A Method for Identifying Abnormal Financial Products in E-business Based on Deep Learning

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Abstract. In order to study the identification of abnormal financial commodities in e-business, this article proposes an algorithm for identifying financial risks in e-business commodity transactions based on DL and CAD models. Unsupervised learning is trained by using the model gradient descent method of random automatic learning. At the same time, the algorithm uses automated distributed tables for data distribution, so as to identify the abnormal behavior in e-business transactions. The simulation results show that the accuracy of this algorithm can reach more than 90%, and the highest can reach about 95%. Its accuracy is 9.14% higher than that of traditional NN (Neural network) algorithm and 5.17% higher than that of BPNN (Back Propagation Neural Network) algorithm. Using the model constructed in this article to classify and identify abnormal behaviors in e-business transactions has good results, which can realize rapid and accurate identification requirements. It provides an effective and reliable method for identifying abnormal financial commodities of e-business.

Keywords: Deep Learning; CAD Model; E-Business; Financial Risk
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1 INTRODUCTION

Compared with traditional rule-based or manual classifiers, deep learning models have better performance and higher accuracy. They can automatically adapt to various types of abnormal financial products and do not require manual writing of rules or manual production of classifiers. However, deep learning technology requires a large amount of data and computing resources, so when dealing with large datasets, it may be necessary to consider computational costs and data storage issues. Collect abnormal financial product keywords and search on e-commerce platforms. It can perform rough screening on search results to filter out a large number of non abnormal financial products. Manually annotate the remaining results to clarify which are normal financial products and which are abnormal financial products. Balancing the proportion of normal and abnormal financial products to avoid deep learning models overly focusing on certain types of financial products. Build a model using a deep learning framework and train it. Simultaneously validate the model to ensure that it can accurately identify abnormal financial products. E-business refers to the stage of trading goods and services in the form of computer networks, such as the Internet and online social networks, or convenient trading. At present, the traditional econometric equation model or the model with parameters no longer has the ability to analyze and model the complex, high-dimensional and noisy e-business market data series. DL is inspired by artificial neural network and gets inspiration from many fields, and it is an important branch of machine learning. It is a feature learning method, which transforms the original data from a low-level simple nonlinear model to a high-level abstract model. Unsupervised learning: solving various problems in pattern recognition according to unknown training samples. DL has a strong learning ability, and its technological development has profoundly affected many fields and achieved success in more and more fields.

With the continuous exploration of the application scenarios of DL and computer vision, it provides a new idea for financial data analysis. With the increasing complexity of financial data, the demand for its analysis has increased. With the internet becoming the trend of social development, the network began to spread to all aspects of people's lives, and gave birth to various e-business businesses and network companies based on business websites. At present, the e-business platform is developing rapidly, and online shopping has become an important part of people's lives. While the e-business platform continues to develop, it also creates many risks. Commodity consumption is a scene closely related to public life, and commodity identification, as a key link, is related to consumers' consumption experience and merchants' service quality. In addition, the quantity of 3D CAD models has increased geometrically in recent years. How to process, analyze and understand a large quantity of 3D CAD models has become the focus of research in the field of digital geometry. Different from the traditional methods, DL algorithm can make the machine learn features and classification automatically, and it has excellent performance in the field of images in recent years. As the intuitive information of the model, the view conforms to the human visual system and can be used as the input information of DL. In order to study the identification of abnormal financial products in e-commerce, combined with previous literature research, this paper proposes a financial risk identification algorithm for e-commerce commodity transactions based on DL and CAD models. The simulation results show that the model constructed in this article has good classification and recognition performance for abnormal behavior in e-commerce transactions, and can achieve fast and accurate recognition requirements.

