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Research Article

A Deep Convolutional Neural Network Based Risk Identification Method for E-Commerce Supply Chain Finance

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With the popularity of the Internet, the rise of e-commerce platforms has led to the rapid development of supply chain (SC) financial services in China, and the competitiveness of commercial banks and core enterprises in the supply chain is now gradually increasing, rapidly expanding into an important area of competition between the two. As an emerging force rebounding from the economic downturn, e-commerce platform transactions, with their unique characteristics of informatization, diversification, and convenience, have provided a broad space for Internet SC finance. The article mainly analyzes the risk identification method of e-commerce SC finance, analyzes its risk from the financing process, gives corresponding data support for the matters or processes that may cause financing risk based on DCNN model, and takes Jingdong SC finance as an example and analyzes its main financing methods and risk identification process; based on different experimental comparisons, a multigroup experimental study shows that the accuracy of supply chain finance risk identification using deep convolutional neural network models can reach 95.36%, which demonstrates the effectiveness of the proposed method by providing better performance compared to traditional BP and SVM networks.

1. Introduction

With the popularization of the Internet, more and more e-commerce enterprises rely on the Internet platform to complete multichannel financing for their projects. The steadily increasing number of online platform institutions and e-commerce enterprises has led to increasing diversity. With the encouragement of economic policies and the wave of "Internet+," people are trying to use the Internet to build a modern intelligent SC system that integrates big data [1], shared Internet, artificial intelligence, and blockchain. In response to the domestic economic transformation and upgrading and the impact of the Internet culture, traditional enterprises are beginning to change and open up new markets based on the concept of following the past. Banking and finance as intermediaries are actively building their own data platforms, forming the advantages of numerous branches, gathering financial talents, and extensive reach to make customer data more three-dimensional while retaining the original customers [2].

In the supply chain, apart from the core enterprises, the upstream often has difficulties in financing and expensive financing due to their own scale, which has become a bottleneck in the development of the SC, which integrates logistics, information flow, commercial flow, and capital flow in the SC, provides a new way to break the bottleneck of SC development, and is developing rapidly. In 2014, Shanghai Chunyu SC Management Co [3], Ltd. was exposed by the media that its capital chain was in trouble and it owed a huge amount of money, and the "Chengxing International Incident" in 2019 involved a huge amount of money. In 2019, the CBIRC issued the "Guidance on Promoting SC Financial Services," stating that it is necessary to adhere to precise financial services, the authenticity of transaction backgrounds, the availability of transaction information [4]; from offline SC finance to online SC finance transformation and upgrading, due to the rapid development, the research of SC finance has long existed in a situation where theory seriously lags behind practice [5].

Foreign scholars mostly start from the perspective of enterprise financing. Timme [6] believes that SC finance is a new type of financing business in which all the participants in the SC chain cooperate with financial institutions outside the chain to provide convenient SC financing. Hoffmann [7], from the perspective of the flow of funds between industrial organizations, proposes that SC finance is a number of organizations inside and outside the SC, through planning and controlling; therefore, Berger and Udeel [8] proposed a "government policy financial structure-lending technology" financing approach. Michael Lamoureux [9] made a new definition of the concept of SC finance on the basis of a synthesis of previous research done by scholars, and he believes that SC finance is a process of capital optimization, in which the flow of capital, logistics, information, and commerce is integrated, and the various means of financing and costs are optimized. Lamoureux [10] believes that SC finance is a process of optimizing the financing of the system, through the integration and use of transaction information, the integration of capital flow, logistics, information flow and commercial flow, embedded cost management analysis, and the optimization of the availability of funds and costs by various financing instruments. Li et al. [11] start from the perspective of enterprise capital flow and point out that SC finance is a financial service activity that provides credit and settlement for enterprises in the SC through capital optimization and monitoring in order to reduce the costs of suppliers and retailers. It can be seen that foreign scholars understood SC finance from the earliest as only a means of financing, to later focus on the flow of funds in the SC system and the capital optimization process [12], and gradually considered SC finance as a comprehensive financial service to improve the efficiency of the SC and financial value added.

Compared with foreign scholars, domestic scholars' research on SC finance started later and with a different entry point. At the earliest, Khan et al. [13] extracted the concept of "rongtong warehouse" from logistics finance, and "rongtong warehouse" is divided into two definitions: narrow and broad, but nowadays, the narrow definition is mostly taken: rongtong warehouse is a comprehensive service platform that integrates credit for SMEs, covers logistics enterprises, and connects traditional commercial platforms with e-commerce platforms. It is a comprehensive service platform that integrates credit for SMEs [14, 15], covers logistics enterprises, and connects traditional commercial platforms with e-commerce platforms and is believed to break the "bottleneck" of external financing for SMEs. Some other scholars define SC financial services in terms of the business model of commercial banks.

