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RESEARCH ON SPACE IMAGE FAST CLASSIFICATION BASED ON BIG DATA

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Abstract. In order to improve the accuracy and effect of space image classification, the author proposes a space image classification method based on Big data analysis, aiming at the shortcomings of low accuracy and long time of current image classification. First, analyze the current research progress of image classification, find out the shortcomings of different classification methods, then collect aerospace images, preprocess the images, and use big data analysis technology to establish image classifiers, image classification was performed using an image classifier, and finally simulation experiments were conducted with other methods for image classification. The results indicate that: The average classification time of this method for aerospace images is 3.5 minutes, which saves 14 minutes and 29 minutes compared to traditional method 1 and traditional method 2, respectively. This indicates that this method has the shortest image classification time and improves the classification efficiency of aerospace images. This method has been proven to have high accuracy in image classification, the shortest classification time, and significant advantages compared to other image classification methods.

Key words: Big data analysis; Image classification; Convolutional neural network; Classification accuracy; Classification effect

1. Introduction. In recent years, intelligent spacecraft have increasingly attracted the attention of aerospace practitioners. Image recognition is one of the main conditions for spacecraft intelligence, and it is also an important research topic in fields such as computer vision, machine learning, and pattern recognition. With the rapid development of computing technology and image sensors, image acquisition methods have been expanded and the field of vision has been promoted. More and more devices have the ability to obtain images, sparking a wave of device intelligence [1]. However, limited by the computing power of flight controllers in current spacecraft, popular deep learning models typically require massive amounts of data and storage space, as well as a large amount of computing resources for long-term model training. If applied in spacecraft, specialized computing equipment is required, which increases the cost and takeoff quality of the spacecraft. At the same time, the space scene is constantly changing over time. By solving the problem of fast online training, spacecraft can have the ability to autonomously recognize targets and have better adaptability to the space environment. Therefore, it is necessary to propose a fast image classification method that can be flexibly adjusted according to practical applications at the software level. Big data analysis methods have been widely used in the field of natural image classification, and detection, registration, generation and other technologies are also gradually applied in image classification [2]. The big data analysis method is used for multi-level processing of information, simulating human brain thinking mode. Different spaces correspond to different layers of features, with different semantic information, hierarchical feature structure of classification, and high classification ability. In order to obtain ideal image classification results, a space image classification method based on Big data analysis is proposed, and its performance is analyzed.

2. References. Computer vision is the basic way to achieve machine intelligence, and its basic carrier is image. The rapid development of computing technology and image sensors has provided great convenience for the acquisition and sharing of images, and the scale of image data is showing explosive growth. From obtaining planetary optical images to deep space exploration, from video surveillance to early warning reconnaissance, image and image processing technologies are ubiquitous [3]. Image classification is one of the hot fields in computer vision, machine learning, and pattern recognition, and has also been widely applied in the aerospace

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field. Image classification consists of two parts: classifier learning and testing. During learning, use the feature information extracted from the image to train the classifier and form classification rules. During testing, each identified sample is described as a set of feature vectors, and the classifier determines the category of the feature vectors based on the learned classification rules. Therefore, image classification can be seen as the process of completing the mapping from the "feature space" to the "category space". After years of development, image classification has proposed many effective learning models, including BP networks, support vector machines, and deep learning networks [4]. The BP network uses a sample set to train the network, thereby obtaining the rules within it. It can fit any function with any accuracy, and the learning rules are simple and easy to implement, which has been widely applied. However, the neural network also has obvious shortcomings, such as the training effect is limited by the network size, and the parameter setting theory is not perfect, which leads to the full Rate of convergence of the neural network, and the classification performance is affected by the fitting effect [5].