2 RELATED WORK

Alghofaili et al. [1] conducted an emerging deep learning CAD assisted research on internet financial fraud. In current e-commerce enterprises, financial fraud often poses a system threat through unauthorized access and abnormal attacks. It proposed a true dataset model for automatic encoding of big data and validated it using current detection techniques. Cao et al. [2] have completed the construction of a risk warning mechanism for e-commerce finance. It analyzes and predicts financial risk warning from the perspective of deep learning. Chin et al. [3] innovated from the perspectives of machine learning and the Internet of Things, and constructed new ideas and methods through the core issue of anti-counterfeiting in e-commerce. Dang et al. [4] used blockchain technology and a deep learning model assisted by CAD for risk warning in the e-commerce financial chain market. It has predicted potential risks and conducted effective data analysis models using a high credit and reliable supply chain application system. Du and Shu [5] have conducted comprehensive and effective personal credit assessment management on the current e-commerce application market. A deep learning network credit scoring application model is proposed to address the potential risks of financial enterprises. This model adopts an application model of bidirectional network and recursive network to evaluate the scale management system of integrated financial credit. Jan [6] analyzed the operational sustainability of financial data for current listed companies and the operational model of the capital market. Through the inspection and investigation of financial data, it analyzes the deep learning algorithm detection model of long-term and short-term memory. Kolli and Tatavarthi [7] conducted specific data processing for financial product fraud detection mechanisms. By using transformations to preprocess the data, a deep recurrent neural network classifier is used in the detection stage of the feature set to achieve the fraud detection process. Lei [8] conducted a decision support model analysis on decision-making investment in e-commerce. It studied the background of e-commerce investment objects with the internet as the background, and analyzed the decision-making level of investors by evaluating the number of company decisions using deep learning algorithms. In order to maximize the value of electronic order arrival prediction in daily operational decisions, real-time prediction of electronic order arrival for a single retailer is crucial. Leung et al. [9] conducted phased adaptive neurofuzzy inference using the proposed machine learning prediction method. It has developed a framework for analyzing data characteristics based on time series, which enables practitioners to conduct adaptive phase testing.

Li et al. [10] proposed a CAD assisted neural network financial management risk management algorithm. The accuracy analysis of the optimized company's financial distress prediction results has proven the effectiveness of its algorithm. Lin [11] conducted a financial risk loss classification assessment for commercial banks based on current financial risk analysis. It constructed and analyzed a loss mathematical model through the big data internet. Combining CAD technology and applying BP neural network algorithm, the financial warning of internet enterprises was trained. Liu et al. [12] used a large number of e-commerce datasets for machine learning algorithm risk warning. The results show that the machine algorithm assisted by CAD has good application effects on the intelligent business platform, and the experiment used the principle of sensitive learning Bayesian algorithm to analyze the scalability of large-scale data. Liu et al. [13] conducted deep learning models and neural networks for capacity risk warning analysis and prediction. By analyzing the risk theory of e-commerce development under the influence of the Internet and the algorithm data image based on deep learning, a BPNN based financial risk early warning and timely environmental stability model has been constructed. MatuszelańSki and Kopczewska [14] conducted machine learning limit gradient enhancement and logistic regression. The quality of the model was verified through the area and lift indicators under the curve. Wang and Zhang [15] have conducted various machine learning analyses in this direction, represented by deep learning. Through CAD assistance, it collected integrated data with high model prediction performance. The qualitative analysis of financial risk source is realized by improving the allocation neural network. Yang et al. [16] conducted technical and financial extraction analysis of Big data. It has optimized sustainable strategic development through efficient financial management models through enterprise development. Through the strategic finance of enterprise development, it effectively extracts the Big Data information of technical financial analysis. Zeng [17] conducted an optimization model for enterprise financial management prediction using edge service preloading. The financial risk warning system has been improved through timely prediction of cooperative information risks based on the early warning indicators of e-commerce financial companies. Zhang et al. [18] conducted a multi perspective analysis of investor sentiment index in the securities market of listed companies. We have established an investment system for risk warning indicators under financial risk control. It has established a multi indicator model based on support vector machines for early warning, improving financial security under traditional financial indicators. Zioviris et al. [19] discussed various machine learning algorithms and data processing techniques used by financial institutions for fraud detection. Intended to gain a deeper understanding of the work of financial fraud protection systems and evaluate the cost components of each transaction and the impact of each misclassification made by machine learning models.

3 DL TECHNOLOGY AND CAD MODEL

Internet finance has undergone a combination of traditional industries and new fields of development, among which the financial model with e-business platform as the core is undoubtedly the most striking one. However, different from the traditional financial model, the internal and external environment faced by e-business finance is more complicated and changeable, and its development faces many risks. Compared with the traditional machine learning method, the deep architecture of DL with multi-layer abstract structure has stronger learning ability. Combined with effective learning algorithm, DL can intelligently learn the feature data itself and learn the unlabeled data. It transforms the original data from a low-level simple nonlinear model to a high-level abstract model. DL is the intersection of NN, image modeling, optimization, pattern recognition and signal processing. Typical models of the third generation NN include CNN, BPNN, etc. With the framework of DL, when building NN, it is only necessary to call the module that conforms to the data set under study. Standard NN is composed of basic neurons. In the layer-by-layer greedy unsupervised network, the parameters of each layer are only controlled by the input of the current layer, so it is possible to pre-train unsupervised layer by layer, and then fine-tune the network parameters with supervision, forming a new training mode of "all iteration-updating single layer". The network structure and DL model of basic neurons are shown in Figure 1.

