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Research on Classification of Cross-Border E-Commerce Products Based on Image Recognition and Deep Learning

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ABSTRACT Cross-border e-commerce is a concrete manifestation of "Internet + foreign trade", which is conducive to improving the people's material living standards and quality, and is also the key to promoting my country's industrial transformation and upgrading. E-commerce platform is the carrier of cross-border e-commerce, and product classification plays a very important role in the e-commerce platform. Aiming at the shortcomings of existing product classification, this paper develops a new classification technology. First, obtain the relevant parameters of the product image through image recognition technology. Secondly, a cross-border e-commerce product classification model is constructed through deep learning technology, and Gray and RGB features of convolution and recursive networks are combined when training the classifier to enhance feature expression. Finally, the applicability and efficiency of related models are verified through performance and functional tests. This technology can effectively improve the rationality of the functional design of the e-commerce platform, thereby improving the efficiency of cross-border commerce business.

INDEX TERMS Cross-border e-commerce, image recognition, deep learning, product classification.

I. INTRODUCTION

E-commerce platforms have developed rapidly in recent years, thanks to the in-depth development and support of mobile Internet and smart terminals [1]. In addition, through cross-border e-commerce platforms, products can be quickly sold in another country from one country. This type of technology allows consumers to purchase foreign products in a relatively short period of time, effectively promoting the coverage and development efficiency of cross-border e-commerce. Therefore, it can be concluded that the development of cross-border e-commerce requires an efficient and accurate e-commerce platform. The platform can efficiently classify and display products [2]. However, the existing business platforms have certain deficiencies and deficiencies in the product classification process. Therefore, this article has carried out related research on the classification of cross-border e-commerce products to explore an efficient product classification technology [3].

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In the 1990s, the development of e-commerce received strong support from the U.S. government and enterprises, and e-commerce developed rapidly in the United States. U.S. uses its advanced Internet technology and highly developed market economy, etc., and e-commerce has always led the world [4]. In recent years, US e-commerce has maintained sustained growth.

For example, the American e-commerce giant Amazon has adopted the B2C model to create an online bookstore. Consumers find relevant information about books they are interested in, such as authors, publishers, etc., through search, and then buy books they like [5]. At the same time, Amazon improved its own logistics and distribution facilities and gradually developed into a world-renowned e-commerce company. The system architecture of Amazon's e-commerce platform is based on the principle of distributed and decentralization. Currently, Amazon's product system is constructed with the Dynamo system [6]. Dynamo is a distributed Key-Value storage system that can meet the high reliability, high availability and scalability requirements of e-commerce platforms. In order to ensure the high availability of the system, Dynamo will store any processing on the platform [7]. In the data partition, the Hash algorithm is used to facilitate the expansion of the nodes of the system and achieve the purpose of incremental scalability. In the later stage, virtual nodes were used to make node data more evenly distributed, optimize the performance of the system, and use Sloppy Quorum, the data will not be sent to the failed node, and the failed node can be restored to use after restarting, effectively improving the stability of the entire system And availability [8]. The eBay commodity system architecture divides the system into layers to achieve high cohesion, splits data blocks horizontally according to system functions, and uses distributed cache at the logical layer to improve interface performance [9].

However, some small and medium-sized e-commerce platforms in China currently have insufficient commodity systems [10]. The mixed management of the basic library and the commodity library in the commodity system is not distinguished, which is not conducive to the expansion of the e-commerce platform. At the same time, the maintenance of the basic commodity library consumes a lot of time and labor costs [11]. When maintaining the basic commodity library, it only relies on the operators to maintain it, without including the merchants, and unified management of the basic commodity library [12].

How to design a product system with excellent performance in response to the above shortcomings and optimize the performance of the e-commerce platform has important application value. Aiming at the shortcomings of existing product classification, this paper develops a new classification technology. Construct a new type of cross-border e-commerce product classification technology by combining image recognition and deep learning technology. This technology can effectively improve the rationality of the functional design of the e-commerce platform, thereby improving the efficiency of cross-border commerce business.

II. OVERVIEW OF RELATED TECHNOLOGIES

A. IMAGE RECOGNITION OF CROSS-BORDER E-COMMERCE PRODUCTS

The product system is the core of the e-commerce platform, which can provide support and product information interaction for other systems. At the same time, cross-border e-commerce platforms are also the key to e-commerce business [13]. The rationality, stability, throughput, and scalability of the product system play an important role in determining whether the entire e-commerce platform will develop toward a high-quality platform. If the product system is not properly designed, it will not be able to meet the subsequent complex functional requirements. Therefore, a good product system is very important to the entire e-commerce platform [14].

