.1 BD application pattern

Among the RS image processing technologies combining NN and BD, BD technology mainly provides a variety of optimization methods related to RS image data processing. The application mode of BD technology in RS image processing is shown in Figure 9.

Figure 9 shows the application mode of BD technology before and after the preprocessing stage of RS image processing technology combining NN and BD. In this process, BD technology is mainly used to provide five optimization methods for RS image processing. The five optimization methods are parallel processing, data fusion, efficient data storage and retrieval, real-time monitoring, and high-dimensional data analysis. When processing BD, parallel computing models can be adopted to fully utilize computing resources and improve data processing efficiency. For multi-source data, data fusion technology is used to integrate them together to obtain more comprehensive and accurate data. In terms of storage, distributed storage can be used to disperse data to different nodes, reducing storage pressure on individual nodes and improving system scalability. Meanwhile, for data that require frequent access, caching technology can be used to accelerate the speed of data reading and reduce the number of disk reads. Then, real-time monitoring is achieved through technologies such as real-time data collection and stream computing. Finally, by performing dimensionality reduction on high-dimensional data, we can better understand and analyze the essence and laws of the data. In the traditional RS image processing technology, parallel processing technology is rarely used in the process of processing a large number of RS images. In the image preprocessing stage of RS image processing technology combined with NN and BD, the same type of RS image can be preprocessed simultaneously through parallel data processing. This image processing mode can better speed up the execution of image processing algorithm and improve the processing efficiency of image processing. Data fusion: data fusion is to integrate RS image data from different types of sensors and different times, which can help staff in related fields to get more accurate data. Efficient data storage

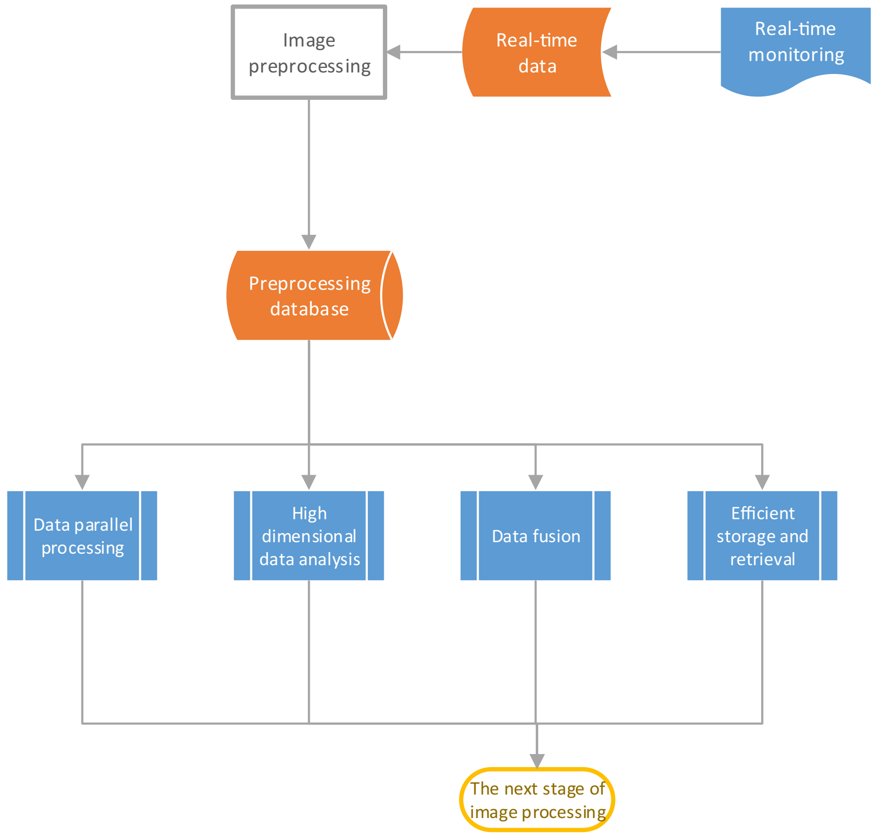

Figure 9: Application model of BD technology in RS image processing technology.