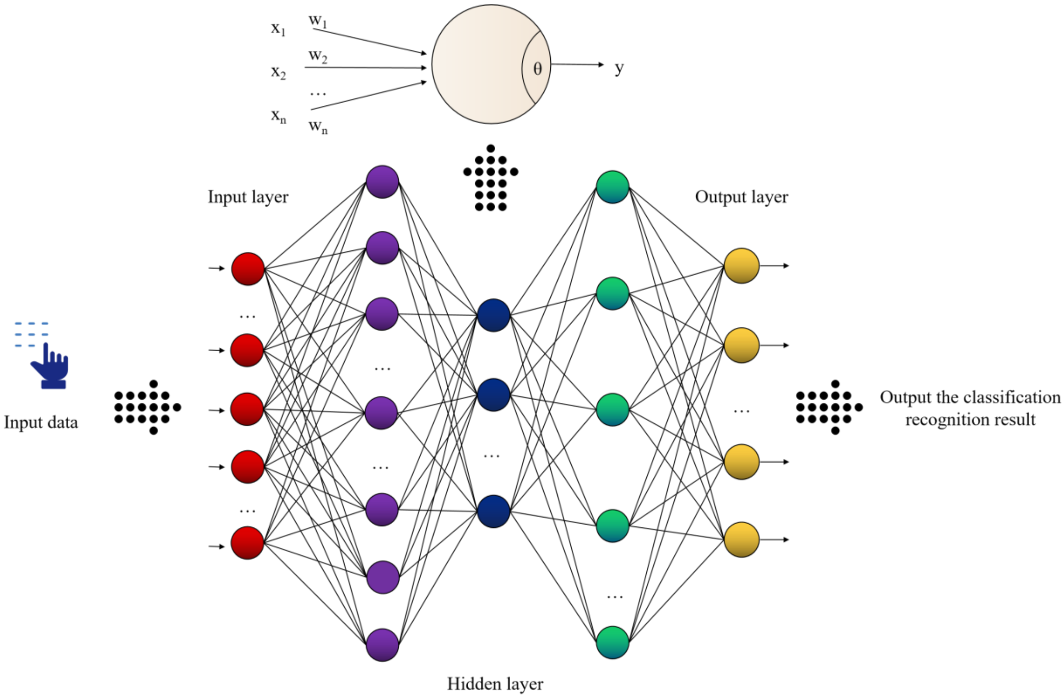

Figure 1: Network structure and DL model diagram of neurons.

Where x_1 and x_2 represent input vectors, w_1 and w_2 are weights. Multilayer perceptron is a typical model. Perceptron is composed of linear combiner and hard limiter. The summing node in NN calculates the linear combination of inputs and applies it to neurons, which contains bias. The sum result is applied to the hard limiter, and if the input of the hard limiter is positive, the output generated by the neuron is+1; If it is negative, the output is -1. The functional relationship expression of NN model is:

$$y_i = sign\left(\sum_i w_{ji} x_i - \theta_j\right) \tag{1}$$

Among them, the input and output are binary quantities; w_{ji} is a fixed weight. After determining the network weights and parameters, the output of NN can be expressed as:

$$y_j = \sum_{i=1}^{h} \omega_{ij} \exp\left(-\frac{\left\| x_p - c_i \right\|^2}{2\sigma^2} \right), j = 1,2,3,\ldots,n \tag{2}$$

Where ω_{ij} is the weight of hidden layer and output.

According to the different input information of DL model, DL algorithm for 3D CAD model can be divided into: DL algorithm based on incomplete representation of 3D model; DL algorithm based on original representation of 3D model. If feature descriptors are extracted from the view information of 3D model or the model itself as the input of DL model, it is called DL algorithm based on incomplete representation of 3D model. The input descriptor is an incomplete three-dimensional model feature, which excessively extracts the information of the model. If the original representation of the model is taken as the input signal of DL, it is called DL algorithm based on the original representation of 3D model. In the field of financial risk, DL is mainly used to predict and evaluate risks. Different from the traditional methods, DL model does not need to make assumptions and estimate the variance of the distribution of returns. In machine learning, labeled data refers to the data whose classification results are already known, and the network output can be compared with these data. Unmarked data refers to data whose classification results are unknown. The DL algorithm can be used to train without labeled data.