Due to the difficulty in overcoming these issues, the popularity of related research has gradually decreased, and researchers have turned their attention to support vector machines. Support vector machines use sum functions to classify nonlinear problems through mapping. The advantage of support vector machines is that they have a complete theoretical foundation, are suitable for small sample learning problems, and have high learning efficiency. Therefore, they have been widely applied since their introduction [6]. The above two classification models are both Supervised learning models. The disadvantage is that the premise of learning is that experts need to provide category information of samples. The deep learning method is a redevelopment of traditional neural network methods, and has achieved many remarkable achievements in fields such as speech recognition and artificial intelligence. It is currently one of the cutting-edge research content in the field of image classification. The deep learning method believes that the training difficulty of multi-layer neural networks can be effectively overcome through unsupervised methods. Deep learning can be achieved by learning deep nonlinear neural networks, mapping low-level features to higher-level forms of features, and learning features with hierarchical structures from them. This not only preserves the advantage of traditional neural networks being able to approximate complex functions with arbitrary accuracy, but also solves the problem of parameter tuning and overfitting in traditional neural network methods, significantly improving the accuracy of image classification, it has received widespread attention from the academic community since its inception, and various types of research and applications have emerged endlessly. But the drawbacks of deep learning are also very obvious. Firstly, deep learning methods weaken image feature extraction, resulting in the learning process requiring massive amounts of data to obtain satisfactory results, resulting in low learning efficiency; Secondly, the learning process requires a large amount of computing resources, which has high time and Space complexity, and is difficult to deploy on the resource constrained rocket borne computer. It usually requires additional dedicated hardware to complete the classification task, increasing the flight cost [7].

Zhengwen Li proposes a new image classification method based on the cleaning of inaccurate image data. The effectiveness and effectiveness of this method have been demonstrated through testing real cat and dog images. In the process of studying the relationship between the proportion of incorrectly labeled images in the dataset and classification accuracy, we found that deeper neural networks have a certain degree of robustness to erroneous images in the dataset. However, when there is a high proportion of tag noise images in the image data set [8]. On this basis, Wang .J proposed a data integration scheme for the enterprise Human resource management system based on Big data. Firstly, a unified standard for EIS data integration was established and EIS data was classified. Based on the relationship between data, data types were defined and the data in the employee information system was classified. After classification, inconsistent and duplicate data was eliminated to reduce the interference of invalid data and improve the efficiency of data integration [9]. Based on existing power supply area data, Li and Z have defined four indicators: minimum negative line loss rate, maximum positive line loss rate, minimum power factor, and maximum number of negative line loss values. On this basis, combined with the four indexes before, after, after and after error correction, and combined with the decision tree algorithm, the Discriminative model of the error correction area after error correction is constructed. This identification model was used to identify incorrect wiring areas in all areas of the power company, and on-site inspections were conducted on areas identified as incorrect wiring by the model [10].

Based on the current research, this paper proposes a space image classification method based on Big data analysis. First, analyze the current research progress of image classification, find out the shortcomings of different classification methods, then collect aerospace images, preprocess the images, and use Big data analysis technology to establish image classifiers, and use image classifiers to classify images. Finally, carry out simulation experiments with other methods for image classification.

3. Space image classification method based on Big data analysis. Convolutional neural network (CNN) is a Big data analysis technology, which simulates the information processing process of human brain, and uses Convolutional neural network algorithm to classify images, the neural network is composed of several neurons, which generate high-level abstract features through low-level single features, and is applied to aerospace image classification.

3.1. Composition of Convolutional neural network. Convolutional neural network is evolved from the basic model of artificial neural network. The artificial neural network model is composed of multiple nodes, which form a network according to a specific connection mode. The data flows into the network from the input node, undergoes a series of calculations and transfers, and the results are obtained at the output node. The basic unit of this model is neurons. Each neuron receives input data, processes the input through a certain Activation function, and then transmits the processed results to the next layer of neurons. This connection method forms a multi-layer neural network, with each layer having different feature representation capabilities. The higher the level, the more accurate the semantic representation of the features. The structure diagram of the artificial neural network model is shown in Figure 3.1. As shown in Figure 3.1, the artificial neural network model connects various data nodes and calculates the results after the data flows into the network. Convolutional neural network introduces convolution layer and pooling layer on the basis of artificial neural network, which is the main difference between it and traditional neural network. The convolutional layer utilizes convolutional operations to extract local features from input data, effectively capturing spatial relationships in the data through shared weights and local connections [11]. The output of the convolutional layer is transmitted to the pooling layer, which is used to reduce the size of the feature map and retain the main feature information, thereby reducing computational complexity and enhancing the robustness of the model. Convolutional neural network gradually extracts advanced feature representation of input data by stacking multiple convolution layers and pooling layers. Finally, the extracted features are mapped to the output nodes through a fully connected layer to obtain the final classification or regression results [12]. The multi-layer structure of Convolutional neural network enables it to automatically learn the feature representation of input data, and has certain invariance to translation, scale, deformation and other transformations. This makes Convolutional neural network perform well in computer vision and image processing tasks, such as image classification, object detection and image generation. In addition, Convolutional neural network can also be applied to tasks in other fields such as text data and time series data. In a word, Convolutional neural network constructs a multi-level neural network model with hierarchical feature representation ability by introducing convolutional layer and pooling layer to adapt to data analysis and processing requirements in different fields.

