Hindawi
Wireless Communications and Mobile Computing
Volume 2021, Article ID 3138398, 11 pages
https://doi.org/10.1155/2021/3138398

Research Article

Image Classification Algorithm Based on Big Data and Multilabel Learning of Improved Convolutional Neural Network

Haibin Chang [1] and Ying Cui [2]

[1] *Academic Affair Office, Shaanxi Xueqian Normal University, Xi'an, 710100 Shaanxi, China*
[2] *College of Equipment Management and Support, Engineering University of Chinese Armed Police Force, Xi'an, 710086 Shaanxi, China*

Correspondence should be addressed to Haibin Chang; 34019@snsy.edu.cn

Received 27 July 2021; Revised 24 August 2021; Accepted 31 August 2021; Published 23 September 2021

Academic Editor: Zhihan Lv

More and more image materials are used in various industries these days. Therefore, how to collect useful images from a large set has become an urgent priority. Convolutional neural networks (CNN) have achieved good results in certain image classification tasks, but there are still problems such as poor classification ability, low accuracy, and slow convergence speed. This article mainly introduces the image classification algorithm (ICA) research based on the multilabel learning of the improved convolutional neural network and some improvement ideas for the research of the ICA based on the multilabel learning of the convolutional neural network. This paper proposes an ICA research method based on multilabel learning of improved convolutional neural networks, including the image classification process, convolutional network algorithm, and multilabel learning algorithm. The conclusions show that the average maximum classification accuracy of the improved CNN in this paper is 90.63%, and the performance is better, which is beneficial to improving the efficiency of image classification. The improved CNN network structure has reached the highest accuracy rate of 91.47% on the CIFAR-10 data set, which is much higher than the traditional CNN algorithm.

1. Introduction

The convolutional neural network can read attributes. The convolutional neural network should be useful for Internet learning. The user does not need to pay too much attention to the specific function that has been trained, as long as the weight is exercised. The disadvantage is that a lot of examination data is required, the number of counts is large, and the coefficient needs to be adjusted. By increasing the size of the data set, improving the computing power of the computer, and proposing some good examples for the Internet, the amount of layers of useful convolutional neural networks is updated. Figure 1 is a schematic diagram of the structure of a convolutional neural network.

In our real life, there are various systems and networks that can be described by complex networks [1]. The definition of a complex network is a network in some or all of the properties of self-organization, similarity, tractor, small world, and scaleless. It is called a complex network. There are many specific networks in the environment where we live, such as between friends, the Internet, public transportation networks, and mobile communication networks [2, 3]. At the same time, there are also some things that can be described by the network, such as the food chain network and the language vocabulary network; there are many networks that actually exist in the microscopic world, such as protein networks and cellular chemical reaction networks. Human development and social progress have made some networks have the scale to continue cognitive ability to make network understanding further, and complex network research allows us to understand. Object recognition based on convolutional neural networks has been applied to autonomous driving and real-time traffic monitoring systems.

Multilabel learning comes from the research of text classification problems and has become an important research hotspot in the field of international machine learning. Many

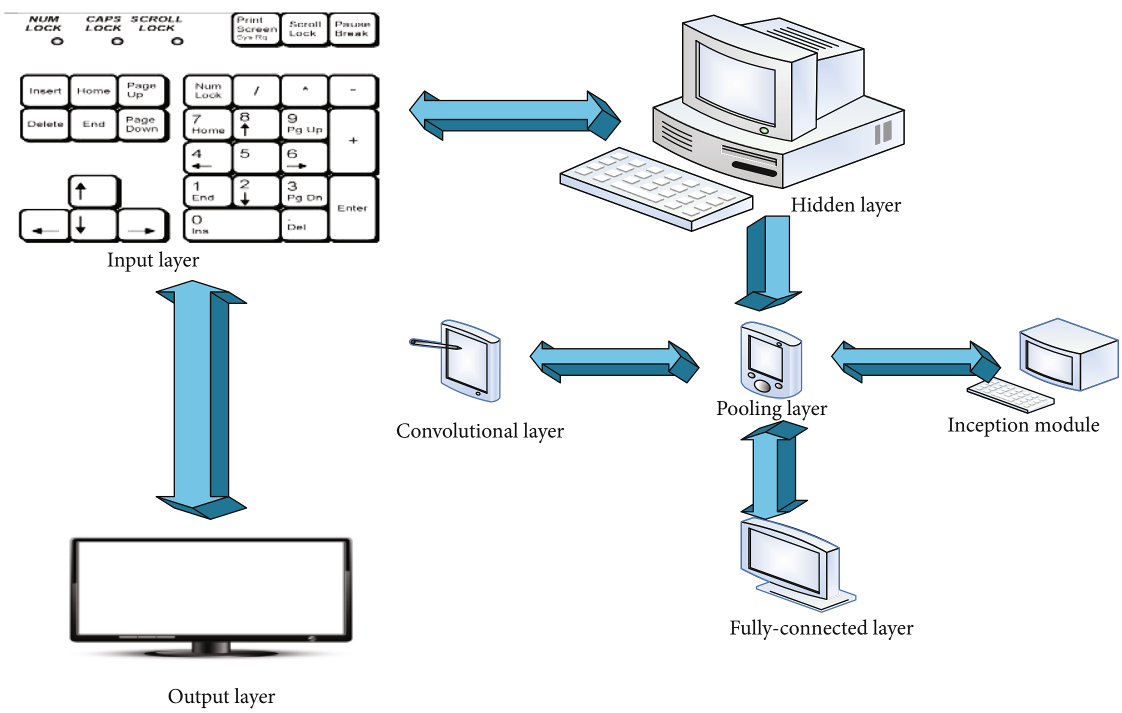

FIGURE 1: Schematic diagram of the structure of a convolutional neural network.

learning problems in real life can be regarded as problems of classifying multiple tags [4]. In practical applications, it is necessary to manually process a large amount of multilabeled data, which has attracted many experts and studies in this aspect to actively participate in the research of multilabel learning in the field of data mining and machine learning. For example, in a large amount of data information retrieval on the Internet, it is necessary to filter documents, images, multimedia, etc., to obtain retrieval materials that meet specific functional requirements.