Automatic encoder consists of three layers of network: input layer, coding layer and decoding layer. Automatic encoder belongs to the category of unsupervised learning, which uses unlabeled samples. Stack automatic encoder and depth confidence network model are composed of automatic encoder and restricted Boltzmann machine in series. When dealing with a large quantity of data, this kind of structure has unsupervised learning. Suppose there are N samples, each sample has p features, and the input sample is x. The automatic de-noising encoder first destroys the input sample x, that is, by sampling from binomial distribution, the automatic de-noising encoder will randomly destroy the subset of samples and introduce noise. The formula is as follows:

$$n = N \quad p = p_q \tag{3}$$

The denoised automatic encoder maps the damaged input x to the high-level representation y, and the mapping process is carried out through a layer of hidden NN. Given the weight matrix W, deviation b and coding function $h(\cdot)$, y can be expressed as:

$$y = h(Wx + b) \tag{4}$$

The decoder reconstructs y into z, which has the same structure as the input x. z can be regarded as a prediction of x. The stage of reconstructing z is a denoising process, which reconstructs the input according to the corrupted sample x. Similar to the encoder, the weight matrix $\tilde{W}$, deviation $\tilde{b}$ and decoding functions $g(\cdot)$ and z of a given decoder can be expressed as:

$$z = g\left(\tilde{W}y + \tilde{b}\right) \tag{5}$$

During the training of the automatic encoder, a new signal will be generated at the decoding layer for each training sample. The function of offset is to shift the boundary area from the original position. The synaptic weight of perceptron is adjusted by iteration, which adopts error correction rules and is called perceptron convergence algorithm. Its application not only promotes the improvement of prediction methods in this field, but also optimizes the algorithm suitable for deep network and solves the invalid training problem, which brings the progress of traditional empirical application research methods.

4 CONSTRUCTION OF ABNORMAL FINANCIAL GOODS IDENTIFICATION MODEL OF E-BUSINESS

This article applies the depth NN model and CAD model to the financial risk identification of e-business commodity transactions to study the identification of abnormal financial commodities in e-business. For depth NN, the deepening of network layers usually means that richer features can be extracted. But this does not mean that the network can learn better simply by stacking more layers. Different from the traditional NN structure, the residual network uses the residual block structure, which makes the network deeper and still has lower complexity. This makes it easier to optimize the depth residual network. In the financial risk identification of e-business commodity trading, the deep confidence network is combined with multi-layer perceptron to identify the financial risk of e-business commodity trading, and the identification model is divided into multi-layer perceptron module and deep confidence network module. Among them, the deep confidence network module is used to receive input signals and learn the features of input data, so that higher-level abstract features can be obtained, while the multi-layer perceptron module performs classification tasks in the recognition model. The model standardization formula is:

$$\bar{\mathrm{x}}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \tag{6}$$

Where:

$$\begin{cases} \mathrm{x}_j = \dfrac{1}{n}\sum_{i=1}^{n} x_{ij} \\ s_j = \dfrac{1}{n-1}\sum_{i=1}^{n} (x_{ij} - x_j)^2 \end{cases} \tag{7}$$

The initial decision table composed of standardized data is used to construct the difference matrix and reduce the attributes.

For consumers, when entering the main page of a product display, they usually pay special attention to the indicators of "description, service and logistics", product details, cumulative evaluation and transaction records. This article collects the registration information, order details, logistics information and payment information of consumers, and analyzes the transaction behavior from the aspects of consumers, commodities, orders and logistics, so as to identify the abnormal financial risk behavior of e-business commodities. The CNN model structure of e-business abnormal financial goods identification is shown in Figure 2.

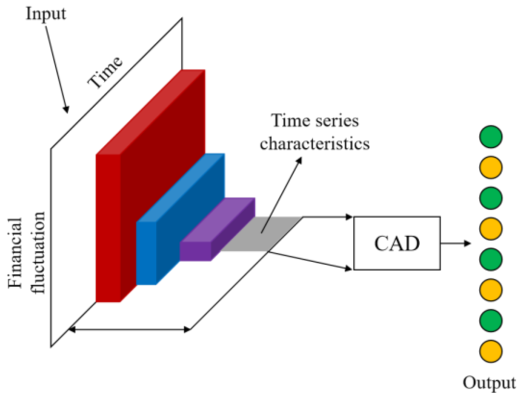

Figure 2: CNN model for identifying abnormal financial products of e-business.