(1) Convolutional layer. The original input matrix utilizes a convolutional kernel sampler to generate convolutional layers.

(2) Downsampling layer. Implement pooling computing based on convolutional layers and generate downsampling layers.

(3) Fully connected layer. By iteratively constructing multiple intersecting sampling layers and generating fully connected layers with multiple convolutional layers, CNN construction is completed. The CNN structure is shown in Figure 3.2.

3.2. CNN training process. By convolving the sample matrix in the first layer, y is obtained through multi-level transformation. Assuming y represents the expected output of the sample, the error between the two is described by E [13]. When performing backpropagation, fine-tuning the convolutional kernel matrix is based on the principle of minimizing error. Assuming the output of the y-th neuron in layer v, there is:

$$c_j^v = \sum\nolimits_k m_{jk}^v e_k^{v-1} + d_j^v \tag{3.1}$$

Among them, the correction term, the output of the k-th neuron in layer $v-1$, and the weight of the connection between the jth and k-th neurons in layer v are described by $d_j^v, e_k^{v-1}, m_{jk}^v$, respectively. The output

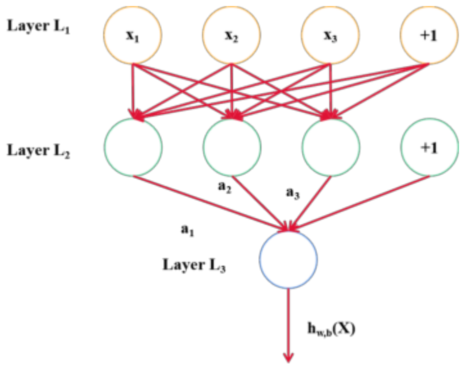

Fig. 3.1: Structural diagram of the artificial neural network model.

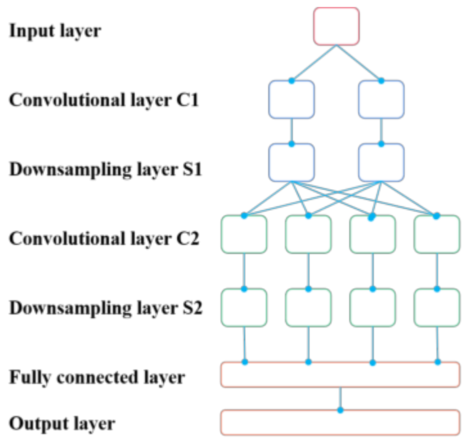

Fig. 3.2: Structural diagram of the artificial neural network model.

of the y-th neuron in layer v is described by c_j^v. The formula for calculating the output e_k^{v-1} of the k-th neuron in layer $v-1$ is shown in formula (3.2):

$$e_k^{v-1} = \delta\left(c_j^{v-2}\right) \tag{3.2}$$

Where: The Activation function is described by δ.