As the focus of pattern recognition and image analysis, image segmentation technology is one of the key processes. Image segmentation can directly determine the accuracy of the subsequent image analysis and processing. This process will create the basis for the image and judgment on the final result of image analysis. The technical process is mainly through segmenting the picture into different feature regions and extracting information from a specific region.The purpose is to separate the different areas with special meaning in the image. Shape is an important feature of an image, and people often recognize and understand a scene through the shape. Shape feature extraction includes two parts: image segmentation and shape feature description. The shape can be composed of its outline (or edge), or it can be composed of the area occupied by the scene, that is, the outline or area can separate the range of the useful scene from the image [15].

This process of segmenting an image into some meaningful ranges is often called image segmentation or image segmentation. In the research of e-commerce product image recognition, shape is also an important feature to distinguish categories. Shape description refers to the quantitative expression of its range with appropriate shape feature parameters. To extract feature parameters, first segment them from the acquired image.

B. DEEP LEARNING TECHNOLOGY

The research of artificial neural network promotes the process of deep learning. This technology combines low-level features to form more abstract high-levels. By analyzing high-level feature points and related attributes, the information features of the research topic can be expressed.In order to solve the problem of "gradient disappearance" during the training of the previous multilayer network, the weights were initialized through unsupervised pre-training, and then supervised fine-tuning was performed. Training makes it possible to train multi-layer neural networks. In 2012, Hinton's research team built a CNN network, AlexNet, and won the championship of the ImageNet image recognition competition with an absolute advantage over the second place. After that, deep learning attracted many attentions and began Enter explosive development [17].

The development of deep convolutional neural networks has become the most prominent advancement in image recognition. This method imitates the hierarchical structure of biological neural networks. The low level represents abstract details, and the high level represents specific semantics. The essential information of the data is highly mined by extracting layer by layer. Complete recognition and classification [18]. And the learning process is completely automatic and does not require manual intervention, which is the biggest advantage of its application potential. In recent years, the deep convolutional neural network model obtained through massive sample set training has achieved unprecedented performance in speed, recognition accuracy.

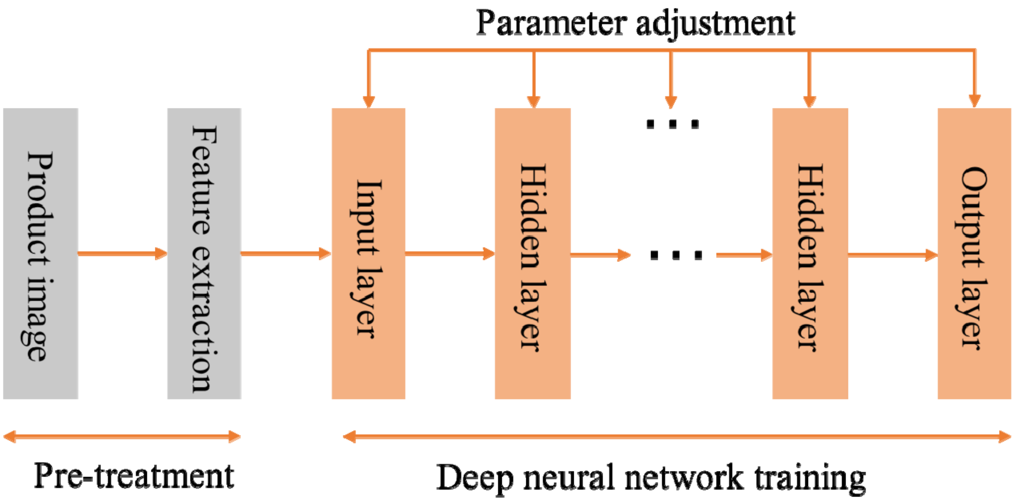

FIGURE 1. Cross-border e-commerce product classification and identification process.