Yang believes that target recognition is a well-known and important problem in computer vision, so he proposed a new method of target recognition using an improved convolutional neural network. However, this research is relatively single and impractical [5]. Cao et al. believe that data collection is an important way to reduce the power fee of networks (WSN). He combined the theory of the original set with the improved convergence neural network and proposed a new wireless sensor network information collection algorithm. However, this method lacks experimental data support and is not very convincing [6]. Xu et al. analyzed the local Rademacher complexity of a multilabel learning algorithm based on empirical risk minimization (ERM) and proposed a new multilabel learning algorithm [7]. But such algorithms have not been used in real life, and the specific situation remains to be seen.

The new trying innovations of this paper are the following: (1) propose an ICA based on improved convolutional neural network multilabel learning, (2) propose model compression technology, and (3) propose dense convolutional neural network (DenseNet) technology.

2. Method of ICA Based on Multilabel Learning of Improved Convolutional Neural Network Based on Big Data

2.1. Image Classification Process. Image data has exploded. The traditional method of image classification is feature description and detection. Manual classification consumes a lot of time and manpower, and the classification phenomenon is not ideal, so image classification technology is gradually developing. Image classification technology uses a computer to analyze an image and divide it or part of the image into specific categories, without the need to judge with eyes. The image classification process is divided into four steps: image preprocessing, image feature extraction, algorithm design, and classification result analysis [8].

2.1.1. Image Preprocessing. Image preprocessing is the process of reducing unnecessary image information and restoring or marking effective information. Commonly used methods include normalization and spatial transformation. Image preprocessing can improve image quality and reduce noise, thereby improving the reliability of image classification results [9]. The algorithm is a prerequisite operation for feature extraction. The input image is generally smoothed in the scale space through a Gaussian blur kernel. After that, one or more features of the image are calculated by local derivative operation.

2.1.2. Image Feature Extraction. The export image function uses a computer to export relevant features and determine whether the points in the image represent its function. This article expresses the characteristics of images in the form of media. The method of feature extraction determines the result of classification. High-quality image functions should not only describe the information expressed by the image as accurately as possible but also have a certain degree of stability and flexibility to respond to environmental changes [10].

2.1.3. ICA Design. The design and application of algorithms have a great influence on classification phenomena. According to the correlation between images and related measurement methods, the mapping relationship between image features and categories is determined. Finally, these images are classified in a specific category [11]. However, image classification has many problems. Therefore, it is difficult for ICAs to establish an accurate mapping relationship between image features and image categories. Different algorithms will have different classification results. Therefore, designing a suitable classification algorithm has important research significance [12].

2.1.4. Analysis of Classification Results. After the results of image classification are obtained, specific evaluations are used to explode objectively the algorithm, such as the number of correctly sorted images and the number of incorrectly sorted images in each category. At the same time, different classification algorithms are compared, and the advantages and disadvantages of each algorithm and the future direction of improvement are analyzed and summarized [13].

2.2. Convolutional Neural Network. Traditional machine learning algorithms need a feature extraction process to collect useful information from initial data samples to obtain a set of feature vectors and then use a trained classifier for final classification and recognition [14]. A convolutional neural network imitates the construction of a biological visual perception mechanism, which can perform supervised learning and unsupervised learning. The convolution kernel parameter sharing in the hidden layer and the sparsity of interlayer connections enable the convolutional neural network to perform smaller calculations or quantity-to-grid features. The difference of the CNN model is that the model combines feature output and classification recognition, and a series of feature extraction processes are hidden in the network [15]. Figure 2 shows the description of several common combined creep models.

This process is called feedforward operation [16]. In the last layer, the target task is formalized; that is, classification or regression is performed in the target function. The use of local receptive fields, weight sharing, and pooling in CNN greatly reduces the number of network parameters and improves network performance [17]. The principle of the local receptive field is the correlation between adjacent pixels of the image [18, 19], and weight sharing is beneficial to reduce the number of network parameters [20, 21]. The pooling operation reduces the feature dimension while removing part of the redundant information [22].

Neural network and X-ray scattering effect:

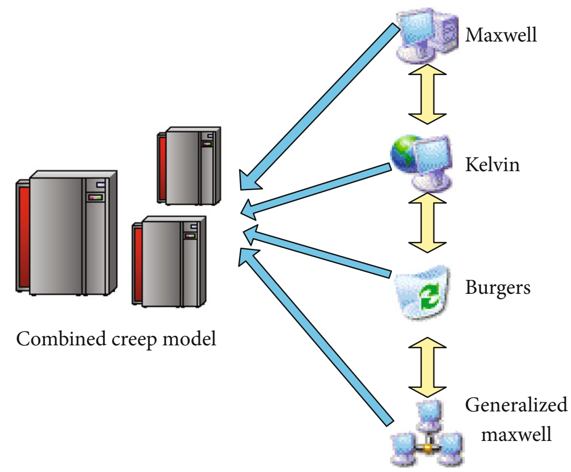

FIGURE 2: Several common combined creep models.