The Error function is calculated according to the error between the calculated value and the expected value. The specific calculation process is shown in Formula (3.3):

$$\theta = f\left(y, y'\right) \tag{3.3}$$

Among them, the Error function is described by θ, and the quadratic Algebraic function is described by f. The error calculation formula for the j-th neuron of layer v is shown in formula (3.4):

$$\vartheta_j^v = \frac{\partial \theta}{\partial c_j^v} \tag{3.4}$$

The formula for calculating the last layer error of CNN is shown in formula (3.5):

$$\vartheta^v = \nabla_{e^v} \theta \Theta \delta'\left(c^v\right) \tag{3.5}$$

Among them, the gradient value of the last layer, the product operator, and the output of the v layer are described by $\nabla_{e^v}, \theta, \Theta, c^v$, respectively.

The error calculation formula for other layers is shown in (3.6):

$$\vartheta^v = \left(\left(m^{v+1}\right)^T \vartheta^{v+1}\right) \Theta \delta' \left(c^v\right) \tag{3.6}$$

The weight of $v+1$ layer is described by m^{v+1}, the error of $v+1$ layer is described by ϑ^{v+1}, and the function is described by T.

The weight gradient calculation formula is shown in (3.7):

$$\frac{\partial \theta}{\partial m_{jk}^v} = \vartheta_j^v e_k^{v-1} \tag{3.7}$$

The formula for calculating the bias gradient is:

$$\frac{\partial \theta}{\partial d_j^v} = \vartheta_j^v \tag{3.8}$$

The update formula for convolutional kernels is to use gradient descent, and the update formula for convolutional kernels is as follows:

$$m^v = m^v - \eta \sum\nolimits_x \theta^{x,v} \left(e^{x,v-1}\right)^T \tag{3.9}$$

$$d^v = d^v - \eta \sum\nolimits_x \theta^{x,v} \tag{3.10}$$

Among them, m^v, d^v represents the weight and correction term of layer v.

3.3. Space image classification process based on Big data analysis. The aerospace image classification process based on Big data analysis is to achieve aerospace image classification by constructing a five layer Convolutional neural network. The following are the detailed steps:

(1) Data collection and preprocessing: Collect a large number of aerospace image datasets, including images of different categories and scenarios. Preprocess the collected image data, including image denoising, size normalization, brightness adjustment, etc., to improve the accuracy and robustness of subsequent classification [14].

(2) Build a Convolutional neural network (CNN) model:

Design a five layer Convolutional neural network structure. It usually includes convolution layer, Activation function layer, pooling layer and full connection layer.

Select the appropriate number and size of convolutional and pooling layers based on specific tasks and data characteristics, and decide whether to add batch normalization and regularization layers. For each convolution layer and fully connected layer, an appropriate Activation function (such as ReLU) is defined to introduce nonlinear transformation. Set the number of neurons in the output layer to be equal to the number of classification categories of aerospace images, and use an appropriate Activation function (such as Softmax) for multi category classification.

(3) Parameter adjustment and model training: initialize the weight and bias parameters of the Convolutional neural network. Divide the dataset into a training set and a validation set, and use the training set for model training. The network parameters are adjusted by Backpropagation and optimizer (such as random gradient descent) to make the model gradually adapt to the training data and minimize the Loss function. In the training process, monitor the classification accuracy and Loss function values on the validation set, and adjust the model structure and super parameters (such as Learning rate and batch size) as needed.

(4) Model evaluation and tuning: use independent test sets to evaluate the performance of the trained Convolutional neural network model. Analyze the classification accuracy, accuracy, recall, and F1 values of the model in different categories to evaluate its classification performance. Based on the evaluation results, adjust

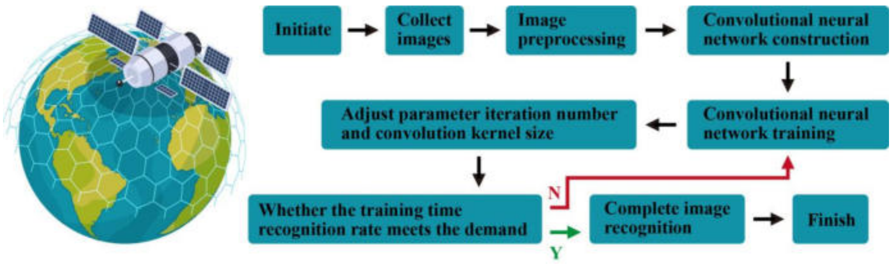

Fig. 3.3: Massive image classification process based on big data analysis.

the network structure, optimize algorithms, and hyperparameters to further improve the performance of the model [15].