As the research progressed, it gradually shifted from the research on logistics finance and financing to the analysis of SC structure [16]. This phase defines it as follows: SC finance is based on the analysis of its internal transaction structure, introducing variables such as core enterprises, logistics supervisory companies, and capital flow instruments, and using a self-repaying trade credit model to provide closed credit, settlement, financial management, and other financial services to enterprises in the SC nodes [17]. Apostolopoulos and Mpesiana [18] have since made a new interpretation and expansion of the definition, arguing that SC finance is the provision of targeted financial management solutions by specific financial institutions or organizers in the SC (core enterprises, third-party logistics enterprises) for specific links in the SC or for the whole process of the whole node.

The concept of online SC finance (OSCF) was first proposed by Wang and Wong [19]. Internet SC finance refers to a new comprehensive financial service model in which an e-commerce platform, which is qualified to operate and provide funds at the same time, or a commercial bank, has a credit system with a large amount of customer data accumulated by the platform, and uses the credit model of self-reimbursement trade finance to provide commercial credit, issue loans, and make payments and settlements for SMEs and individual users on the platform. According to Goodwill et al. [20], Internet SC finance is an industrial ecosystem and financial, ecological platform that builds cross-sectoral and cross-regional through the Internet, the Internet of Things, and other advanced technological means on an online platform and is widely integrated with enterprises, industries, and governments. This paper will analyze the main risks faced by SC finance and the corresponding risk control methods from both theoretical and practical aspects, DCNN model, and take Jingdong SC finance as an example to analyze its main financing methods and risk identification process. Through experimental comparison, the results show that the accuracy of the proposed deep convolutional neural network model for supply chain finance risk recognition is 95.36%, which is an improvement compared with BP, SVM, and LeNet-5 models, showing the superiority of the model, but because of a large number of parameters in the operation of the model, improving the operation speed is also a direction worthy of research.

2. SC Financing Model for E-Commerce Enterprises

The traditional SC finance model takes commercial banks as the center of capital financing, with commercial banks playing the role of credit assessment and credit decision-making. There are three main modes of operation: accounts receivable financing, order financing, and warehouse financing, among which accounts receivable financing involves accounts receivable and commercial paper pledge mode; order pledge financing has spot financing and order pledge [21–23], warehouse financing is divided into inventory pledge and ticket first and then goods mode.

The Internet SC finance model is a way to use the Internet platform for transaction financing. At present, Internet SC finance contains three financing models, namely intermediary-type e-commerce transactions, P2P, and self-operated e-commerce platform-led. The intermediary-type e-commerce trading platform-led SC finance model is to put forward loan applications to the platform when the e-commerce enterprise has capital needs, and the merchant repays the principal and interest to the intermediary platform after completing capital turnover; the P2P platform-led is a third-party network platform that connects individual funds borrowing and lending parties [24], and it is difficult for the P2P platform to act as a financial institution alone for independent risk control; the self-operated e-commerce platform-led model participates in all aspects of its self-operated The self-operated e-commerce platform-led model is involved in all aspects of its own products and can provide credit services to its own suppliers, so the self-operated model has access to the most comprehensive data information of the three models.

2.1. The Financing Process of E-Commerce Enterprises under SC Finance. In the context of SC finance, e-commerce enterprises use data directly or indirectly to direct resources into play through emerging fields such as data analysis, network cloud computing, and blockchain economy, forming the initial authorized credit and risk control system of the e-commerce platform [25]. At the same time, e-commerce enterprises rely on national policy support and the vast resources of the Internet platform to accumulate financial data related to the operation and sales of suppliers involved in the financing chain, So it makes the financing much more time-efficient. This allows e-commerce businesses to have more goods supplied by their suppliers, even in the case of e-commerce shopping festivals or promotions under the new media, where there may be a shortage of supply, so the solution of pledging goods to third-party storage enterprises is proposed, and the resulting receivables can be applied for financing from factoring financing products, and the suppliers will receive a certain percentage of the loan for the goods. The process is illustrated in Figure 1.

When suppliers of e-commerce enterprises generate a large number of orders, they may also choose to use the orders as pledges for financing. After the supplier platform applies for the SC factoring financing product, the commercial bank analyzes and compares the data transmitted by the e-commerce company to determine the credit rating of the supplier and issues a certain percentage of the loan. When the purchaser pays the final payment for the goods to the e-commerce company. The remaining funds are transferred back to the supplier. The process is illustrated in Figure 2.

