Research Article

Analysis and Application of Enterprise Performance Evaluation of Cross-Border E-Commerce Enterprises Based on Deep Learning Model

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With the rise and gradual development of the Internet, today’s era has been transformed into the information age. The network transaction mode has involved all levels. At the same time, a new business model is gradually emerging, that is, e-commerce enterprises. Compared with the traditional business model, e-commerce enterprises are more information technology, networking, and convenience. In the current cross-border e-commerce enterprise development model, e-commerce enterprise performance evaluation and application have always been a key concern. Based on the lag of performance calculation and analysis of cross-border e-commerce enterprises, this paper carries out experimental analysis by combining the in-depth learning model. The results of the experiment are as follows: (1) it analyzes the growth situation of overseas Internet sales enterprises, determines the research direction of the experiment, puts forward the construction principles of the performance index system of overseas Internet sales enterprises, and constructs the performance evaluation system of overseas Internet sales enterprises according to the principles, to ensure the reliability of data and effectiveness of performance accounting. (2) On the basis of retaining the traditional performance calculation and evaluation mode of cross-border e-commerce enterprises, the in-depth learning mode is integrated into the performance evaluation process of overseas Internet sales enterprises. Using the in-depth learning mathematical algorithm combined with the enterprise performance calculation algorithm of cross-border e-commerce enterprises can not only ensure the effectiveness of performance calculation but also classify more quickly, facilitate the later use, and reduce the pressure on business enterprise enterprises.

1. Introduction

To optimize the performance of perceptron, a computing algorithm combining the deep learning mode and the computing network protocol is designed. Saemda designed a feature extraction and classification model to extract and classify the data features of nodes in each cluster and then send the features fused in the same class to the sink node. The simulation results show that under the condition of similar energy consumption, the data fusion accuracy of Saemda can be improved by up to 7.5 percentage points [1]. In many countries, flash floods cause loss of life and heavy property losses. If land use planners and emergency management personnel properly use flood sensitivity maps, flood sensitivity maps can help reduce flood risk in areas vulnerable to this hazard. The main purpose of this study is to use a new modeling method to draw an accurate flood sensitivity map for the Haraz basin in Iran. This method is based on the back-propagation (BP) algorithm optimized by the depth belief network (DBN) and inheritance algorithm. The method of this experiment is to collect the factor indicators of the target flood location through the accounting and prediction technology and establish the factor indicator database. Machine model algorithm and depth learning method are used to build the target model frame, and factor indicators are considered to predict the location and time of
the flood. The validity of the model is ensured by evaluating the built model [2]. When people travel, the choice of means of transportation plays a vital role in the design and improvement of railway products. With the continuous innovation of science and information technology, the application of in-depth learning model has spread all over various fields. This paper is based on the data of passengers’ ticket purchase. Study the choice of transportation mode for passengers, and make statistics on the choice of high-speed trains and seats according to passengers’ tickets. Experimental data show that this method is highly persuasive [3]. The uniqueness of constructing a computing network is that it can self-generate a network even without the necessary equipment. So, it has been widely used in the military field, emergency relief, road traffic, and other fields that need temporary communication. If the test result is harmful, the alarm will be triggered. Therefore, it can help us prevent the extensive expansion of harmful factors. This method can be used as a hazard alarm. Whenever a hazardous factor enters, the alarm can sense and give an alarm. In the experiment, we add the deep learning method to the alarm, because the deep learning method has high accuracy and effectiveness. Next, we use DNN, convolutional neural network (CNN), and long-term and short-term memory (LSTM) detection models to detect XSS and SQL attacks. The results show that the time efficiency between the two methods is acceptable [4]. In order to further optimize the accuracy of expressway camera monitoring and better monitor the road driving conditions, the expressway management department handles and inspects the corresponding projects. The depth learning model is integrated into the intelligence of the highway camera, and the daily running vehicles and road conditions of the highway are counted according to the designed depth learning framework. At the same time, the microscopic simulation software is used to simulate the traffic flow, which further verifies the feasibility of the LSTM algorithm [5]. Overseas warehouses, bonded warehouses, international express delivery, and postal parcels are the main logistics channels of overseas Internet sales. The innovation research of joint warehousing and distribution is to use informatization to promote the integration of warehousing and distribution resources and provide integrated warehousing and distribution services. It is applicable to small and medium-sized and micro cross-border e-commerce enterprises [6]. As for the intuition is not obvious and multifaceted strategy that makes the trouble integrated unaware of 8 information, some intuitionistic fuzzy operation processes will introduce all the operational processes that determine the attribute weights based on their information entropy, in which the attribute weights are determined and then established. 18 pieces of information give the weighted Hamming distance between each international and active solution and then recalculate according to other weighted Hamming distances, so as to finally calculate the relativity of active solutions and evaluate the logistics service quality [7]. With the advent of big data and its application in the development of enterprises in various fields, it plays an important role. Of course, integrating big data technology into overseas Internet sales model is indispensable for enterprise development. At the same time, in the process of overseas Internet sales, there are a large number of unqualified low-quality supply products and rude after-sales services. Therefore, the research direction of this paper is to formulate correct and effective enterprise management and development planning and analyze the environmental factors around product supply according to big data technology. Using the success factors of multinational corporations for reference, the summarized marketing development model was applied to local cross-border enterprises. It was found that compared with the previous marketing model, management model, and strategic planning, the effect has been significantly improved, and overseas Internet sales enterprises integrating big data technology have made higher-level achievements [8]. With the rise of the Internet field, business enterprises under the Internet continue to develop. In recent years, the number of e-commerce transactions has gradually increased. Overseas e-commerce has opened the barrier for overseas sales and established a bridge to the overseas market. The purpose of this study is to establish an environmental protection sales model according to the overseas e-commerce sales model and construct an effective sales relationship between suppliers and customers. Through the actual browsing and analysis of the historical data of each sample data, the deep learning mode is integrated into the simulation experiment. This chapter divides the supply source business model of environmental protection into sectors, and optimizes and improves the functions of each supply sector. E-commerce enterprises can improve the efficiency of commodity supply and meet customers’ needs through the supply functions in different sectors and further optimize the functionality of each sector through the feedback of customers’ needs. In this paper, the factor indicator check method is used to check multi-experimental pattern, and the standard deviation and variance are used to check the correlation between clues [9]. With the acceleration of economic globalization, China’s cross-border e-commerce has entered the track of rapid development. Nowadays, the development speed of cross-border e-commerce has far exceeded the growth speed of traditional foreign trade, and cross-border e-commerce which plays a leading role in overseas Internet trade. This paper selects nine indicators, such as human resources, financial resources, market share, and market growth rate, to build a competitiveness evaluation model of cross-border e-commerce enterprises based on factor analysis. The main influencing factors of competition are of great significance to enhance the overall level of overseas Internet sales in Shandong Province [10]. Over the theory of human error, an enterprise safety culture index system is established, which mainly includes the decision-making level, management level, implementation level, and external environmental factors. Then, considering the data constraints and trying to use the factor index system to mine the advantages of data processing in the content components, design various enterprise data security accounting models that conform to the factor index system. This model shows the methods that can be used for enterprise data security accounting, and this model also provides a guarantee for enterprise data security.