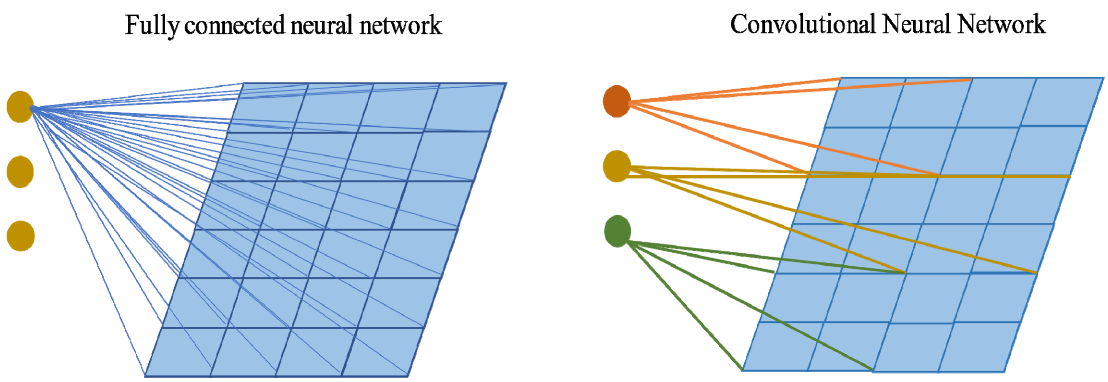

FIGURE 2. The difference between DNN and CNN connection methods.

III. CROSS-BORDER E-COMMERCE PRODUCT CLASSIFICATION MODEL

A. PRODUCT IMAGE FEATURE EXTRACTION

Convolutional neural network is a neural network with multiple hidden layers. The hidden layer is mainly composed of convolutional layer and down sampling layer alternately. Each hidden layer is composed of multiple feature planes. It was first applied to handwritten digit recognition.

The most famous representative network is LeNet-5. Cx represents the convolutional layer, Sx represents the down-sampling layer, and Fx represents the fully connected layer, where x represents the layer number. LeNet-5 has eight layers, which are input layer, two convolutional layers, two down-sampling layers, two fully connected layers, and output layer [19].

$$y_i = \sum\nolimits_j \left(x_j - w_{ij}\right)^2 \tag{1}$$

The activation function of the network adopts the stretched hyperbolic tangent function, as shown in formula (2).

$$f\,(\mathrm{x}) = Atanh\,(Sx) \tag{2}$$

Among them, A is set to 1.7159 and S is set to 2/3.

The input image size of the LeNet-5 model is 32×32. The C1 layer is the first convolutional layer, and the size of the convolution kernel is 5×5. The number of feature maps is 6, and the size of the feature maps is 28×28 [20]. The C1 layer has a total of 156 parameters and 122,304 connections.

The S2 layer is a down-sampling layer, which is mainly responsible for down-sampling each feature map of the C1 layer in different dimensions. The final output layer is composed of Euclidean Radial Basis Function (RBF) units, and each unit represents a category. In the handwritten digit recognition model, there are ten digits from 0 to 9, that is, 10 categories, so there are 10 output layer units. The calculation method of each RBF unit output is shown in formula (1) [21].

Each 2×2 area of the feature map of the C1 layer is mapped to a pixel of the S2 layer, that is, the size of the feature map of the S2 layer is reduced by 1/2 compared with the feature map of C1 in both the length and width dimensions, so the feature of S2 The size of the picture is 14×14. The S2 layer has 12 parameters and 5880 connections. The C3 layer is a convolutional layer, with a total of 16 convolution kernels with a size of 5×5. Therefore, this layer has 16 feature