The financing warehouse refers to the inventory pledge loan model. Considering the instability and variability of the goods, it usually requires the participation of a third-party storage enterprise to cooperate with the e-commerce company to carry out value estimation and goods management of the enterprise's inventory, so the e-commerce company is both a distributor and a logistics enterprise at the same time. The process is illustrated in Figure 3. The commercial bank and the e-commerce company receive an application from an enterprise with a financing need for finance through warehouse financing and agree that the enterprise will store its inventory in the warehouse of the captive logistics, which takes over the management inspection and assessment work; subsequently, the commercial bank determines the limits of the loan based on the feedback assessment report; finally, the financing enterprise withdraws the inventory in batches after repaying the loan in batches [26].

Self-supply is a more specific management model, while self-managed e-commerce is involved in the whole process of "production—purchase—transaction—transport" of its own products, and the self-managed e-commerce platform can provide credit to its own suppliers. The role in the supply chain is more like that of a core business, so access to data is more comprehensive. It plays a more central role in the SC and therefore has access to more comprehensive data. At present, Jingdong Group's SC financing model is more complete than that of its peers, and this paper will explore its financing risks in conjunction with an analysis of Jingbao Bei's financing model.

3. Principles of DCNN Models

3.1. Time-Frequency Transformation. The time-frequency diagram obtained by the time-frequency analysis method of transformation contains a wealth of information about the state of the equipment and intuitively reflects the transformation. The Fourier transform uses a fixed window function and its resolution is also fixed [27, 28], making the short-time Fourier transform somewhat limited. The wavelet basis of the continuous wavelet transform is scalable and solves the time resolution and frequency. The one-dimensional continuous S-transform of the signal $x(t)$ is defined as follows:

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-(t-\tau)\cdot r/2} e^{-j2\pi f t} \mathrm{d}t, \quad (1)$$

where $w(t, f) = (|f|/\sqrt{2\pi})\exp(-t^2 f^2/2)$ is the Gaussian window function. Its corresponding S-inverse transform is as follows:

$$x(t) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} S(\tau, f) e^{-j2\pi f t} \mathrm{d}\tau \mathrm{d}f, \quad (2)$$

where τ means time shift factor, f means frequency, t means time, Gaussian window function $\omega(t, f)$ is both a function of time and frequency, the window width at low frequencies is large with good frequency resolution, and the window width at high frequencies is small with good time resolution.

3.2. Deep Learning Convolutional Neural Networks. Different from the traditional neural network, the deep learning convolutional neural network model has the characteristics of weight sharing. This structure can greatly reduce the complexity of the model and also has the ability to extract features automatically. Compared with the traditional neural network, the deep convolution The performance of the neural network in recognition of two-dimensional images is even better. The functions of each part of the DCNN [29] are shown in Figure 3.

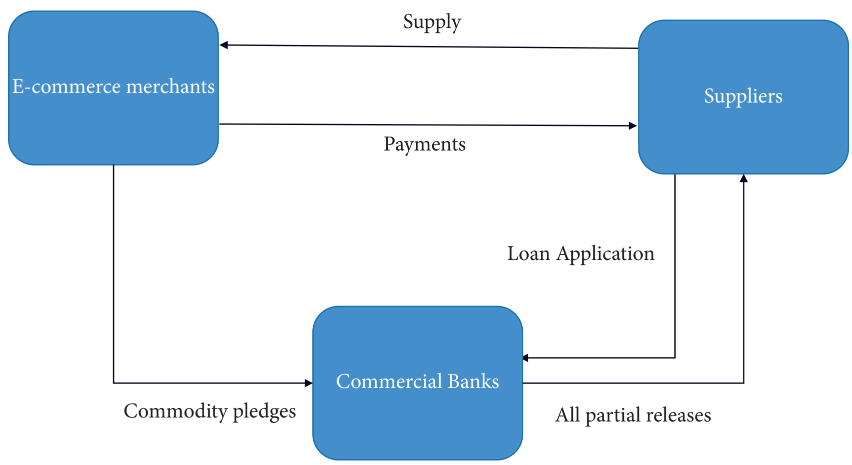

Figure 1: Flow chart of accounts receivable financing.