2.1. Overview of Cross-Border E-Commerce. E-commerce is a kind of commercial activity, which combines commerce with modern information technology. It can generally refer to commercial activities all over the world. In the process of carrying out commercial activities, sellers and consumers can realize online transactions. When using web servers, consumers can shop and trade online. As a new business operation mode, e-commerce can accelerate the economic acquisition of overseas trading enterprises. The transformation of enterprise production and management has provided development space for the development of traditional business activities. Cross-border e-commerce mainly applies e-commerce in the field of foreign trade. When realizing various logistics processes such as transactions, it can be carried out through various activities on the international business platform. Cross-border e-commerce has the characteristics of timeliness and high profitability.

Initiation and gradual development based on Internet, e-commerce has developed rapidly, various online shopping platforms have emerged endlessly, and cross-border e-commerce has gradually broken through regional restrictions and ushered in explosive growth. Since the offline transaction, payment, logistics, and other processes have been electronic, online transactions have become increasingly popular. Through the electronic network platform for purchase and consumption, and through cross-border logistics to complete the transactions between merchants and users, it has gradually met the various needs of different groups. In recent years, the Internet transaction mode has been deeply loved and used by major enterprises and has facilitated the needs of customers.

2.2. Construction Principles of E-Commerce Enterprise Performance Index System. Accurate and effective performance statistics can analyze the required information from data statistics, study the development of overseas Internet e-commerce, predict the future trend of e-commerce enterprises, and provide objective and effective development strategies and decision support for the national government, e-commerce enterprise managers, and enterprise investors. Analysis of the income of Internet overseas trade enterprises should follow the following principles.

2.2.1. Purposive Principle. The performance results of overseas Internet sales enterprises directly affect the subsequent strategic planning. In order to achieve the strategic planning prominently, the strategic objectives of cross-border e-commerce enterprises should be determined to ensure that the performance evaluation fully serves the cross-border e-commerce enterprises.

2.2.2. Systematic Principle. The overseas Internet trading system is a multifunctional and public-oriented platform, in which the interaction links are complex and the functions are numerous. Therefore, there must be a logical relationship between the indicators and the overall system, in order to conduct a comprehensive and complete performance evaluation of e-commerce enterprises from the perspective of all aspects of e-commerce enterprises.
2.2.3. Scientific Principle. The design of the indicator system and the selection of evaluation indicators must be based on the principle of scientificity and reflect the actual operation of overseas Internet sales enterprises in order to be objective and reasonable.