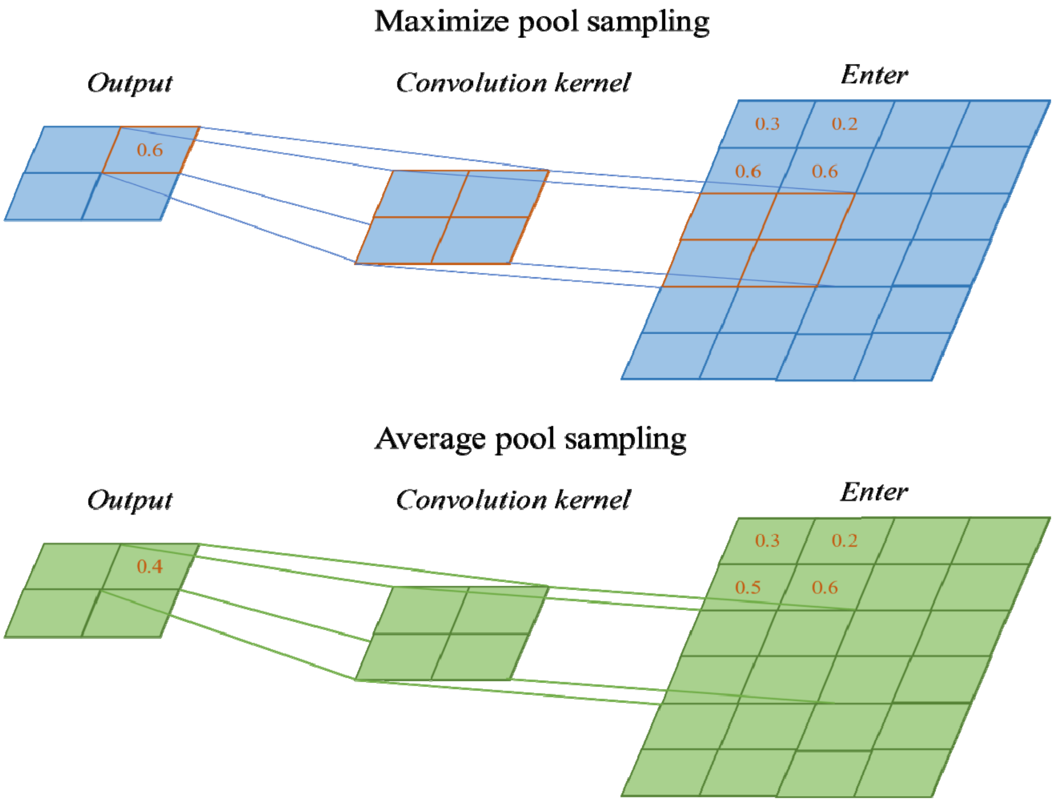

FIGURE 3. Schematic diagram of two down sampling methods in convolutional neural network.

maps, and the size of the feature map is 1Ox10°. The connection relationship between the C3 layer and the S2 layer feature map is shown in Table 1. X indicates that there is a connection, and the C3 layer has 1516 parameters and 15160 connections [22].

B. PRODUCT CLASSIFICATION BASED ON DEEP LEARNING

The convolution kernel is usually represented by a small square. On the feature map, the entire map is scanned sequentially in pixels according to the preset step size [23]. There can be multiple convolution kernels working on a feature map at the same time, and each convolution kernel represents the detection of a certain feature on this feature map. The use of convolution kernel structure greatly reduces the amount of network parameters, speeds up the calculation, and also reduces the risk of overfitting [24]. In the sub-sampling layer, there are usually two forms, maximum pooling sampling and average pooling sampling, which can be regarded as a special convolution process, as shown in Figure 3.

The weight of each neuron in the convolution kernel of average pooling sampling is 0.25, and the step size of the convolution kernel is 2 when sliding on the input tensor. The result of mean sampling is equivalent to reducing the input mapping blur to the original 1. /4[25]. Maximum sampling uses a similar method to slide on the input, and uses the maximum neuron (a certain pixel in the picture problem) detected by the sampling window as the sampling result. The effect shown in the figure is that the size of the original image is reduced.

Among them, the ResNet_50 used in this paper is a ResNet model with a 50-layer structure provided on the Keras framework, and a zero-padding method is selected to achieve self-mapping [26]. After comparison, it is found that although the use of linear projection can slightly improve the effect, it is not obvious, that is, the use of this projection method is not necessary, so the use of zero padding can ensure the lowest model complexity, which is conducive to the construction of deeper networks [27].

The back-propagation formula of the output layer:

$$\partial^L = f'(u^L)^\circ(y^n - t^n) \tag{3}$$

$$\frac{\partial E}{\partial w^\tau} = x^{\tau-1}(\delta^\tau)^T \tag{4}$$

The ResNet model proposes a new residual structure. The traditional fitting goal is to make the network output F(x) as close to the expected mapping H(x) as possible. In direct fitting, as the depth of the network increases, the magnitude of the change in the network gradient becomes smaller and smaller after multi-layer transmission [28].

$$\Delta w^\tau = -\eta \frac{\partial E}{\partial w^\tau} \tag{5}$$

Error of the output layer:

$$E = \frac{1}{2} \sum\nolimits_{K=1}^{L} (d_k - o_k)^2 \tag{6}$$

TABLE 1. C3 layer and S2 layer feature map connection relationship.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	√				√	√	√			√	√	√	√		√	√
1	√	√				√	√	√			√	√	√	√		√
2	√	√	√				√	√	√			√		√	√	√
3		√	√	√			√	√	√	√			√		√	√
4			√	√	√			√	√	√	√		√	√		√
6				√	√	√			√	√	√	√		√	√	√

At this time, the influence on F (x) will become so small that it cannot contribute to the weight update; therefore, it will try to fit another mapping. Then the original expected mapping becomes F(x) + x, that is, F(x) + x is used to approximate H(x).