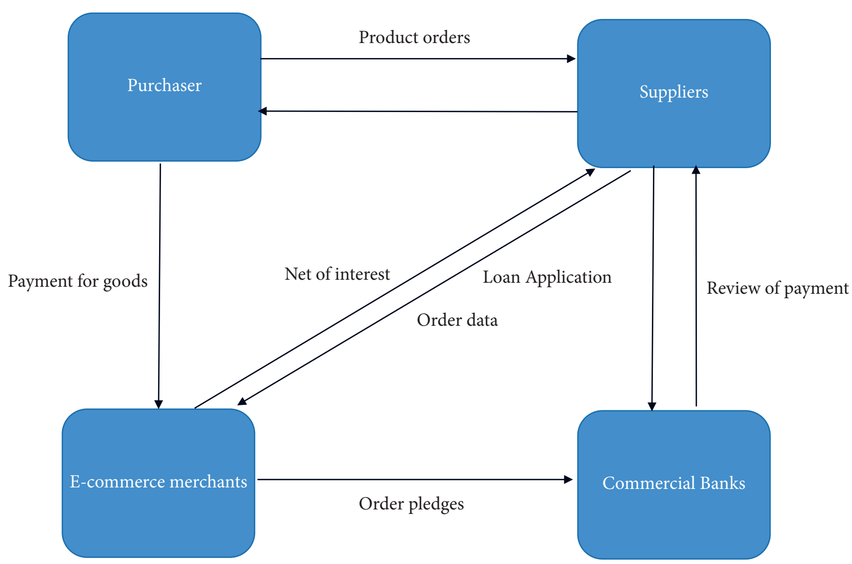

Figure 2: Flow chart of order financing.

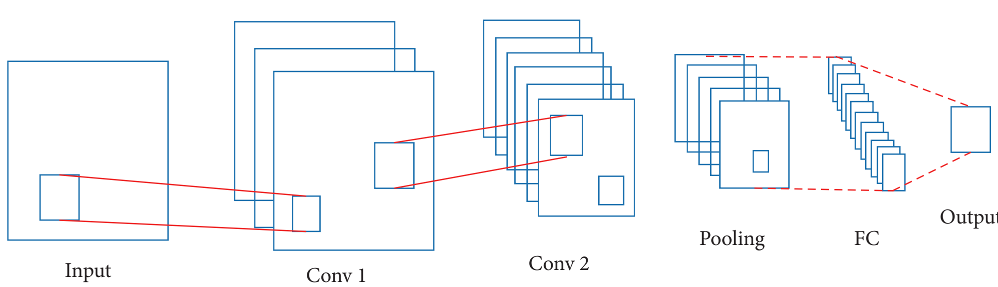

Figure 3: Convolutional neural network structure diagram.

(1) The input layer, which is the spectral image obtained by the time-frequency transform.

(2) The convolution layer, where the input image matrix is convolved with a convolution kernel from the original image. One of the features of the convolution operation is the sharing of weights, which reduces the noise of the original signal through the convolution operation.

(3) The pooling layer, also known as the downsampling layer, is usually referred to as the convolution layer and the pooling layer as the convolution layer. we use maximum pooling to build the pooling layer, through convolutional operations, retaining the main information of the output features of the convolutional layer on the basis of reducing the

number of feature dimensions to improve the network training network.

(4) Fully-connected layers.

(5) The number of nodes in the output layer corresponds to the category of classification, and the output value represents the probability of the corresponding category. The Softmax classifier was chosen to implement the classification task.

3.3. Forward Propagation. The convolutional neural network with sample sets (X, Y), X as inputs and Y as ideal output vectors is forward propagated as follows [30]:

(1) Random initialization of network parameters. Before training, the parameters of the convolutional neural network are initialized: the weights of the convolutional kernel, the bias, and the parameters of the tail perceptron. A small random number close to zero is chosen to ensure that the training is carried out properly, but also to ensure that the weights do not become saturated and lead to training failure.

(2) Calculating the network output.

3.4. Backpropagation. The operation of the deep convolutional neural network model is forward-transmitted, but in the process of adjusting the model parameters, it is from the back to the front. The model adjusts the parameters of the corresponding model layer according to its own recognition accuracy, that is, minimizing the error cost function is used to fine-tune the network parameters to gradually improve the model performance. The error between the ideal output vector Y and the actual output vector O is calculated.

$$e = \frac{1}{2}\sum_{r}^{k=1}\left(Y_k - O_k\right)^2 = \frac{1}{2}\mathbf{Y}_k - \mathbf{O}_k^2, \tag{3}$$

where r represents the total number of categories, Y_k represents the k th dimension of the label corresponding to input X, and O_k represents the k th dimension of the output corresponding to X the input network.

The convolutional neural network error back propagation is trained using a backpropagation algorithm.

(1) Calculate the partial derivative of the error with respect to the weights, backpropagating along the gradient direction with a partial derivative of the following:

$$\Delta\omega_{ij}(n) = -\rho\frac{\partial e(n)}{\partial\omega_{ij}(n)}. \tag{4}$$

Weights updated to the following:

$$\omega_{ij}(n+1) = \Delta\omega_{ij}(n) + \omega_{ij}(n). \tag{5}$$

The gradient can be solved by the partial derivative:

$$\frac{\partial e(n)}{\partial\omega_{ij}(n)} = \frac{\partial e(n)}{\partial e_j(n)}\cdot\frac{\partial e_j(n)}{\partial v_L^j(n)}\cdot\frac{\partial v_L^j(n)}{\partial\mu_L^j(n)}\cdot\frac{\partial\mu_L^j(n)}{\partial\omega_{ij}(n)}. \tag{6}$$