(5) Space image classification: use the trained Convolutional neural network model to classify new space images. Input the images to be classified into the model and calculate the probability distribution of each category through forward propagation. Assign aerospace images to corresponding classification categories based on the highest probability category or set threshold.

Through the above detailed steps, the aerospace image classification process based on Big data analysis uses five layer Convolutional neural network to classify aerospace images. This process can improve the accuracy and efficiency of image classification, and provide strong support for aerospace image analysis and application.

The process of aerospace image classification based on big data analysis is as follows: first collect aerospace image data, which is divided into test data and training data; Implement preliminary data preprocessing for aerospace images, decolor the aerospace image, convert it to Grayscale, extract some features of the aerospace image, and implement normalization processing to 30×30; The convolutional kernel is 5×5. A fully connected layer, two downsampling layers, and two convolutional layers form the CNN model, the lower sampling layer uses non repeated pooling with a scale of 2. Six feature maps constitute the first layer of convolution, and 16 feature maps constitute the second layer of convolution [16]. The output categories are multi categories, and the sigmoid function is the Activation function; The Convolutional neural network is used to change the model structure, adjust the iteration number, convolution core size and other parameters, and determine whether the training time and classification rate meet the requirements, when the requirements are met, the classification of aerospace images can be completed. If not, Convolutional neural network training needs to be conducted again until the requirements are met. Therefore, the aerospace image classification process based on Big data analysis is shown in Figure 3.3. Aerospace image data preprocessing process: Due to the impact of external environment, the quality of aerospace images decreases, and preprocessing of aerospace images is required. The aerospace image is divided into several sub images, and 8 sub images are set. The discrete cosine wave transformation calculation process of the sub images is shown in formula (3.11):

$$\begin{gathered} F\left(u,v\right)=\frac{1}{4}C\left(u\right)C\left(v\right)\sum_{m=0}^{7}\sum_{n=0}^{7}f\left(m,n\right) \\ \cos\frac{\left(2m+1\right)u\pi}{16}\cos\frac{\left(2n+1\right)v\pi}{16} \end{gathered} \tag{3.11}$$

Among them, the sub images are described by f (m, n), $0 \leq u \leq 7, 0 \leq V \leq 7$,

$$C\left(u\right)=C\left(v\right)=\begin{cases}\frac{1}{\sqrt{2}}, u=v \\ 0,\ \text{otherwise}\end{cases} \tag{3.12}$$

The inverse transformation using discrete cosine transform is shown in formula (12):

$$F(x,y) = \frac{1}{4}\sum_{u=0}^{7}\sum_{v=0}^{7} C(u)\,C(v)\,F(u,v) \cos\frac{(2m+1)\,u\pi}{16}\cos\frac{(2n+1)\,v\pi}{16} \tag{3.13}$$

In the case of a small number of samples, the data preprocessing process is as follows:

(1) Enhance the dataset using mirror symmetry method.

(2) Implement background segmentation on scratch datasets with prominent features.

(3) Implement principal component analysis for dimensionality reduction of transformed aerospace images.

4. Simulation experiments.

4.1. Experimental subjects. To verify the effectiveness of our method in aerospace image classification, we conducted simulation experiments in the Matlab R2013c experimental environment of the Windows 7 operating system. We selected 15000 images as experimental samples, of which 10000 were used as training data and the remaining 5000 were used as testing data. We compare the method proposed in this paper with the image classification methods of Traditional Method 1 and Traditional Method 2, and evaluate their differences in image classification accuracy, performance under different iterations, classification error curve, and image classification time. During the experiment, we used the method proposed in this paper and traditional methods 1 and 2 to classify the training data into images, and evaluated their classification accuracy on the test data. We also compared their performance under different iterations and the changes in classification error curves. In addition, we also recorded the time required for image classification to evaluate the computational efficiency of different methods [17]. Through the above comparative experiments, we can comprehensively evaluate the performance of our method in aerospace image classification and compare it with traditional methods to verify the advantages and effectiveness of our method. The experimental results will provide detailed information about the classification accuracy, Rate of convergence, calculation efficiency and other aspects of different methods, thus providing a reference for the practical application of aerospace image classification tasks.