This mapping introduces the original independent variable x [29].

$$\Delta w^{\tau} = -\eta \frac{\partial E}{\partial w^{\tau}} \tag{7}$$

At this time, the influence on F (x) will become so small that it cannot contribute to the weight update; therefore, it will try to fit another mapping. Then the original expected mapping becomes F(x) + x, that is, F(x) + x is used to approximate H(x), and the original independent variable x is introduced into this mapping. F(x) is easier to optimize as a residual term.

The principle of this structure is similar to a differential amplifier. When the network depth is extremely large, and when trying to fit F(x), since x) is the difference between the original input x and the desired mapping H(x), small changes in x will more easily affect F(x). This new mapping is easier to optimize, making the network Loss value more sensitive to changes in input samples, and improving the accuracy of the network weight update. The proposal of this structure really realized the construction of deep network [30].

IV. CASE ANALYSIS OF CROSS-BORDER E-COMMERCE PRODUCT CLASSIFICATION

A. DATA SOURCE AND TEST ENVIRONMENT

The experimental environment used in this chapter is Windows 10 Professional Edition, the computer memory is 32GB, and a GTX 1080ti graphics card with 10 GB video memory is used to complete the experiment. The external computing libraries are CUDA8 and cuDNN6. Since there are many ways to transform the source model, in order to evaluate the impact of fine-tuning on performance when migrating the source model, experiment one is designed to first replace the classifier without fine-tuning, test its accuracy as a control group, and then apply fine-tuning Modify the model and perform the same training process and observe the results. In order to compare the impact of different fine-tuning strategies on the model's performance, Experiment 2 is designed to train the classifier and convolutional layer at the same time, and adjust the number of trainable parameters during fine-tuning, and conduct in-depth research and comparison between InceptionV3 and ResNet_50 models.

The data set used in the experiment comes from a product image sample of a cross-border e-commerce platform. In the process of selecting training samples, some pictures containing non-target objects (such as containers, human hands, background objects, etc.) are used to simulate random noise.

B. FINE-TUNING STRATEGY INFLUENCE EXPERIMENT AND ANALYSIS

If training the classifier and fine-tuning the convolution module at the same time. The accuracy of the model will be relatively low at the beginning and the loss value of the cost function will show a rapid downward trend. After a certain number of iterations, it tends to converge, and finally obtains the performance similar to the experiment. The second exper-

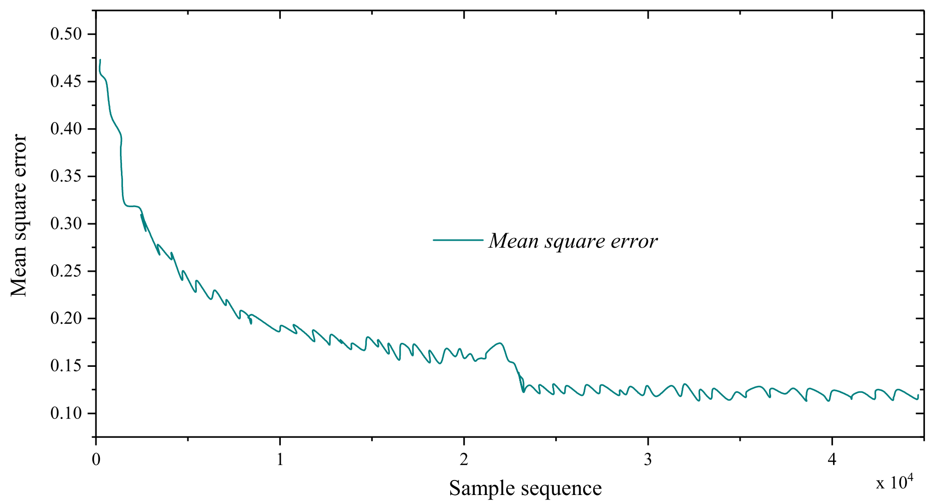

FIGURE 4. Mean square error diagram of product classification model.