Of which,

$$\begin{gathered} e_j(n) = \frac{\partial e(n)}{\partial e_j(n)}, \\ \frac{\partial v_L^j(n)}{\partial\mu_L^j(n)} = g\prime\mu_L^j(n), \\ \frac{\partial\mu_L^j(n)}{\partial\omega_{ij}(n)} = v_K^j(n). \end{gathered} \tag{7}$$

Forward propagation of error signal: Adjustment of the input layer and implied layer weights ω_{mi}.

$$\Delta\omega_{mi}(n) = \rho\delta_K^j v_M^m(n), \tag{8}$$

where $v_M^m(n)$ is the output of the input neuron:

$$\delta_K^j = f'\left(\mu_K^j(n)\right)\sum_{L}^{j=1}\delta_L^j\omega_{ij}. \tag{9}$$

3.5. Risk Identification Model Based on Deep Learning. Softmax is used as the classification layer, and the classification is performed by the probability $p(y^{(i)} = j/f^{(i)})$ that the sample vector X belongs to the j nd classification (j indicates the number of classes). The output of the classification layer is a k-dimensional vector whose unit values sum to 1, with the following equation:

$$h_{\gamma^r}\left(f^i\right) = \begin{bmatrix} p\left(y^{(i)} = 1|f^i;\gamma_1^T\right) \\ p\left(y^{(i)} = 2|f^i;\gamma_2^T\right) \\ \vdots \\ p\left(y^{(i)} = k|f^i;\gamma_k^T\right) \end{bmatrix} = \frac{1}{\sum_k^{j=1} e^{\gamma^\gamma f^i}}\begin{bmatrix} e^{\gamma^\top f^{(i)}} \\ e^{\gamma_2^T f^{(i)}} \\ \vdots \\ e^{\gamma_i^T f^{(i)}} \end{bmatrix}, \tag{10}$$

where $\gamma_1^T, \gamma_2^T, \ldots, \gamma_k^T$ is the parameter of the iterative regression model, $(1/\sum_k^{j=1} e^{\gamma^\gamma f^i})$ is used to normalize the output, k represents the dimensionality, $e^{\gamma^\gamma f^i}$ represents the exponential function of the current i element, $f^{(i)}$ represents the current i th element, $y^{(i)}$ represents the classification probability of the i th element and $y^{(i)}$ represents the relative probability output of Softmax.

The output of Softmax is logged and the higher the output value, the higher the relative probability of the correct category. The training samples are fed into the DL network and the network parameters are trained to build the deep learning network model. The test samples are fed into the deep learning network to test the classification performance. The actual vibration signal features are fed into the trained deep learning model to obtain the risk identification results of SC finance.

4. Experimental Analysis

4.1. Data Sources. After the selection of risk factors for Jingdong SC finance, that is, after constructing the target layer, subtarget layer, and criterion layer, this paper scores these risk factors through the expert review scoring method. In the selection of risk factors for Jingdong SC finance, this paper is based on the research on SC-related financial risks at home and abroad. Through the advice of experts within Jingdong Finance, six primary indicators and 19 secondary indicators were selected. Questionnaire data from practitioners related to online SC finance and academic researchers in related fields of finance were then used.

4.2. Selection of Risk Factors for SC Finance in Jingdong. Through the results of the analysis of the risk factors of Jingdong SC finance, we selected these risk factors as the object of our study. For Jingdong SC Finance, first of all, our target layer is Jingdong SC Finance Risk. In terms of the macro aspect, the risk of Jingdong SC finance is mainly influenced by the macroeconomic and legal system. Therefore, the macroeconomic environment and the improvement of the legal system are selected as secondary indicators: For the microaspect, the risk of Jingdong SC finance mainly includes of the relationship between the e-commerce platform and bank. Overall credit risk, supply chain relationships, pledge risk, and operational risk all play an important role in the selection of risk factors for Jingdong's supply chain finance. The risk of Jingdong's relationship with banks mainly includes the degree of close cooperation between Jingdong and commercial banks, the current status of commercial banks, and the current status of Jingdong's e-commerce platform. We can represent the risk hierarchy model of Jingdong's SC finance in Table 1.

4.3. Constructing Pairwise Comparison Matrices. The "1–9 scale" is used when comparing two risk factors, i.e., on a scale of 1 to 9. Then, n secondary indicators are compared to obtain a pairwise comparison matrix, which gives the following:

$$A_{ij} = \frac{1}{A_{ji}},$$
$$\mathrm{A} = \left(A_{ij}\right)_{n\times n} = \begin{pmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{pmatrix}. \tag{11}$$

Next, we need to carry out the relative weight calculation, let the relative weight of the first level indicator A correspond to the second level indicator $A_{11}, A_{12}, \ldots, A_{1n}$ of Jingdong SC financial risk is $W_{11}, W_{12}, \ldots, W_{1n}$, and its vector form is $W1 = (W_{11}, W_{12}, \ldots, W_{1n})^T$.