and retrieval: in addition, after the combination of RS image processing technology and BD technology, the RS image processing technology combined with NN and BD can disperse RS image data in multiple storage systems through distributed storage systems, which can improve the storage capacity of RS image data to a certain extent. On the other hand, specific RS data in the database can be retrieved through the index technology and distributed query in BD technology, which further reduces the requirements and costs of RS image processing technology. Real-time monitoring: In the RS image processing technology combined with NN and BD, the advantages brought by its combination with BD technology are also real-time monitoring function for the target. This RS image processing technology combined with NN and BD can not only help relevant departments of urban management to complete real-time monitoring of urban buildings and farms but also complete all-day monitoring and early warning of storage tanks storing dangerous goods in the storage field of dangerous goods, further reducing risks in all aspects. The last is high-dimensional data analysis.

High-dimensional data analysis: In the RS image processing technology combined with NN and BD, BD technology is generally used for high-dimensional analysis of RS image data. In high-dimensional analysis, the first thing people need to face is the selection of dimensionality reduction algorithm. This study mainly uses Autoencoder (AE) in NN technology to reduce the dimensionality of data in image processing. The AE dimension reduction operation process is shown in Figure 10.

In the process of dimensionality reduction of RS image data using AE, sliding window filter is given, and feature extraction of data is carried out through NN algorithm. In this process, the weight of data is guaranteed not to change. At the same time, the algorithm in NN is used to process the non-linear mapping of the resulting data, and its formula is shown below [21].

$$O = f\sum_{i=1}^{n} wx_i + b, \tag{2}$$

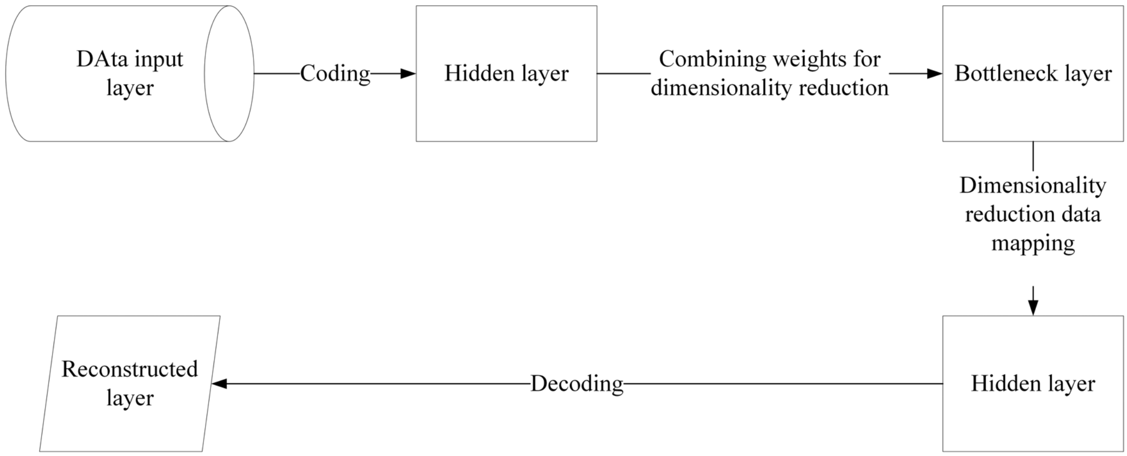

Figure 10: Display of the operation process of dimensionality reduction of AE high dimensional data.

where f represents the activation function, w represents a parameter, and n represents the number of training samples. At the same time, the parameters of the model in AE are constantly updated, that is, back-propagation is used, as shown in formula (3).

$$E = \frac{1}{2}\sum_{i=1}^{n}(y_i - T)^2. \tag{3}$$

In the high-dimensional data analysis, the above steps are used to continuously train and update the data of multiple layers in AE to reduce the dimensionalization of high-dimensional data. Then, feature extraction is carried out on the data after dimensionality reduction. In this process, parallel processing is also used, that is, the image data is cut into smaller images for processing, and the final image data are obtained by merging the results. This kind of high dimensional data analysis work can reduce the complexity and number of tasks of computation.