(1) *Neural Network Construction [23].* The input of a single neuron is shown in

$$O(y, x) = \sum_{u=1}^{k_1} \sum_{v=1}^{k_2} K(u, v)\, I(y + u, x + v, i). \tag{1}$$

According to the above two formulas, u, v are constants and can take any value but cannot be 0. The learning rate was multiplied to update each weight parameter and bias vector until the error value of the loss function is small enough:

$$O(y, x, j) = \sum_{i=1}^{c_1} \sum_{u=1}^{k_1} \sum_{v=1}^{k_2} K(u, v, i) I(y + u, x + v, i, j). \tag{2}$$

In actual research and application, we delimit the probability function distributions, as shown in

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{3}$$

Tanh function expression is

$$\mathrm{Tanh}(x) = \frac{1 - e^{-2x}}{1 + e^{-2x}}. \tag{4}$$

ReLu function expression is

$$y = \begin{cases} 0(x < 0), \\ x(x \geq 0). \end{cases} \tag{5}$$

The offset of the visible layer unit is expressed as [24]

$$L(W) = \frac{1}{|D|} \sum_{t}^{|D|} f_w\left(x^{(t)}\right) + \lambda_r(W). \tag{6}$$

Design space degradation [25]:

When the evolution unfolds in a certain generation, if the first few atoms of the fitness function value from large to small are all in a subset of the same string:

$$L(W) \approx \frac{1}{N}\sum_{t}^{N} f_w\left(x^{(t)}\right) + \lambda_r(W). \tag{7}$$

2.3. Multilabel Learning Classification Algorithm. Suppose $X = ?^d$ represents a d-dimensional example space, and $Y = \{y_1, y_2, \cdots, y_q\}$ represents a label space containing q categories. For a given multilabel training set $D = \{(x_i, Y_i) \mid 1 \le i \le m\}$, where $x_i \in X$ is a d-dimensional feature vector $(x_{i1}, x_{i2}, \cdots, x_{id})^T$, and $Y_i \subset Y$ is a set of labeled subsets corresponding to x_i, the goal of multilabel learning is to learn a function $h : X \longrightarrow 2^Y$, that is, from the training set D map a set of suitable category tags for each unseen example. Based on this, for any given example $x \in X$, the class label subset of the example predicted by the classifier is $h(x) \subseteq Y$. In addition, a multilabel classifier $h(\cdot)$ and a multilabel test set $S = \{(x_i, Y_i) \mid 1 \le i \le p\}$ are defined, where Y_i is a related label set belonging to the example x_i.

2.3.1. Hamming Loss. This indicator is used to evaluate the error rate between the real label of the sample and the label predicted by the system; that is, the sample has the mark Y_i but is not recognized or does not have the mark Y_i but the possibility of being misjudged:

$$\text{Hamming loss}(h) = \frac{1}{p}\sum_{i=1}^{p}\frac{1}{q}|h(x_i)\Delta Y_i|. \tag{8}$$

2.3.2. Sorting Loss. This indicator is used to investigate the status of classification errors according to the classification order of the sample category indicators, that is, the probability that the indicator classification is lower than the nonindicator classification:

$$\begin{aligned}\text{Ranking loss}_S(h) = \frac{1}{p}\sum_{i=1}^{p}\frac{1}{|Y_i||\overline{Y_i}|}\Big|\Big\{\left(y', y''\right) \mid f\left(x_i, y'\right) \\ \le f\left(x_i, y''\right), \left(y', y''\right) \in Y_i \times \overline{Y_i}\Big\}\Big|.\end{aligned} \tag{9}$$

2.3.3. 1-Error Rate. This evaluation indicator is used to investigate whether it is possible to follow the classification order of the sample category labels. The label with the highest classification is not the actual label of the sample. When learning a label, it will evolve into a general error rate:

$$\text{One-error}_S(h) = \frac{1}{p}\sum_{i=1}^{p}\left\{\left[\arg\ \max_{y\in Y} f(x_i, y)\right] \notin Y_i\right\}. \tag{10}$$

2.3.4. Coverage Rate. This grading indicator checks the average search depth required to cover all relevant sample labels in the sample category label ranking row:

$$\text{Coverage}_S(h) = \frac{1}{p}\sum_{i=1}^{p}\max_{y\in Y_i}\ \text{rank}_f(x_i, y) - 1. \tag{11}$$

2.3.5. Average Accuracy. This rating indicator checks the situation in the ranking row of the sample category labels. The labels with high membership are still their relevant labels or reflect the average accuracy of the expected category labels:

$$\text{AveragePrecision}_S(h) = \frac{1}{p}\sum_{i=1}^{p}\frac{1}{|Y_i|}\sum_{y\in Y_i}\frac{\left|\left\{y' \mid \text{rank}_f\left(x_i, y'\right) \le \text{rank}_f(x_i, y), y' \in Y_i\right\}\right|}{\text{rank}_f(x_i, y)}. \tag{12}$$

2.3.6. Classification Accuracy. This evaluation index reflects the degree of consistency between the label predicted by the system and the true label of the sample:

$$\text{Classification accuracy} = \frac{1}{p}\sum_{i=1}^{p} I(h(x_i) = Y_i). \tag{13}$$

Then, we use the weighted kernel function to convert the standard distance x_t to x_i and get

$$p(x_i \mid x_t) = \frac{1}{2\pi}\ \exp\left(-\frac{D(x_t, x_i)}{2}\right). \tag{14}$$

Then, calculate the posterior probability of x_t belonging to class $\omega_r (r = 1, 2, \cdots, s)$ based on the k nearest neighbors x_t; there are

$$P(y_i \mid x_t) = \frac{1}{\alpha}\sum_{i=1}^{k} p(x_i|x_t) I(y == \omega_r), \tag{15}$$

$$I(A) = \begin{cases} 1, & \text{true}, \\ 2, & \text{false}, \end{cases} \tag{16}$$

$$a = \sum_{i=1}^{N} P(x_i \mid x_t). \tag{17}$$

Finally, the simplified overall function of the algorithm is obtained by introducing a way that the data obeys a certain

Table 1: Technical process.