In this article, the commodity statistical characteristics of three-dimensional model are taken as the input of DL model. The specific process is as follows: the geometric features of the three-dimensional model are counted, and the D2 descriptor is obtained, and then it is input into the depth belief network for classification. The extraction stage of D2 descriptor is as follows: firstly, the 3D model is discretized so that the surface of the 3D model is composed of triangular patches; Discrete points are randomly generated on the surface of triangular patch, and the Euclidean distance between any points is calculated to obtain the probability distribution expression of three-dimensional model. In traditional NN, the elements of a weight matrix are often used only once and will not be used again. In this network, every element will affect every position of the input. This parameter sharing can realize feature extraction by training only one set of parameters without training individual parameters. It is obvious to optimize the parameters by this method. Two-dimensional time series is obtained through data statistics:

$$f_1(T_n) \quad f_2(T_n) \tag{8}$$

The identification of financial risks in e-business commodity trading is transformed into the detection of abnormal points in two-dimensional time series. The points in the time series are fitted into broken lines respectively, and then the abnormal points on the broken lines are found. Digitize the commodity information, and then accurately identify the commodity number corresponding to the abnormal data, and find the corresponding commodity through the commodity number. Among them, in the data processing stage, the information of shops and commodities is digitized to improve the processibility and ensure the final positioning accuracy.

The DL network classifier in this article consists of one input layer, four hidden layers and one output layer, and the quantity of neural units in each layer is 1200, 12, 120, 36, 8 and 1. In order to train the network, the algorithm assigns a label to each anchor point, and realizes multi-classification tasks through Softmax classifier. IoU is defined as the following formula:

$$IOU = \frac{A \cap B}{\mathrm{A} \cup \mathrm{B}} \tag{9}$$

Where: A and B represent the set of two border areas, and IOU is the ratio of the intersection and union of the predicted border and the real border. Thus, a multi-task loss function is defined, such as the formula:

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) \tag{10}$$

$$L_{cls}(p_i, p_i^*) = -\log\left[p_i^* p_i + (1 - p_i^*)(1 - p_i)\right] \tag{11}$$

Among them, the greater the L_{cls} value, the greater the difference between the predicted value and the real value.

The storage form of three-dimensional model in computer is triangular patches, and voxelization is the stage of transforming these geometric representations into voxel representations of three-dimensional space. Voxelization can be divided into binary voxelization and multivalued voxelization. The value of binary voxel model depends on whether the voxel space is occupied by the model. If a voxel is completely occupied by the three-dimensional model, the value is 1, and if the model is no longer in the voxel space, the value of this voxel is 0. The value of multivalued voxelization is in the interval of [0-1]. Due to the increasing and updating of the training set of the identification system, the system will learn new financial risk behaviors of abnormal trading of e-business products, thus increasing the accuracy of identification.

5 MODEL SIMULATION TEST

In order to study the identification of abnormal financial commodities in e-business, this article proposes a financial risk identification algorithm for e-business commodity transactions based on DL and CAD models. In this section, an experimental simulation platform is built to simulate the algorithm model. Use the network information collection software to collect various data of e-business, including the cumulative quantity of comments, the quantity of successful transactions, the collection of treasures, the dispute rate of refund, the registration time of the store, the record of commodity sales and the record of commodity comments. The CAD model and OpenCV visual library are used to preprocess and expand the data of commodity images, and the NN model is iteratively trained by TensorFlowDL framework. Pre-process the data before starting. The specific processes include: data import, data cleaning, data classification, category feature and time feature processing, text feature processing, target statistics and cross-engineering. In the data processing stage, by merging data, deleting duplicate values, filling blank values, and converting data types into int and float, so as to obtain standard, clean and continuous data for later use. Firstly, the algorithm is trained for many times. Select four of them and draw them into a data graph. The training results of the algorithm are shown in Figure 3.