3.2 Application scenario of ConvNext-CNN

In the RS image processing technology combined with NN and BD, NN mainly has three functions: RS image feature extraction, RS image target detection, and RS image change detection [22].

In the RS image classification process combining the RS image processing technology of NN and BD, the sample dataset is first divided into three main datasets: training data set, verification dataset, and test dataset [23]. In this study, we use the leave-out method to divide the dataset into two mutually exclusive sets, and the common ratio is 70% as the training set and 30% as the test set, which is required to maintain the consistency of the data distribution in the process of dividing the training set and the test set. According to the RS image preprocessing stage, the geometric transformation of 388 available RS image sample datasets is carried out to obtain 2,328 RS image data. The 2,328 RS image data are divided into three datasets, each of which contains 776 RS image data to complete the division of sample data [24].

Then, NN model needs to be established to process the sample data and complete the extraction of image features [25]. In this process, this study mainly uses the ConvNext-CNN model. The ConvNext CNN model is a CNN model used for image classification and semantic segmentation. It adopts spatial pyramid pooling technology. This technology changes the conventional operation of pooling layers in traditional CNN, capturing features at different scales by pyramid pooling inputs at different scales, and combining these features to improve the accuracy of CNN. It also incorporates the idea of residual networks. ConvNext CNN improves the performance of the network by combining shallower features with deeper features. Compared to traditional models, the ConvNext-CNN model emphasizes deeper understanding of data and feature capture to achieve higher accuracy. However, this requires more complex technical design and parameter adjustment, as well as higher requirements for computing resources and training time. First of all, it needs to train the model with the training sample dataset, and in the process of model training, the weight and bias of the model are adjusted by using backpropagation [26]. Then, the model hyperparameters are tuned in the validation dataset, which can further improve the classification performance and generalization ability of the model. Finally, the performance of the model is evaluated experimentally by using the test sample dataset, and the image classification model based on ConvNext-CNN is constructed.

In order to show the classification effect of this image classification model based on ConvNext-CNN, this study selects 6 RS images from the original 388 gray scale images for image detection and classification display, and the results are shown in Figure 11.