A graph of the linear relationship of these factors to Tier 1 indicator A_2 is shown in Figure 4.

Credit risk A_2 is used here as an example. The results of the two-by-two comparison of the impact of the factors of the Level 2 indicator $A_{21}, A_{22}, A_{23}, A_{24}$ on Level 1 indicator A_2 are shown in Table 2 below.

The comparative effect of the relationship between the secondary indicators is shown in Figure 5.

The weights of the Tier 1 indicators were then collated as shown in Table 3 before proceeding to risk identification.

The comparative weighting relationships for these first-level indicators are shown in Figure 6, which gives a pie chart of the weights twice.

Through the weight values of each level of indicators given in Table 3, it is easy to see that among the level 1 indicators, corporate credit risk has the largest influence on the risk of Jingdong's SC finance: the next major risks are economic environment and legal and regulatory risks. The subsequent risk weights are, in descending order, the relationship risk between Jingdong e-commerce and commercial banks, platform operational risk, and the relationship risk between SC enterprises. Relatively speaking, enterprise pledge risk has the least impact weight on Jingdong's SC finance risk. Meanwhile, it can be seen from Table 3 that, in terms of enterprise credit risk, the secondary indicators that have the greatest weight on the risk of Jingdong's SC finance mainly focus on the credit status of enterprise counterparties; in economic environment and legal regulatory risk, the indicators that have the greatest impact on it are mainly legal regulatory mechanisms. In the risk of the relationship between Jingdong's e-commerce and banks is mainly influenced by the cooperation between Jingdong's e-commerce and banks and the support of commercial banks together.

The data of the above first-level indicators were randomly selected using a DCNN model, in which a total of 15,000 sample data were obtained, and the training and test sets were randomly selected in the ratio of 8 : 2. The experiments were conducted twice, and the specific composition of the data of the two experiments is shown in Table 4.

A comparison of the data set distributions for the two experiments is shown in Figure 7.

On the basis of the two data sets, five experiments were conducted on each data set in order to improve the accuracy of risk identification and to avoid the influence of chance on the experimental results, and the specific identification results are given in Table 5.

A comparison of the recognition results for the two sets of data is shown in Figure 8.

In this paper, the average value of five experiments was finally selected as the identification result of SC finance risk. The comparison results of this paper's method with other methods are given in Table 6.

A visual comparison of the recognition accuracy of the proposed method with other methods is shown in Figure 9.

As can be seen from Figure 8, compared to other research methods, the risk identification accuracy of the

Table 1: Jingdong SC finance risk evaluation system table.

Macroeconomics and legal regulation (A1)	Macroeconomic environment (A11) Legal regulation (A12)
Corporate credit risk (A2)	Corporate credit profile (A21) Corporate solvency (A22) Business development prospects (A23) Corporate credit profile (A24)
Relationship risk between SCs (A3)	Enterprise SC cooperation (A31) SC status (A32)

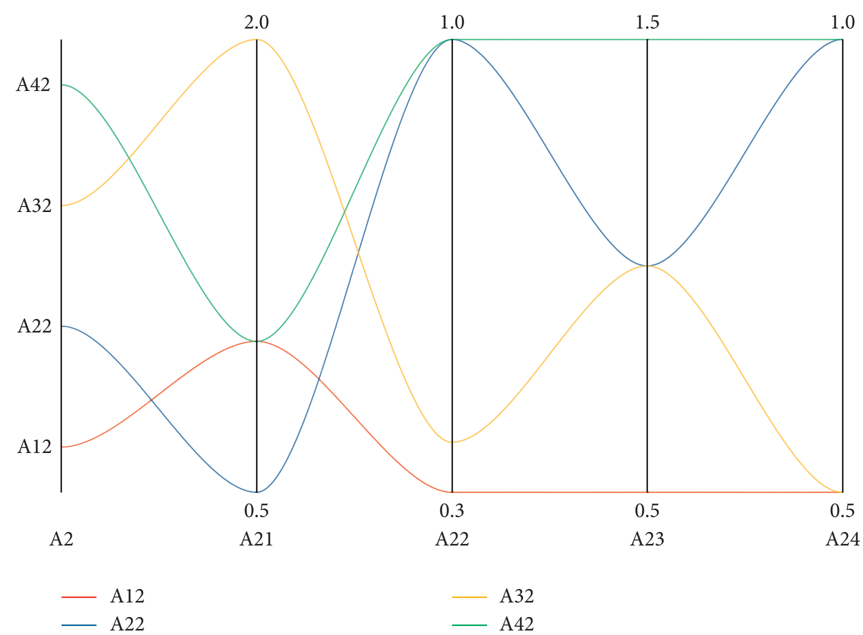

Figure 4: Linear relationship between secondary and primary indicators.