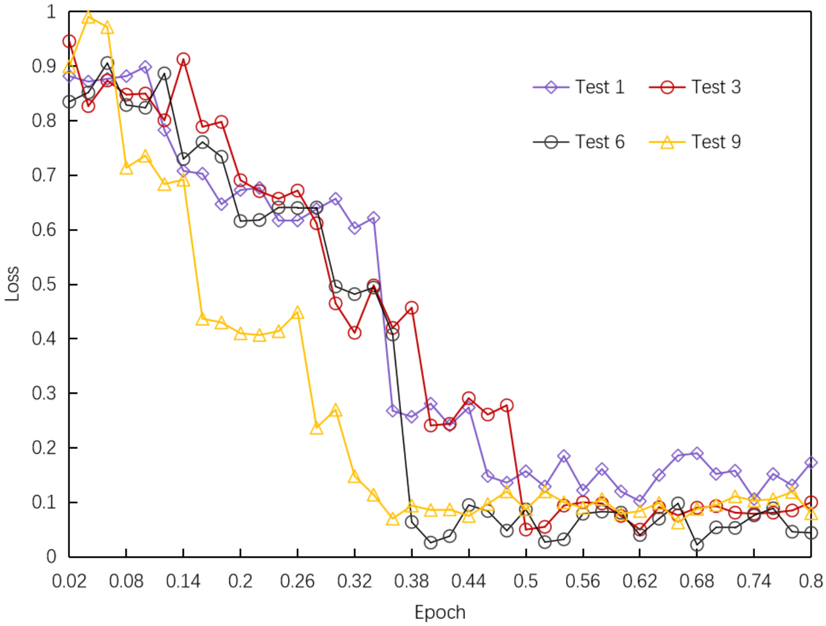

Figure 3: Algorithm training situation.

Suppose traders are divided into 10 different groups, and traders in the same group share a trading style. Using non-distributed representation requires 10 different feature functions to represent each cluster, while distributed representation only needs 6 features to model the cluster. Table 1 shows the RMSE test results of the algorithm.

Iterative index	*RMSE*	*Iterative index*	*RMSE*
80	0.748	180	0.53
90	0.767	190	0.577
100	0.782	200	0.553
110	0.717	210	0.553
120	0.76	220	0.55
130	0.739	230	0.555

140	0.522	240	0.509
150	0.553	250	0.507
160	0.563	260	0.534
170	0.568	270	0.507

Table 1: RMSE test results of the algorithm.

In order to further verify the reliability and superiority of the algorithm, the RMSE comparison of different algorithms is shown in Figure 4.

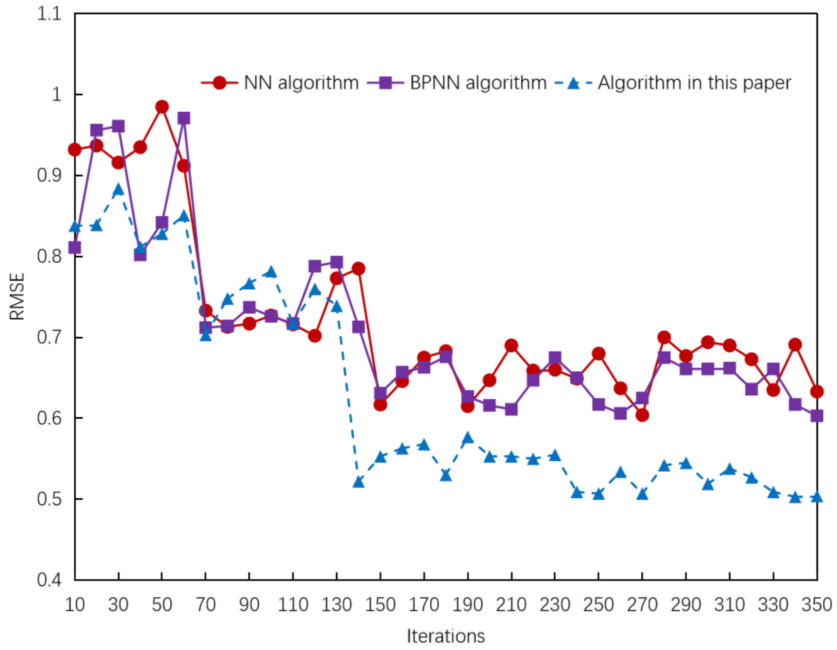

Figure 4: RMSE comparison of the algorithm.

The content of Figure 4 shows that the algorithm proposed in this paper has more advantages compared to traditional testing algorithms. The method proposed in this article reduces the quantity of parameters by sharing weights, and also extracts salient features. By changing the parameters of gradient descent algorithm, the accuracy of the model is greatly improved. Therefore, compared with the traditional NN algorithm and BPNN algorithm, the RMSE of the algorithm proposed in this article is smaller and the accuracy is improved more.