Research method of ICA based on multilabel learning of improved convolutional neural network					
2.1	Image classification process	2.2	Convolutional neural network	2.3	Multilabel learning classification algorithm
1	Image preprocessing	1	Convolutional layer	1	Hamming loss
		2	Fully connected layer	2	Ranking loss
2	Image feature extraction	3	Nonlinear layer	3	One-error
		4	Pooling layer	4	Coverage
3	ICA design	5	Optimization	5	Average precision
4	Classification result research			6	Classification accuracy

distribution composed of a mixture of L Gaussian distributions as shown in

$$f(x \mid \theta) = \sum_{l=1}^{L} a_l f(x \mid \theta_l). \tag{18}$$

In summary, we have completed the optimization process of the dichotomy in the safety monitoring and evaluation algorithm. Let us start the experiment.

ICA is to find out the mutually independent parts that constitute the signal, corresponding to high-order statistical analysis. ICA theory believes that the mixed data matrix X used for observation is obtained by linear weighting of the independent element S through A. This part uses the above method to study the ICA based on multilabel learning as shown in Table 1.

3. Experiment on ICA Based on Multilabel Learning of Improved Convolutional Neural Network Based on Big Data

3.1. Improvement of Convolutional Neural Network

3.1.1. Improvement of Convolutional Neural Network Structure. Network deepening is accompanied by improvements in network components. Components with better properties can support deeper and more complex networks. Therefore, there is a lot of work around how to improve or design components in the network.

There are often better choices for the components in the network. ReLU can be used as an activation function in the network, which can ensure that no loss occurs during the back propagation of errors. Compared with the traditional sigmoid activation function and tanh activation function, it has a faster convergence rate and has a neuroscience explanation. In contrast to the proposed new model component, in order to avoid network overfitting, adding random components to the original network components will often have good results, such as random pooling and random Maxout. There are also some components that can improve network performance, such as smooth pooling, partial maximum pooling, and intranetwork networks.

Batch standardization can standardize the output of each layer of the network, so that the information can be spread in the network as much as possible. Batch standardization avoids the possibility of gradient disappearance and gradient explosion, which makes it possible to design deeper networks. The deconvolution layer is an inverse convolution operation, which can restore the signal obtained by the convolution, thereby obtaining an output signal of the same size as the original input image, which can be used to process pixel-level marks.

3.1.2. Improvement of Convolutional Neural Network Training. The training process of the convolutional neural network is divided into two stages. The first stage is the stage of data propagation from a low level to a high level, that is, the forward propagation stage. Another stage is the stage in which the error is propagated and trained from the high level to the bottom level when the results obtained by the forward propagation do not match the expectations, that is, the back propagation stage. First, we need to determine the final loss function of the network. Deep neural networks generally use negative maximum likelihood, cross-entropy loss, Euclidean distance loss, contrast loss, and triple loss.

During the training process, the input image can be transformed, such as flipping, rotating, and adding noise. The transformed image can be used as an expansion of the original data set, thereby increasing the training data. At the same time, the robustness of the network to specific transformations can be increased [26]. A similar operation can also be used on the label. For example, DisturbLabel deletes some labels randomly during the training process.

3.2. Improved Convolutional Neural Network for Image Classification Based on Multilabel Learning

3.2.1. Model Compression Technology. SqueezeNet is a classic lightweight convolutional neural network model. The design and application of the Fire module is the most important factor to significantly reduce the parameters of the SqueezeNet model. SqueezeNet mainly reduces the number of network parameters through the following three design strategies.

(1) Part of the $3 * 3$ two-dimensional convolution kernel in the network structure is replaced by a $1 * 1$ convolution kernel. Generally speaking, the size of the convolution kernel set in the convolutional neural network model is mostly $3 * 3$. Related experiments demonstrate the effectiveness of this alternative method. The goal of SqueezeNet is to reduce the number of network parameters. Too many $1 * 1$

Table 2: Improvement of CNN.

Research experiment on ICA based on multilabel learning of improved CNN	3.1	Improvement of CNN	1	Improvement of CNN structure
			2	Improvement of CNN training
	3.2	Improved convolutional neural network for image classification based on multilabel learning	1	Model compression technology
			2	Model compression technology
			3	DenseNet technology

convolution kernels will affect the feature extraction ability of the entire model. Therefore, only a part of the $3*3$ convolution kernels are replaced in the SqueezeNet network

(2) The number of input channels of the two-dimensional convolution kernel is reduced in the network. The initial layer of the convolutional layer is decomposed into two layers, one is the compression layer (squeeze layer), the other is the expansion layer (expand layer), and the two layers are encapsulated in a Fire module

(3) The delayed downsampling operation in the network structure retains more critical features or information for the convolutional layer, which can improve the accuracy of model recognition. The Fire module is the most important part of SqueezeNet. It splits the original convolutional layer into two layers, namely, a compression layer (squeezeayer) and an expansion layer (expand layer), each of which performs ReLU regularization operations

3.2.2. Convolution Kernel Separation Technology. The InceptionV3 network structure based on GoogLeNet has good recognition performance. It mainly introduces the idea of factorization into small meetings, which is to separate a larger two-dimensional convolution kernel into two smaller one-dimensional convolution kernels, such as dividing a $5*5$ two-dimensional convolution kernel into one-dimension convolution kernel $5*1$ and $1*5$. The advantages of this strategy are the following: in the process of extracting features through convolution operation, it can save a lot of calculation time and save the number of parameters, accelerate the operation speed of the model, effectively alleviate the problems of network overload and fading, and further enhance the nonrelevance of the extended model. The separation of this asymmetric cluster structure is more effective than the symmetric two-dimensional small cluster core. This structure can handle more complex and abstract key features, can output the information capability of multiple targets on multiple scales, and improve the performance of network recognition. The process of decomposing a large convolution operation into a horizontal convolution in series with a vertical convolution is called convolution separable. Convolution separable is a common optimization technique in image processing, and its effect is the same as the original convolution.