Table 2: Comparison chart of the impact of secondary indicators on primary indicators.

A_2	A_{21}	A_{22}	A_{23}	A_{24}
A_{12}	1	0.25	0.5	0.5
A_{22}	0.5	1	1	1
A_{32}	2	0.333	1	0.5
A_{42}	1	1	1.5	1

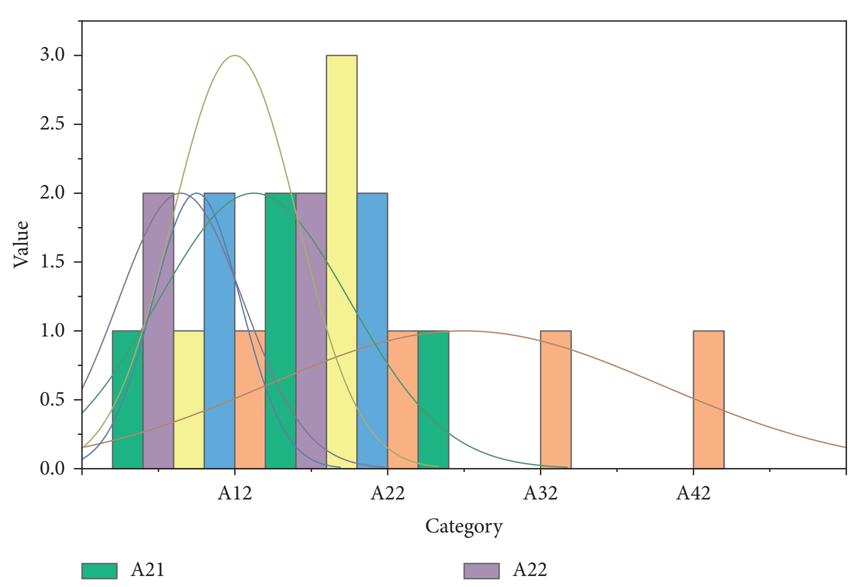

Figure 5: Comparative effect of the relationship between secondary indicators.

Table 3: Distribution of weight values for level 1 indicators.

Tier 1 indicators	Tier 1 indicator weighting values
EELR	0.222
CCR	0.300
ICRC	0.102
CPR	0.058
POR	0.150
RBRB	0.168

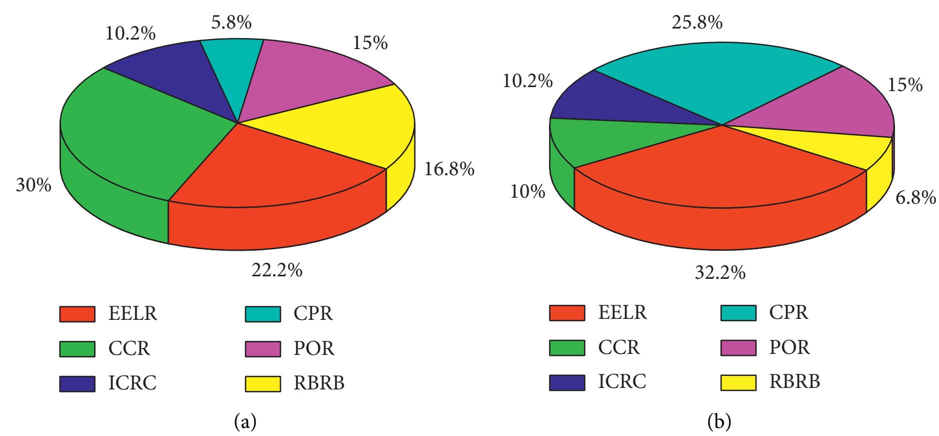

Figure 6: Comparison of the two weighted pie charts. (a) Experiment 1. (b) Experiment 2.

Table 4: Specific distribution of SC finance risk identification datasets.

Category	Experiment 1	Experiment 2
EELR	2000	2500
CCR	3000	2000
ICRC	2500	2000
CPR	3500	3000
POR	1500	2500
RBRB	2500	3000