4.2. Image classification accuracy. We classified 500 images using traditional methods 1, 2, and our method, and compared their classification accuracy. Figure 4.1 was drawn based on experimental results, demonstrating the classification accuracy of the three methods. From the experimental results in Figure 4.1, it can be concluded that the proposed method and image average classification accuracy are significantly higher than traditional methods 1 and 2, exhibiting better image classification results. This means that in the aerospace image classification task, our method can more accurately classify images into the correct categories, and has higher classification accuracy compared to traditional methods 1 and 2 [18]. This result may be due to the Convolutional neural network model used in this method, which can better extract image features and capture the correlation between images. In contrast, traditional methods 1 and 2 may have certain limitations in feature extraction and pattern recognition, resulting in lower classification accuracy. Therefore, based on the experimental results in Figure 4.1, it can be concluded that in the aerospace image classification task, our method can achieve higher image classification accuracy compared to traditional methods 1 and 2, providing better results and performance for aerospace image classification.

4.3. Classification Error Curve for Different Iterations. Considering the impact of the relationship between the number of samples in the training set and the training error on the image classification performance, the number of iterations is 30 and 60, respectively. The classification error curves for different iterations are described in Figure 4.2. As shown in Figure 4.2, the training error of this method is inversely proportional to the number of iterations and the number of samples in the training set, as the number of iterations and the number of training samples increase, the training error also decreases. In Figure 4.2(b), the minimum training error of this method is 0.02, the minimum training error of traditional method 1 is 0.08, and the minimum training error of traditional method 2 is 0.11, indicating that this training error is the smallest.

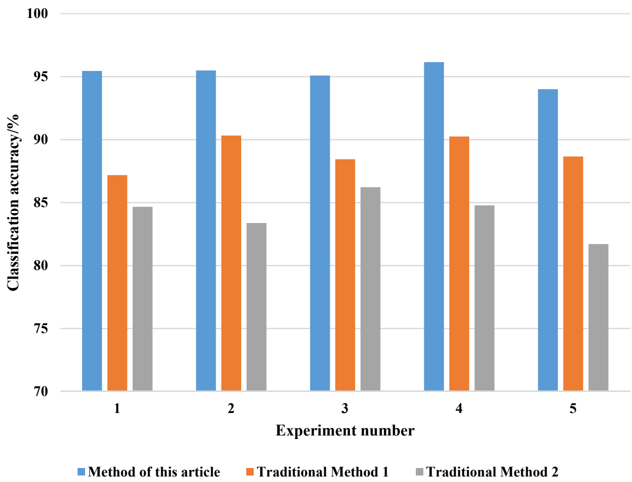

Fig. 4.1: Classification results of the three methods.