3.2.3. Dense Convolutional Neural Network (DenseNet) Technology. The dense network uses dense connection technology to connect any layers to each other, and the input of each layer contains all the previous feature maps. Then output to the subsequent layers of the network, and the deep feature maps are stacked. Dense connection technology can increase the diversity of output and make feature reuse, thereby improving network efficiency. In order to further accelerate the spread of information in the network, dense connection technology uses a different connection method in the past, which directly connects each layer to all subsequent layers of the network structure. The improvement of CNN is shown in Table 2.

Table 3: Comparison of the recognition rate of each algorithm when NTS is different.

	CNN	SAE	Improved CNN
1500	51.26%	49.54%	66.79%
2500	60.79%	57.13%	77.21%
3500	73.46%	69.28%	79.17%
4500	82.07%	79.36%	87.52%

4. ICA Based on Improved Convolutional Neural Network Multilabel Learning Based on Big Data

4.1. Algorithm Comparison

(1) Perform experimental comparisons on the ImageNet image database. The ImageNet database has more than 15 million images, with at least 510 images in each category. In this experiment, we select a total of 5000 images from ten categories for verification. Image preprocessing is 36×36 size. When the number of samples is different, the recognition rate of each algorithm is shown in Table 3 and Figure 3

When NTS is 1500, the number is less than the number of test samples. At this time, the recognition rate of CNN and SAE is extremely low, while the improved CNN algorithm still has a certain degree of recognition rate. It can be seen that no matter what the NTS is, the recognition rate of the improved CNN algorithm is always higher than the other two algorithms.

(2) Experimental comparison is carried out on the Oxfords flowers image library. The Oxfords flowers image library has 80 pictures for each flower type. This article selects five types. The recognition rate of each algorithm when the number of samples is

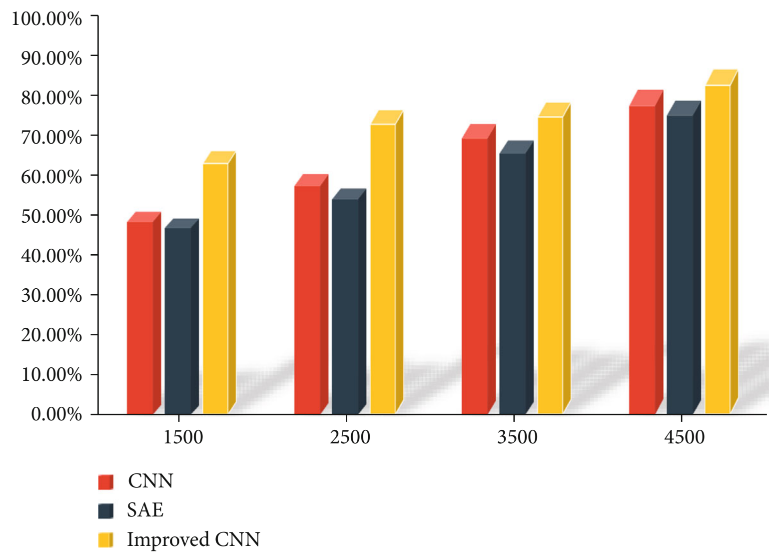

Figure 3: Comparison of the recognition rate of each algorithm when NTS is different.

Table 4: Comparison of the recognition rate of each algorithm when the number of samples is different.

	CNN	SAE	Improved CNN
100	41.37%	39.42%	69.67%
200	49.75%	47.07%	74.61%
300	53.21%	51.49%	82.19%
400	59.31%	57.24%	85.63%
500	67.48%	66.18%	88.21%

different is shown in Table 4 and Figure 4. At this time, the number of iterations is 40, NTS is 500, and the number of test samples is 100~500

It can be seen from the chart that when NTS is 100, the recognition rate of CNN and SAE is extremely low, while the improved CNN algorithm still has a certain degree of recognition rate. It can be seen that when NTS is small, the recognition rate difference between the other two algorithms and the improved CNN algorithm is obvious. As the number of NTS increases, the gap gradually decreases.

(3) The experimental data set in this section uses clothing images of ten categories selected from the e-commerce platform. These image collections come from Jingdong, Taobao, etc. 110 images of each category are basically images with commodities as the main body. The selected images do not have problems such as different viewing angles, insufficient light, blur, and occlusion. The total number of pictures is 1100. The average size of each picture is 216×324, and the format is JPG. For each type of sample, try to select images with large differences between the types. The recognition rate of each algorithm when the number of samples is different is shown in Table 5 and Figure 5. At this time, the

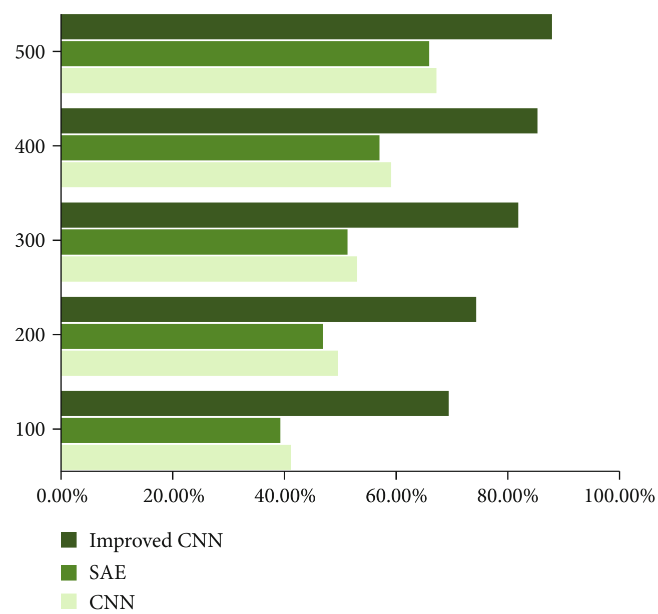

Figure 4: Comparison of the recognition rate of each algorithm when the number of samples is different.