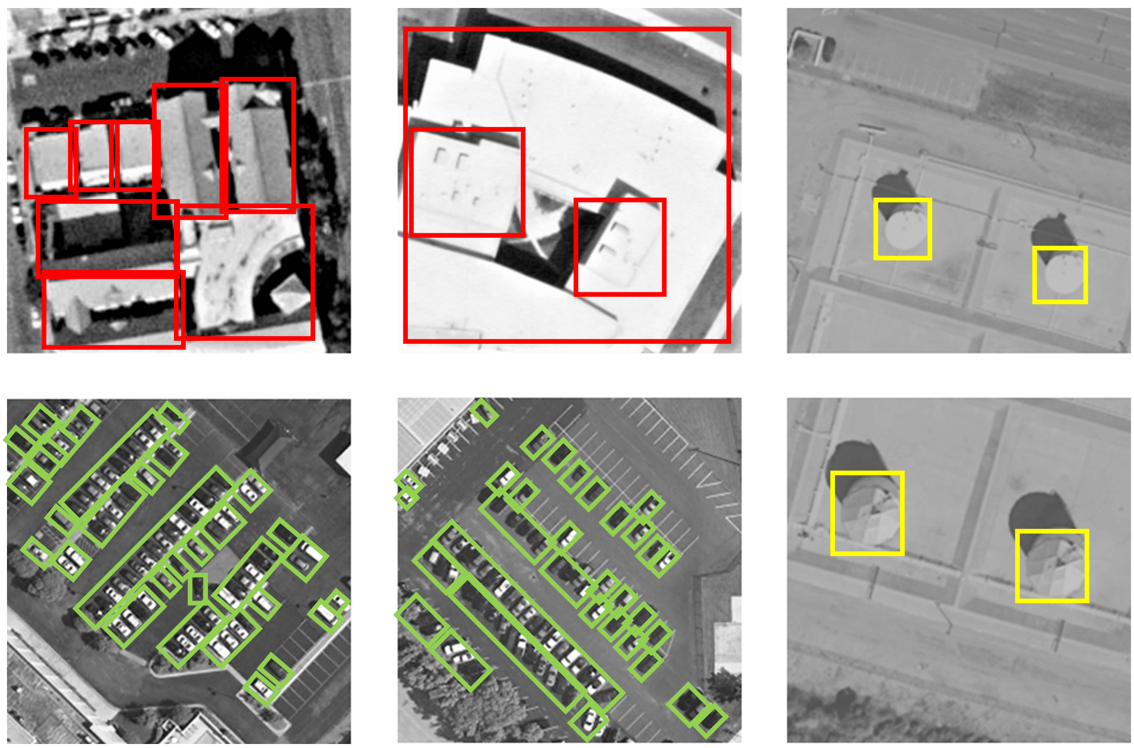

Figure 11: Display of image detection and classification effect of RS gray image.

In these six images, it can be clearly seen that there are two gray RS images of urban buildings, two gray RS images of storage tanks, and two gray RS images of parking lots. In the process of image target detection and image classification of two gray RS images of urban buildings, the red frame is used for marking, the yellow frame is used for processing two gray RS images of storage tanks, and the green frame is used for processing two gray RS images of parking lots. Through the visual detection of Figure 11, the RS images combined with NN and BD can be correctly classified, and most of the targets in the images can be well identified.

In the change detection of RS image, the main method is to compare the pixels of the target in the RS image of different time series in the same region. In this process, a group of RS images are first input into the model, and at the same time, the RS images are detected and classified. Then, a group of RS images in the same area with different input times are used for target detection and image classification, and then the two groups of RS images are compared. This kind of comparison mainly exists in the same type of RS images. If the pixel values in the RS images are compared, it can be considered that the RS images have changed.

The above is the complete operation flow of RS image processing technology combined with NN and BD technology. This RS image processing technology further improves the problems of large-scale RS image data processing difficulties, target recognition difficulties in complex RS image background, and low accuracy and efficiency of RS image processing. This image processing technology can not only be deeply applied in many fields such as urban planning, building monitoring, real-time control of dangerous storage tanks, farm land planning, etc., but also help people to explore the geological and environmental conditions of more regions [27].

4 Experiment of RS image processing combined with NN and BD

This study also carries out experimental analysis on the RS image processing technology combined with NN and BD to determine the feasibility and reliability of this RS image processing technology in multiple fields in reality. In the experimental stage, 2,328 RS gray scale image datasets after geometric transformation in the preprocessing stage were used to carry out a variety of analysis work, among which 4 different images of the 2,328 RS images are shown in Table 3.

Table 3: 2,328 proportion of different types of RS images

	Number of original sample images	Number of sample images after geometric transformation
RS images of storage tanks	95	570
RS images of urban buildings	98	588
RS image of parking lot	98	588
RS images of farms	97	582

According to the data in Table 3, 2,328 RS gray scale images after geometric transformation are analyzed, and the image data of RS images after geometric transformation are difficult to process and easy to process are shown in Figure 12.

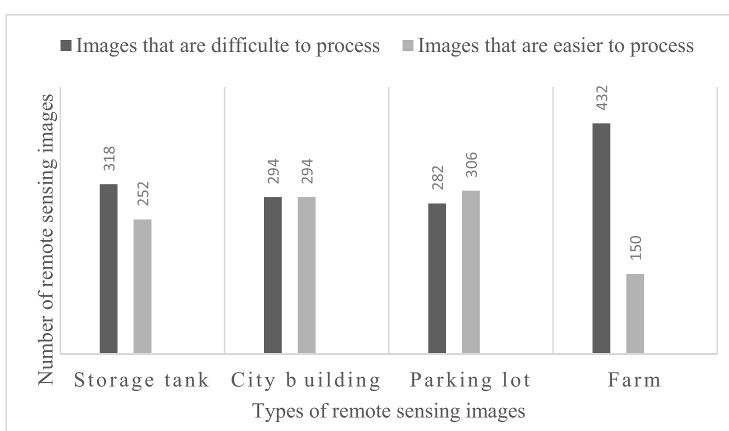

Figure 12: Schematic diagram of data proportion of RS images that are difficult to process and easy to process after geometric transformation.