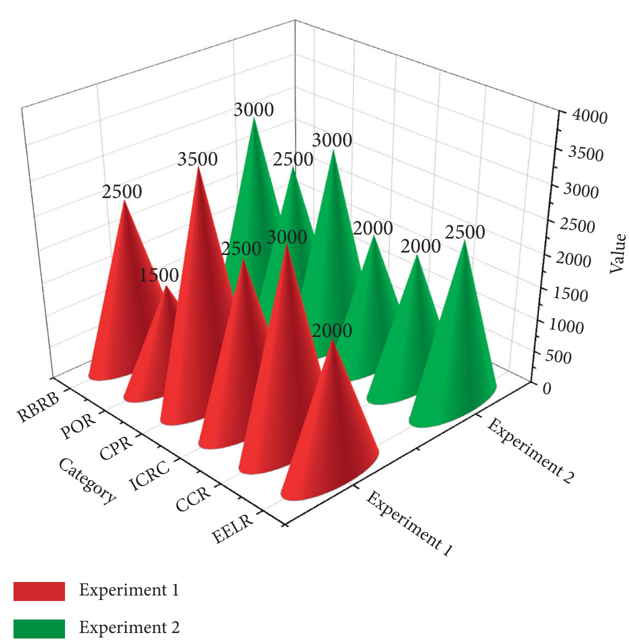

Figure 7: Comparison of the data set distribution between the two experiments.

Table 5: Five experimental identification accuracies for both data sets showing.

Category	Experiment 1 (%)	Experiment 2 (%)	Experiment 3 (%)	Experiment 4 (%)	Experiment 5 (%)
Data1	95.62	94.56	97.14	96.21	93.28
Data2	91.28	93.65	92.54	95.86	94.25

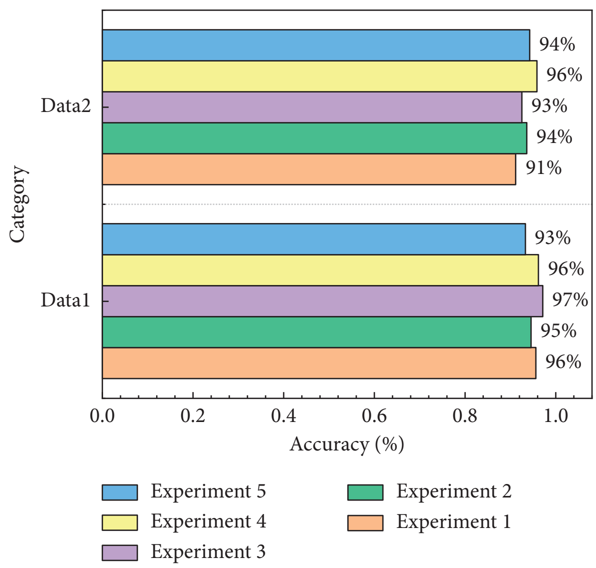

Figure 8: Comparison of the recognition results of the two data sets.

Table 6: Comparison of the results of the proposed method with other methods.

Category	Accuracy (%)
BP	89.26
LetNet-5	90.48
SVM	93.65
CNN	91.43
Proposed model	95.36

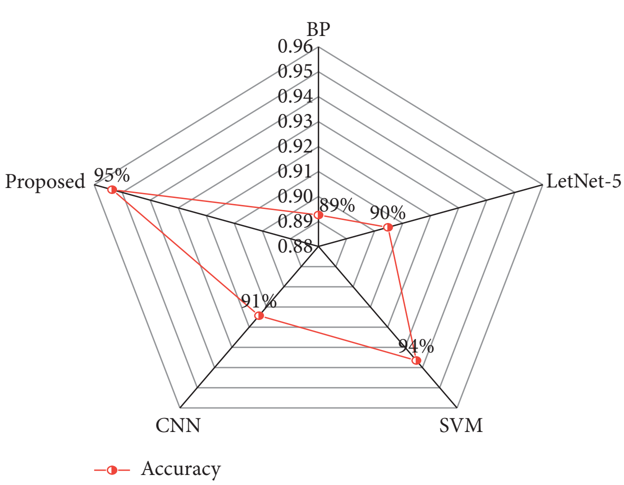

Figure 9: Comparison of the recognition accuracy of the proposed method with other methods.

proposed method has improved significantly, mainly due to the unique model composition produced, which, combined with the optimal weight selection on the data, has led to a further improvement in the identification results and validated the effectiveness of the proposed model.

5. Conclusion

Deep learning provides a way for the risk identification technology of e-commerce SC finance. The risk identification model based on DL proposed in this paper overcomes the problem of cross-interference between the components of the time-frequency analysis method and improves the effectiveness and stability of the time-frequency analysis method. The deep learning model directly processes the time-frequency image, extracts the time-frequency features of the signal, and establishes a two-layer CNN model applied to risk analysis and recognition. The results show that the model can achieve a higher accuracy rate compared with previous algorithms, providing a new way for risk recognition. Although the deep convolutional neural network model used in this paper has shown excellent performance in the process of financial risk identification, it has a longer processing time than other models and is difficult to apply in reality. Therefore, future research work should focus on improving the processing speed of the model, reducing the number of parameters in the model run, and further speeding up the processing speed while improving the recognition accuracy.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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