Table 5: Comparison of the recognition rate of each algorithm when the number of samples is different.

	CNN	SAE	Improved CNN
110	41.26%	37.29%	60.29%
310	44.47%	41.15%	64.31%
510	55.14%	52.27%	67.29%
710	67.25%	64.52%	78.14%
910	76.41%	74.91%	84.32%
1100	84.37%	82.74%	89.56%

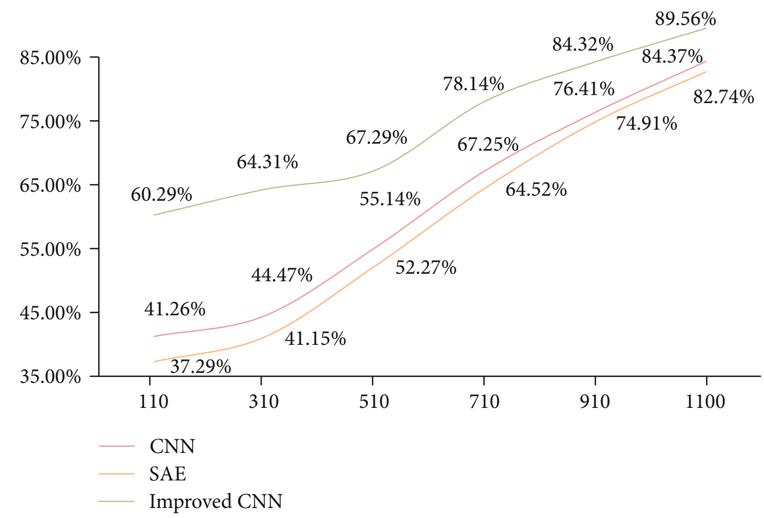

Figure 5: Comparison of the recognition rate of each algorithm when the number of samples is different.

Table 6: Classification results of other networks on the CIFAR data set.

Network structure	CIFAR-10				CIFAR-100			
	ScatNet	VGG	NIN	Improved CNN	ScatNet	VGG	NIN	Improved CNN
Classification accuracy	62.14%	74.16%	83.25%	91.47%	45.22%	61.37%	78.25%	84.26%

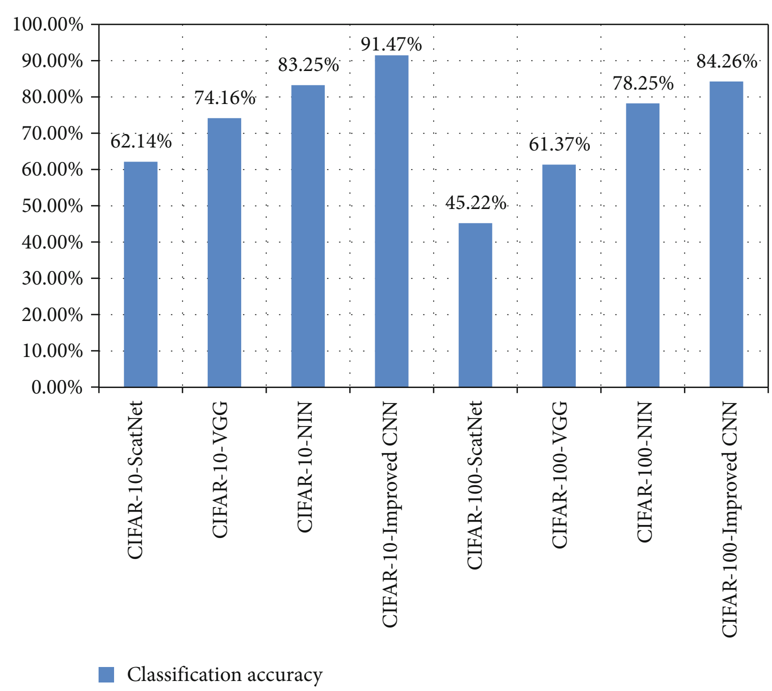

Figure 6: Classification results of other networks on the CIFAR data set.

number of iterations is 50, NTS is 1100, and the number of test samples is 110~1100

It can be seen from the graph that the smaller NTS, the better the recognition effect of improved CNN than CNN and SAE. When NTS is 110, even if iteration is 50 times, NTS is too small, but the recognition rate of CNN and SAE algorithms is still very low. At this time, the improved CNN algorithm can still have a certain degree of recognition rate.

4.2. Experiment Analysis

Table 7: Performance comparison of multiple algorithms.

	Hamming loss	Ranking loss	One-error	Coverage	Average precision
SVM	0.3341	0.5678	1.1527	0.4621	0.4531
BOOST	0.2857	0.3631	0.8841	0.3817	0.5149
BP	0.2614	0.4127	0.7624	0.3024	0.5367
RBF	0.3149	0.3752	0.8139	0.2467	0.5721
Improved CNN	0.1846	0.2573	0.5726	0.1958	0.6529