In DL, the larger the amount of data, the better the performance of the trained model. However, in reality, there will be problems such as limited data needed for training, or inability to obtain a large amount of data for various reasons. In this article, the original data set can be expanded by data enhancement, so as to make the trained network model more robust. At the same time, the model is simply adjusted, and the network parameters trained in the ImageNet competition are used as the initialization parameters of the commodity identification network, and then the network weights are adjusted by using the marked financial risks of e-business commodity transactions by using the back propagation and random gradient descent methods until the model reaches a certain accuracy. The accuracy rate indicates the probability that the sample predicted to be positive is a true positive sample. The calculation method is as follows:

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{12}$$

The numerator in the formula indicates and the denominator indicates how many samples are predicted to be positive. Taking it as an index, through many experiments, the precision comparison results of several algorithms are shown in Figure 5.

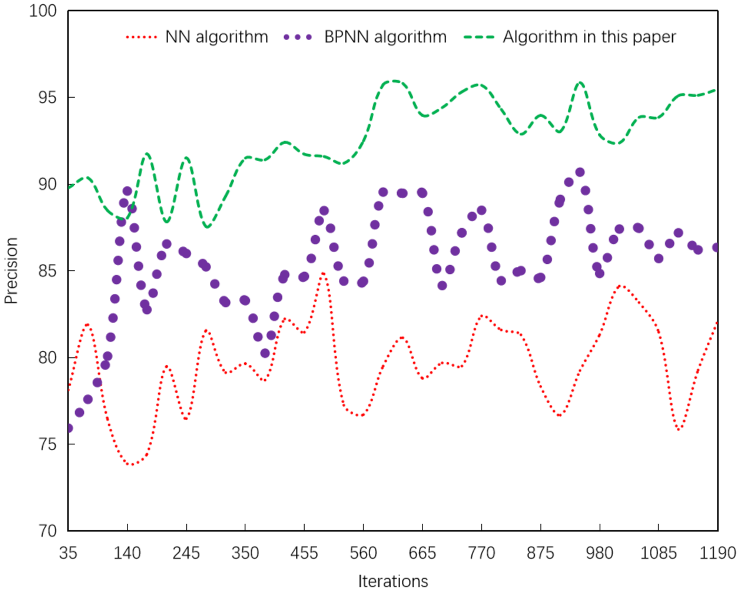

Figure 5: Accuracy comparison chart of the algorithm.

By cross-validation, the initial learning rate is finally determined to be 0.0001. After a series of processing and training, the NN model and parameters with certain accuracy and stability are obtained, which are verified by the test set. Figure 6 shows the false alarm rate of the abnormal financial commodity identification model of e-business.

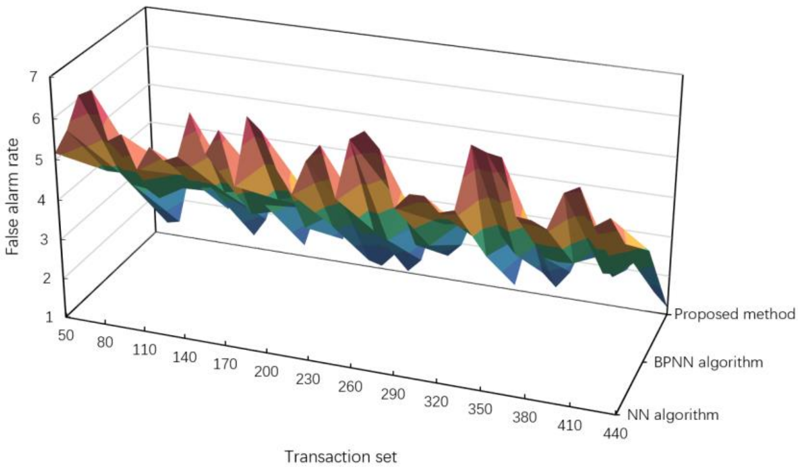

Figure 6: Comparison of false alarm rate.

For the three-dimensional model of the model database, the placement position of the model is arbitrary. In order to make the extracted two-dimensional view uniform, the three-dimensional model is often preprocessed before the view extraction of the model. The view extraction algorithm in this article needs to place the model along the centroid axis, so this article will do translation normalization. For the case that the new data set is small and similar, in order to reduce the over-fitting, the original network can be frozen and used as a feature extractor to retrain the classifier. When the new data set is large and similar, fine-tune the whole network. The test results of model stability are shown in Table 2 and Figure 7.