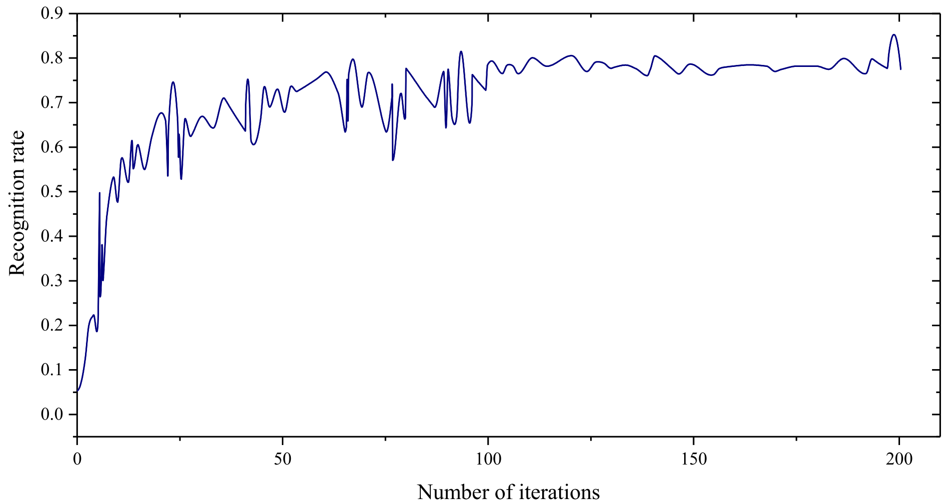

FIGURE 5. Effect diagram of product classification recognition rate.

iment focuses on the InceptionV3 and ResNet_50 models as examples. The training process images are shown in Figures 4 and 5 when the proportion of trainable parameters is the same as 75%.

Both models begin to converge after 50 iterations, and the accuracy and loss value of the InceptionV3 model on the training set and the validation set are very close. The model performed well and there was no overfitting; however, it can be observed that there is a certain gap between the training set image and the validation set image of the ResNet_50 model. Even if the number of iterations is increased to 200, there is still no improvement, so it is considered that overfitting has occurred. This result further verifies that the multi-size filter design of the Inception architecture makes it higher in parameter utilization than the ResNet architecture, which is consistent with expectations. The residual structure of ResNet sacrifices part of the local feature extraction ability. However, this structure can support a deeper structure, which can complement the model's induction ability after expanding the training sample set, which will be verified in later experiments.

The initial learning rate is set to 0.1, and the learning rate is halved when the recognition rate does not increase significantly, that is, when the error curve decreases slowly. That is, the step of searching for the optimal solution at the bottom of the error surface by the gradient becomes smaller and the oscillation amplitude is reduced, which effectively accelerates the convergence of the network. Figure 4 and Figure 5 show the effect of training, and Figure 4 is the mean square error graph. Figure 5 is a graph of the recognition rate. In Figure 5, around the 100th epoch, a drop to 0.05. The error value drops to a certain extent, the recognition rate rises to a certain extent, and the network begins to stabilize.

C. IMPACT OF IMPROVEMENT ITEMS ON EXPERIMENTAL RESULTS

Figure 6 shows the recognition rate curve obtained by 200 iterations of the corresponding network. A solid line

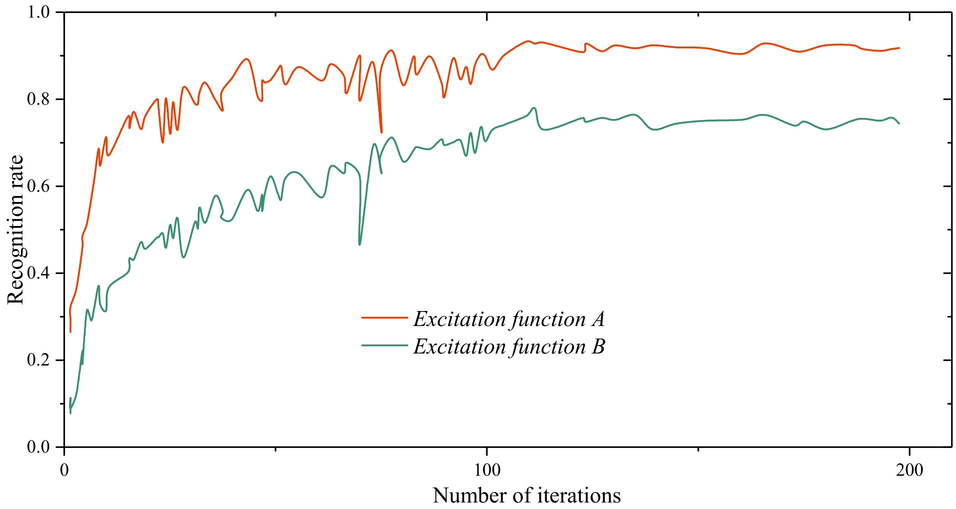

FIGURE 6. Effect diagram of product classification recognition rate.