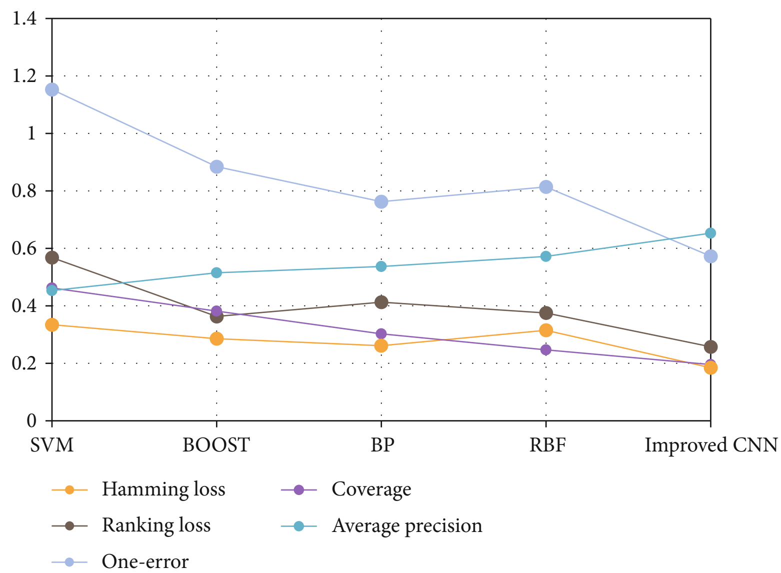

Figure 7: Performance comparison of multiple algorithms.

(1) In order to verify the effectiveness of the improved convolutional network, an experimental comparison with other classic algorithms is also carried out. The classification results of each network structure on the CIFAR-10 and CIFAR-100 data sets are shown in Table 6 and Figure 6

From the chart, it can be seen that the classification effect of ScatNet on images with complex details such as the CIFAR data set is significantly lower than the hybrid convolutional network structure and other deep convolutional neural network structures. The improved CNN network structure achieved the highest accuracy rate of 91.47% on the CIFAR-10 data set and the highest accuracy rate of 84.26% on the CIFAR-100. On CIFAR-10 and CIFAR-100 data sets with relatively large data samples, the improved dense convolutional network and the other three deep convolutional neural networks DCNN, VGG, and NIN have achieved better classification results and improved dense. The classification effect of the convolutional network is optimal. The performance comparison of multiple algorithms is shown in Table 7 and Figure 7.

The experimental results in the table show that the image classification effect of the multilabel algorithm based on the improved CNN neural network is significantly better than that based on the BP neural network and the RBF neural network. Other algorithms consider the correlation between examples and tags, so the classification effect will be better than BOOST and SVM algorithms. From the overall comparison result, the improved CNN algorithm in this paper has a better classification effect.

Table 8: The highest classification accuracy.

	CNN	Improved CNN
ImageNet	87.28%	89.47%
Oxfords flowers	86.31%	90.26%
Clothing image	88.49%	89.37%
CIFAR-10	89.14%	91.47%
CIFAR-100	90.25%	92.58%

(3) Record the highest classification accuracy rate of the improved convolutional network during the experimental training process, and draw it into a chart, as shown in Table 8 and Figure 8

The detailed reference table for the type identification of each device is shown in Table 9.

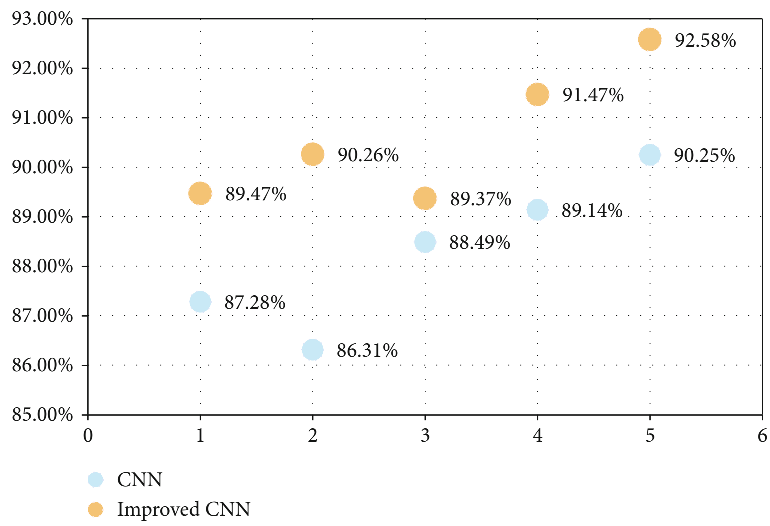

Figure 8: The highest classification accuracy.

Table 9: Refer to the detailed table for the type identification of each device.

Equipment type	Type designation	Remarks
Layer 3 switch	S3	Switch
Layer 2 switch	S2	Switch
Router	R	Router
Firewall	F	Firewall
Terminal equipment	T	Terminal
Wireless AP	W	Wireless access point

It can be seen from the graph that the correct rate of improved CNN is always higher than that of CNN, and the average highest classification correct rate of improved CNN can be obtained from the calculation of 90.63%. This algorithm has good performance and can perform image classification smoothly. Through the above, it can be concluded that the improved CNN algorithm in this article is much higher than the traditional CNN in terms of accuracy and correctness, which also verifies the feasibility of the experiment in this article.

5. Conclusions

The main task of image classification is to analyze the content of digital images and obtain key information in the images. Many application fields have put forward requirements for image classification capabilities, such as automatic image annotation, content-based image retrieval, video surveillance, medical image processing, and automatic robots. Therefore, image classification technology has always been a research hotspot, although a large number of efficient classification methods have emerged in recent years to continuously improve the accuracy of image classification. It is difficult to achieve efficient and accurate classification of large amounts of data. These problems need to be further studied and resolved. This paper proposes a simulation research on the algorithm of monitoring and evaluating the deformation safety of coastal soft foundation pits based on big data. The dense network uses dense connection technology to connect any layers with each other. The input of each layer contains all the previous feature maps, and then the output is output to the subsequent layers of the network, deep-level feature mapping gets stacked. Dense connection technology can increase the diversity of the output and make the feature reuse, thereby improving the recognition efficiency. The training data in this experiment is still too small, resulting in the model's effect on the training sample being good, but the generalization effect on the test data set is not very good.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

References

[1] M. Jahanbakht, W. Xiang, L. Hanzo, and M. R. Azghadi, "Internet of Underwater Things and big marine data analytics – a comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 904–956, 2021.