As can be seen from Figure 12, the storage tanks RS image data have 318 difficult and 252 easy to process images, the city buildings RS image data have 294 difficult and 294 easy to process images, the parking lot RS image data have 282 difficult and 306 easy to process images, and the farms RS image data have 432 difficult and 150 easy to process images. From this it can be seen that among the four types of images, the overall difference between the difficult and easy-to-process images of the storage tank RS image, the city building RS image, and the parking lot RS image are not large, which indicates that the overall quality of the dataset is higher, which is conducive to providing enough data samples for each type of image when RS image processing is carried out, thus avoiding the effect of the processing effect due to the uneven distribution of the data. In RS images of farm, there are many differences between difficult and easy to process images [28].

This study makes an experimental study on the system computing resources, processing time, and image processing performance of the RS image processing technology combined with NN and BD in the process of processing the difficult and easy RS images of four different types. The performance of image processing is mainly based on the accuracy of image processing, recall rate, and $F1$ score. A represents the number of samples that are actually true and predicted to be true, B represents the number of samples that are actually false but predicted to be true, C represents the number of samples that are actually true but predicted to be false, and D represents the number of samples that are actually false and predicted to be false, then the calculation formula of accuracy is as follows (4):

$$\mathrm{Acc} = \frac{A + D}{A + B + C + D} \times 100\%. \tag{4}$$

Second, the calculation formula of recall rate is shown in formula (5).

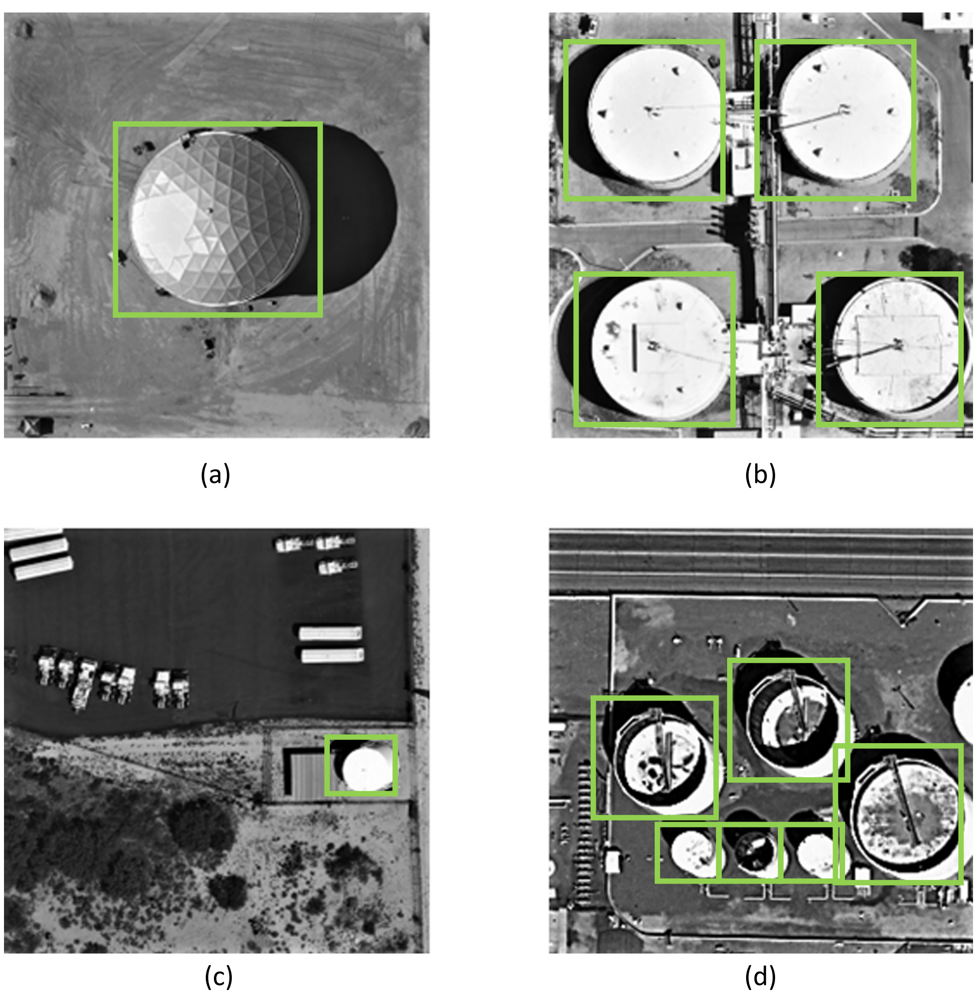

Figure 13: Schematic diagram of image processing results in part of the experimental process. (a) Individual close-up image processing results; (b) Multiple close-up image processing results; (c) Individual vision image processing results; (d) Multiple vision image processing results.