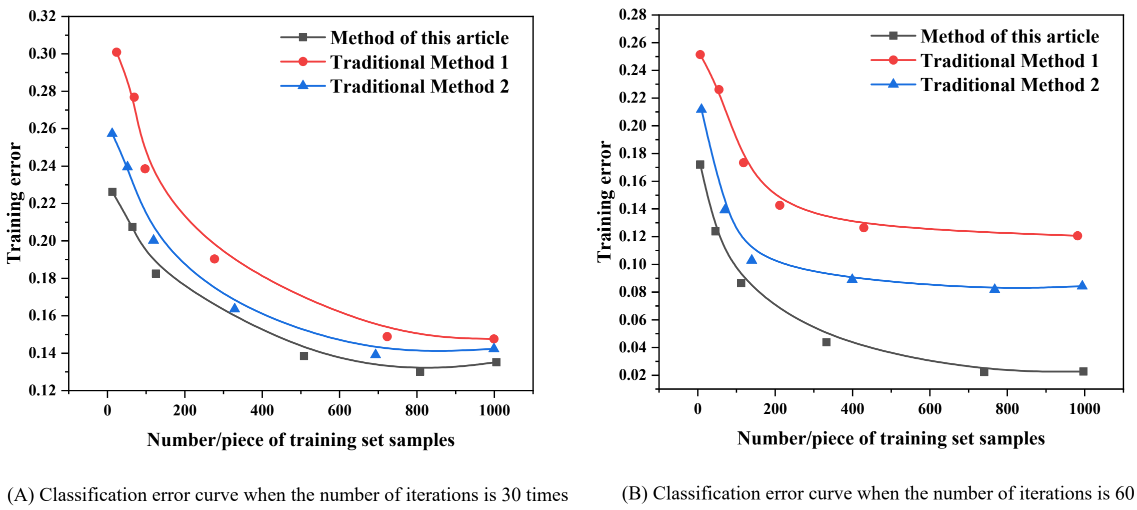

Fig. 4.2: Classification results of the three methods.

4.4. Space image classification time. Compare the classification time of aerospace images using three methods, and the specific results are shown in Figure 4.3. From the results of Figure 4.3, it can be seen that the average classification time of this method for aerospace images is 3.5 minutes, which is 14 minutes and 29 minutes less than traditional method 1 and traditional method 2, respectively. This indicates that this method has the shortest image classification time and improves the classification efficiency of aerospace images [19, 20, 21, 22, 23].

4.5. Conclusion. This paper aims to design a space image classification method based on Big data analysis, and test it through simulation experiments. The experimental results show that the proposed method exhibits the following advantages in aerospace image classification tasks: high accuracy, small training error, short image classification time, and good image classification performance. This indicates that the method proposed in this paper can effectively improve the efficiency of aerospace image classification and provide a strong theoretical basis for subsequent image processing work. However, there are also some shortcomings in

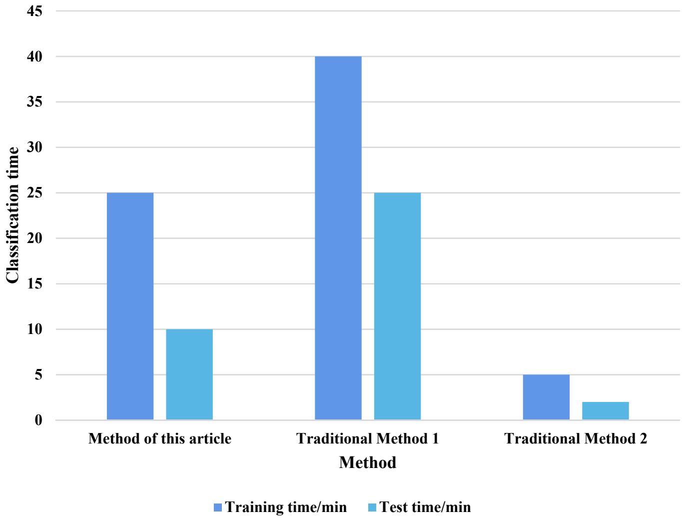

Fig. 4.3: Classification results of the three methods.

this study, including the following aspects: limited time and energy: due to time and energy limitations, this study may not be able to cover all possible situations and details. Therefore, the image classification effects in certain specific scenarios or special circumstances may not have been fully explored. In order to further improve the method of this article, future research can consider the following aspects:

1. Integration of advanced science and technology: With the continuous development of science and technology, more advanced technologies and methods can be integrated into the methods in this paper, such as deep learning, Transfer learning, attention mechanism, etc. These technologies can further improve the speed and accuracy of aerospace image classification.

2. Data augmentation technology: Through data augmentation technology, the training dataset can be expanded, the diversity and quantity of samples can be increased, and the generalization ability and robustness of the model can be improved.

3. Model optimization and parameter adjustment: further optimize the Convolutional neural network model structure, and further improve the image classification performance through appropriate parameter adjustment methods.

In summary, although there are some shortcomings in this study, by integrating more advanced scientific and technological knowledge into this method, and further optimizing and improving it, aerospace image classification can be achieved more quickly, providing better support for image processing work in the aerospace field.

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