[2] Z. P. Cai and Z. B. He, "Trading private range counting over big IoT data," in *The 39th IEEE International Conference on Distributed Computing Systems (ICDCS 2019)*, Dallas, TX, USA, 2019.

[3] X. Zheng and Z. P. Cai, "Privacy-preserved data sharing towards multiple parties in industrial IoTs," *IEEE Journal on Selected Areas in Communications (JSAC)*, vol. 38, no. 5, pp. 968–979, 2020.

[4] S. Feng, C. Zuo, L. Zhang, W. Yin, and Q. Chen, "Generalized framework for non-sinusoidal fringe analysis using deep learning," *Photonics Research*, vol. 9, no. 6, 2021.

[5] L. Yang, "An object recognition method based on the improved convolutional neural network," *Journal of Computational and Theoretical Nanoscience*, vol. 13, no. 1, pp. 870–877, 2016.

[6] J. Cao, X. Zhang, C. Zhang, and J. Feng, "Improved convolutional neural network combined with rough set theory for data aggregation algorithm," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 2, pp. 647–654, 2020.

[7] C. Xu, T. Liu, D. Tao, and C. Xu, "Local Rademacher complexity for multi-label learning," *IEEE Transactions on Image Processing*, vol. 25, no. 3, pp. 1495–1507, 2016.

[8] J. H. Du, "Automatic text classification algorithm based on Gauss improved convolutional neural network," *Journal of Computational Science*, vol. 21, pp. 195–200, 2017.

[9] R. Luo and K. Zhang, "Research on finger vein recognition based on improved convolutional neural network," *International Journal of Social Science and Education Research*, vol. 3, no. 4, pp. 107–114, 2020.

[10] H. Yu, "Retraction: Honggang Yu, an efficient face recognition algorithm using the improved convolutional neural network," *Discrete & Continuous Dynamical Systems*, vol. 12, no. 4-5, pp. 901–914, 2019.

[11] M. H. Yao, M. L. Ma, and J. M. Liu, "Defect detection method of magnetic disk image based on improved convolutional neural network," *Optoelectronics Letters*, vol. 16, no. 5, pp. 396–400, 2020.

[12] G. Tang, R. Liang, Y. Xie, Y. Bao, and S. Wang, "Improved convolutional neural networks for acoustic event classification," *Multimedia Tools & Applications*, vol. 78, no. 12, pp. 15801–15816, 2019.

[13] J. Zhang, K. Shao, and X. Luo, "Small sample image recognition using improved convolutional neural network," *Journal of Visual Communication and Image Representation*, vol. 55, pp. 640–647, 2018.

[14] B. K. Kim, H. S. Kang, and S. O. Park, "Drone classification using convolutional neural networks with merged Doppler images," *IEEE Geoscience & Remote Sensing Letters*, vol. 14, no. 1, pp. 38–42, 2017.

[15] Z. Lu, H. W. F. Yeung, Q. Qu, Y. Y. Chung, X. Chen, and Z. Chen, "Improved image classification with 4D light-field and interleaved convolutional neural network," *Multimedia Tools and Applications*, vol. 78, no. 20, pp. 29211–29227, 2019.

[16] M. G. Kim, "Improved measurement of thin film thickness in spectroscopic reflectometer using convolutional neural networks," *International Journal of Precision Engineering and Manufacturing*, vol. 21, no. 3, pp. 1–7, 2019.

[17] F. Zou, Y. Liu, H. Wang et al., "Multi-view multi-label learning for image annotation," *Multimedia Tools & Applications*, vol. 75, no. 20, pp. 12627–12644, 2016.

[18] L. Chen, R. Wang, J. Yang, L. Xue, and M. Hu, "Multi-label image classification with recurrently learning semantic dependencies," *The Visual Computer*, vol. 35, no. 10, pp. 1361–1371, 2019.

[19] Y. Kongsorot, P. Horata, P. Musikawan, and K. Sunat, "Kernel extreme learning machine based on fuzzy set theory for multi-label classification," *International Journal of Machine Learning & Cybernetics*, vol. 10, no. 5, pp. 979–989, 2019.

[20] D. Li and S. Dick, "Residential household non-intrusive load monitoring via graph-based multi-label semi-supervised learning," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 4615–4627, 2019.

[21] Y. Wei, W. Xia, M. Lin et al., "HCP: a flexible CNN framework for multi-label image classification," *IEEE Transactions on Software Engineering*, vol. 38, no. 9, pp. 1901–1907, 2016.

[22] L. Ma, M. Li, X. Ma, L. Cheng, P. du, and Y. Liu, "A review of supervised object-based land-cover image classification," *Isprs Journal of Photogrammetry & Remote Sensing*, vol. 130, pp. 277–293, 2017.

[23] J.-S. Han and K.-C. Kwak, "Image classification using convolutional neural network and extreme learning machine classifier based on ReLU function," *The Journal of Korean Institute of Information Technology*, vol. 15, no. 2, pp. 15–23, 2017.

[24] R. Yang, L. Su, X. Zhao, H. Wan, and J. Sun, "Representative band selection for hyperspectral image classification," *Journal of Visual Communication and Image Representation*, vol. 48, pp. 396–403, 2017.

[25] R. Jing-Shi, P. Hai-Wei, L. Peng-Yuan et al., "Symmetry theory based classification algorithm in brain computed tomography image database," *Journal of Medical Imaging and Health Informatics*, vol. 6, no. 1, pp. 22–33, 2016.

[26] L. Weng, Y. He, J. Peng, J. Zheng, and X. Li, "Deep cascading network architecture for robust automatic modulation classification," *Neurocomputing*, vol. 455, no. 2, pp. 308–324, 2021.