$$R = \frac{A}{A + C} \times 100\%. \tag{5}$$

The formula for calculating $F1$ score is shown in formula (6).

$$F = \frac{2 \times \frac{A}{A+B} \times R}{\frac{A}{A+B} + R}. \tag{6}$$

At the same time, the processing results of some images during the experiment were shown in this study (Figure 13).

In this study, the same host is used in the process of image processing, and the occupation of computer processor in the process of image processing is recorded. Figure 14a shows the computer processor occupation of traditional RS image processing, and Figure 14b shows the computer processor occupation of RS image processing combined with NN and BD [29,30]. The image processing time of traditional RS image processing is shown in Figure 14c, and the image processing time of RS image processing combined with NN and BD is shown in Figure 14d, where the unit of processing time is seconds.

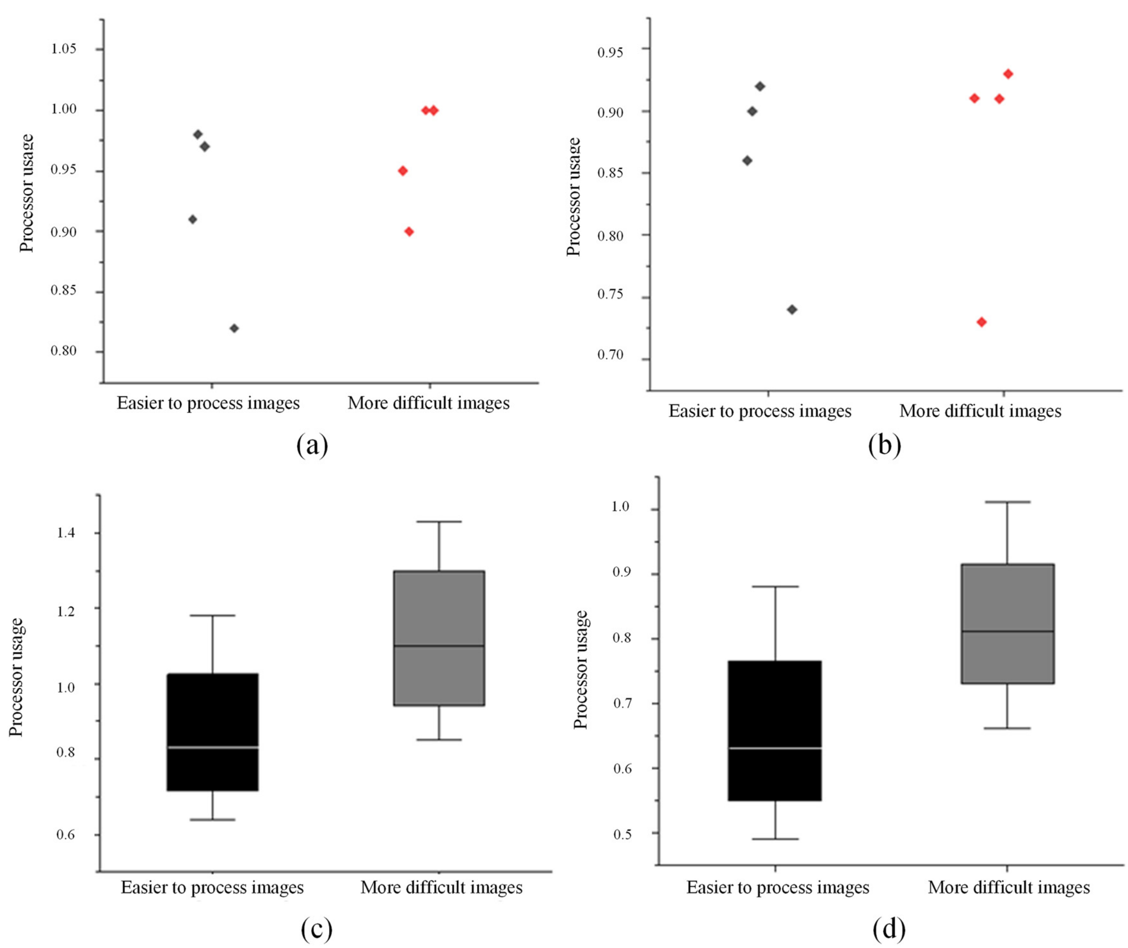

Figure 14: (a) Processor usage of the traditional model. (b) Processor usage of the model combining NN and BD. (c) Traditional model processing time. (d) The combined NN and BD model deals with time cases.

Through the analysis of Figure 14a and b, it can be determined that the RS image processing technology combined with NN and BD has a lower processor occupation in the process of RS image processing. This kind of RS image processing has a relatively small difference between the processing of easier RS images and the processing of more difficult RS images [31]. In the process of processing four types of RS images, the difference of processor occupancy of the RS image processing technology combined with NN and BD was 5, 1, 1, and 1%, respectively, while the difference of processor occupancy of the existing traditional RS image processing technology was 4, 3, 2, and 8%, respectively [32]. After the analysis of Figure 14c and d, it can be seen that the processing time difference values of traditional RS image processing technology were 0.3, 0.24, 0.25, and 0.21 s, respectively. The time difference values of RS image processing technology combined with NN and BD were 0.17, 0.19, 0.13, and 0.17 s, respectively. The traditional model took an average of 0.87 s to process the easier image and 1.12 s to process the harder image [33]. The model combined with NN and BD took an average of 0.6575 s to process the easier image and 0.8225 s to process the harder image. Therefore, it can be determined that the RS image processing technology combined with NN and BD can alleviate the difficulty and low efficiency of large-scale data processing to a certain extent.