Transaction set	*Literature [9] method*	*Literature [11] method*	*The method in this article*
600	84.839	75.462	90.42
625	88.655	76.131	95.907
650	87.652	77.911	91.186
675	76.394	81.736	94.27
700	81.653	79.821	92.944
725	82.751	76.458	90.6
750	71.156	78.545	90.845
775	73.054	71.37	92.46

Table 2: Experimental results of stability of the algorithm.

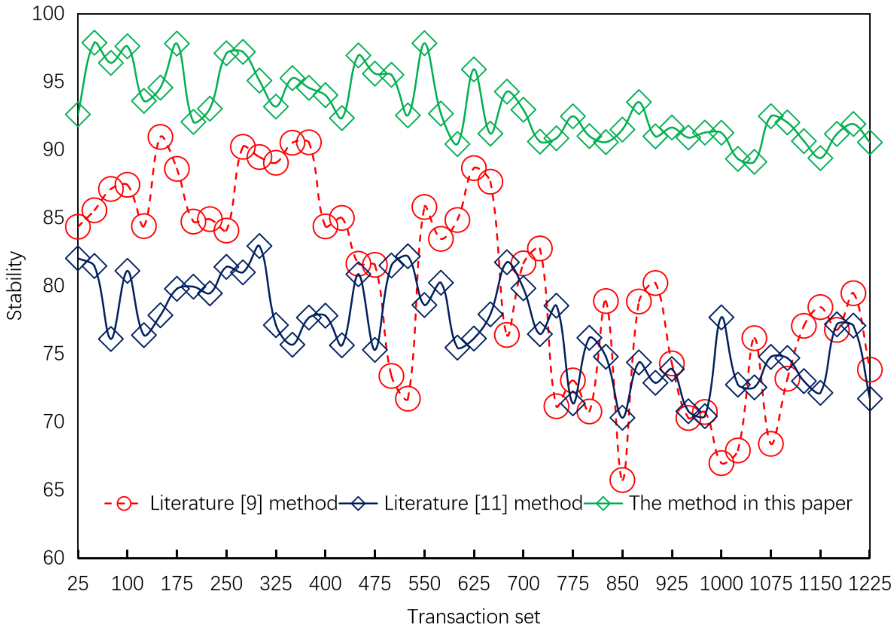

Figure 7: Stability comparison of models.

The test results in this section show that the accuracy of this algorithm can reach more than 90%, and the highest can reach about 95%. Its accuracy is 9.14% higher than that of traditional NN algorithm and 5.17% higher than that of BPNN algorithm. In addition, the response speed of the algorithm in this article is fast, which can basically be kept at about 3s, and it has high stability and small RMSE. Compared with traditional NN algorithm and BPNN algorithm, the algorithm proposed in this article has more advantages. Generally speaking, the model constructed in this article can quickly and accurately identify abnormal financial products of e-business. The effective application of DL and CAD modeling methods in identifying abnormal financial products in e-business will greatly accelerate the processing speed of financial data, reduce labor costs, and promote the optimization of financial risk management processes.

6 CONCLUSIONS

Among which the financial model with e-business platform as the core is undoubtedly the most striking one. However, different from the traditional financial model, the internal and external environment faced by e-business finance is more complicated and changeable, and its development faces many risks. The strong performance of DL in recent years proves the great advantages of this technology in the field of financial risk. Its application perfects the forecasting and analysis methods in the field of financial risk management. This article analyzes the causes of financial risks in e-business commodity trading, and deeply combines DL model and CAD model to propose a new financial risk identification algorithm for e-business commodity trading. In this article, the stochastic gradient descent method is used to optimize the model algorithm, and the abnormal behavior in e-business transactions is identified by analyzing the massive transaction data. Many test results show that the accuracy of this algorithm can reach more than 90%, and the highest can reach about 95%. Its accuracy is 9.14% higher than that of traditional NN algorithm and 5.17% higher than that of BPNN algorithm. Compared with traditional NN algorithm and BPNN algorithm, the algorithm proposed in this article has more advantages. The results of experimental evaluation confirm the effectiveness of recognition based on DL and CAD model. The model can be used to identify abnormal financial products of e-business quickly and accurately.

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