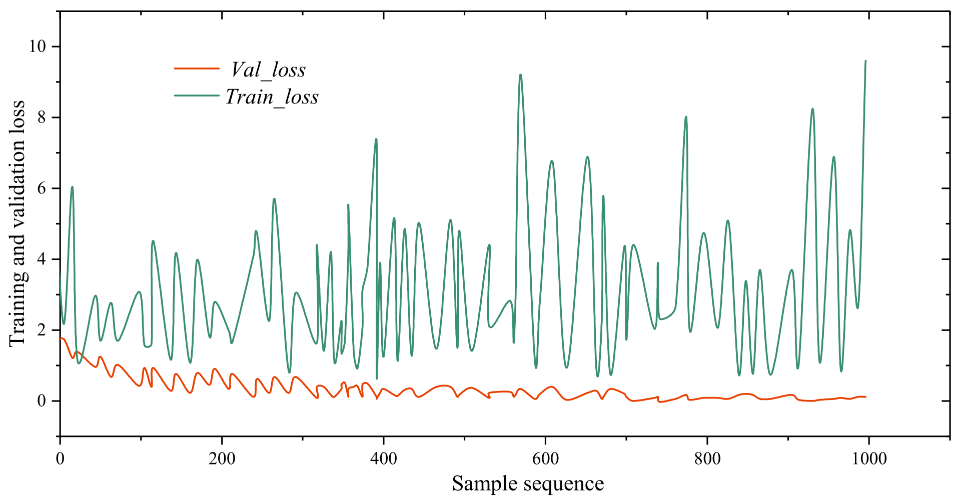

FIGURE 7. Effect diagram of product classification recognition rate.

is the recognition rate curve obtained by adding random Dropout (the set probability value is 0.3) (after debugging, this proportion of Dropout can achieve the best experimental effect). The solid line B is the recognition rate curve obtained without adding random Dropout. It can be seen from the figure that the network stabilizes at 100 epochs. The overall recognition rate with random Dropout is about 84.0%, and without random Dropout is about 79.3%, and the recognition rate is increased by 4.7%.

In addition, data improvement is also very important during the experiment. Although this step does not involve the core calculation process of the neural network algorithm, and the sample obtained after data promotion processing is still in the scope of "fake data" in a strict sense.

Figure 7 The result of fine-tuning and retraining the product classification model.There is still a high correlation with the original data, but experiments show that whether to use this step before training has a great impact on the final model performance. As shown in Figure 7, the ResNet_50 fine-tuned retraining image with 121 layers frozen when no data boosting is used. It can be observed that there are very severe fluctuations in both the training set and the validation set, the model performance is unstable, and there is obvious underfitting phenomenon. Obviously, such training results are not ideal, which proves that the data improvement step is for the overall network training the process is very necessary.

V. CONCLUSION

By studying the current situation of cross-border e-commerce and analyzing its characteristics and shortcomings, this article proposes a new type of cross-border e-commerce product classification model. This technology can provide convenient and efficient use efficiency for e-commerce business. E-commerce platform is the carrier of cross-border e-commerce, and product classification plays a very important role in the e-commerce platform. Aiming at the shortcomings of existing product classification, this paper develops a new classification technology. A product classification model was developed by combining image recognition and deep learning technology. The applicability and efficiency of related models are verified through performance and function tests. This technology can effectively improve the rationality of the functional design of the e-commerce platform, thereby improving the efficiency of cross-border commerce business. The advantages of cross-border e-commerce cannot be demonstrated either. At the same time, the development of cross-border e-commerce has vigorously promoted the transformation and development of e-commerce platforms, and the development of e-commerce platforms has enhanced the advantages of cross-border e-commerce. At the same time, limited to the shortcomings of the current level, the recognition rate and packet loss rate of this technology will be further studied. We will be committed to the in-depth development of cross-border e-commerce platform technology, and provide scientific reference for the development of cross-border e-commerce business.

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