At the same time, a total of 100 RS images including 50 storage tanks and 50 urban buildings were selected from 2,328 RS images for image processing, and the processing performance of the two models was recorded, as shown in Tables 4 and 5.

Table 4: Processing results of traditional RS image processing techniques

	Actual storage tank	Actual city building
Predicted as storage tank	41	10
Predicted as urban architecture	9	40

Table 5: Results of RS image processing technology combined with NN and BD

	Actual storage tank	Actual city building
Predicted as storage tank	49	2
Predicted as urban architecture	1	48

By combining the calculation formula of accuracy rate, recall rate, and $F1$ score, the image processing accuracy rate and recall rate of traditional RS image processing technology were 81% and 82%, respectively. The $F1$ score (which is calculated with two decimal places and rounded) was approximately 0.81. The accuracy and recall rates of the RS image processing technology combined with NN and BD were 97 and 98%, respectively, and its $F1$ score was about 0.97. Through comparison, it can be seen that the processing accuracy of RS image processing technology combined with NN and BD has been better improved [34].

5 Conclusion

After analyzing the existing traditional RS image processing technology, it is determined that it is relatively difficult to process large-scale RS image data, takes a long time to recognize complex RS images, and has relatively low processing accuracy and efficiency. Therefore, in view of these shortcomings, this work studies the feasibility of RS image processing technology fusion of NN and BD technology and the reliability of the final technology. In this study, the RS image processing technology combined with NN and BD can pass parallel processing, data fusion, and high dimensional data analysis in BD technology. To a certain extent, it can improve the traditional RS image processing technology for large-scale RS image data processing difficulties and complex RS image processing time, and better improve the efficiency of RS image processing. The combination of ConvNext-CNN and RS image processing technology can greatly improve the accuracy of RS image processing, mainly through the CNN algorithm model to optimize the multi-dimensional image processing process such as feature extraction in the existing RS image processing technology. Finally, the RS image processing technology combined with NN and BD can not only be applied more deeply in the original field but also expand the application field, bringing convenience to more industries.

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