2.2.4. Principle of Practicality. This principle requires that the performance evaluation index system constructed should be operable. After the system is constructed, the required data can be collected and processed, and the results can be obtained through comparative analysis. The selected indicators should be simple, clear, micro, and easy to collect.

2.2.5. Principle of Balance. When building the system, we must ensure the balance between various application indicators. Macro and micro indicators and static and dynamic indicators are all issues that need attention. The balance of indicators is also one of the characteristics of e-commerce enterprise performance evaluation.

2.2.6. Economic Principle. In the process of collecting, preprocessing, mining, and analyzing the performance indicator data of e-commerce enterprises, the operating cost must be controlled within a controllable range, and the subsequent income should be greater than the initial input cost, and otherwise, the establishment of the indicator system and the data processing process must be readjusted.

2.3. Framework of Performance Index System Construction Model for E-Commerce Enterprises. Through the crawler technology and log files of data collection in big data technology, the relevant information about the production and operation data of e-commerce enterprises is obtained. This paper uses the balanced scorecard as the main method, supplemented by the key performance indicators method to construct the e-commerce enterprise performance indicator system.

2.3.1. Management by Objectives. In the process of planning enterprise strategic objectives, strategic objectives are not only the basis for the management and development of e-commerce enterprises but also the basis for planning the development objectives among enterprise employees. Therefore, the inspection standard of the enterprise should face up to the strategic objectives of the enterprise, and it will be more reasonable to evaluate the work results of the employees and give corresponding rewards and evaluations, which can greatly stimulate the enthusiasm of the employees. This makes the enterprise lively. Adhere to the policy of "results first," the application of the objective management method cannot be subject to the subjective qualitative idea of the evaluator, but through a perfect objective evaluation system and the evaluation of the actual contribution to the enterprise.

2.3.2. Balanced Scorecard. The balanced scorecard is divided into financial indicators and supplementary nonfinancial indicators. The former reflects the past operating results of the enterprise, while the latter is related to the enterprise business, including customer satisfaction, internal processes, innovation, and learning. The latter makes up for the former and better improves the future development level of e-commerce enterprises. At the same time, it also plays a positive role in the strategic planning and adjustment management of the enterprise.

2.3.3. Key Performance Indicators Method. The key performance indicator method decomposes the strategic objectives into operable work objectives, which can encourage the enterprise managers to put their energy into the current port operation status, improve the problems existing in the operation process, and reasonably predict the future development status, so as to improve the enterprise performance level. When using it, the overall strategic objectives of the enterprise and the key performance indicators of each department should be clearly defined, so as to focus on the results without neglecting the process.

3. Enterprise Performance Algorithm

3.1. Formula Based on Deep Learning Algorithm

3.1.1. Gradient Descent Method. At present, the commonly used optimization algorithm is the gradient descent algorithm. If there is an objective function, then the forward and reverse directions along the gradient are the fastest direction for the value of the objective function to rise, and the reverse direction is the slowest direction. The mathematical expression is

$$\theta = \theta - u \cdot \nabla_{\theta} f(\theta).$$

The parameter in formula (1) represents the efficiency of deep learning, which is also the step size of each iteration. The larger the value of parameter $u$, the farther the distance of each iteration, that is, the higher the learning efficiency. On the contrary, the smaller the value of parameter $u$, the shorter the distance of each iteration, that is, the lower the learning efficiency.

In the deep learning model, the multiquantity gradient descent method and the probability gradient descent method are proposed. The advantages and disadvantages of the two mathematical methods are revealed. The solution obtained by the multiquantity gradient descent method is more global but less efficient, and the advantages of multiquantity gradient descent method and probability descent method are usually combined, which not only meets the efficiency of solving problems but also meets the quality of solving problems.

3.1.2. Circulatory Neural Network. The main use of recurrent neural network is to make statistics on the sequential system data. It can correctly and efficiently extract the demand information from the data.
Figure 1 shows the basic architecture of the recurrent neural network. The mathematical expression of the recurrent neural network is

\[
\begin{aligned}
n_{t+1} &= W_n m_t + b_n m_t = \sigma (W_r m_{t-1} + h_o).
\end{aligned}
\]  

(2)

In formula (2), \(W_r\) is the resource parameter providing data resources, \(W_m\) is the latent parameter of the latent layer, and \(W_n\) is the transport parameter of the transport layer.

The memory neural network is improved and optimized on the basis of the cyclic neural network, and the switch mechanism is mainly used. By using the switch mechanism, the lost data information in the system database can be counted effectively.

In addition, a new computing process is added to the framework model of the recurrent neural network, which is used to store the model computing message. The function of the transmission gate of the framework is to transmit the effective data in the system. \(f(V, \text{he mathematical algorithm})\) is calculated by the attention mechanism, and the mathematical expression of \(c_t\) is

\[
c_t = \sum_{i=1}^{T} a_{ij} s_i,
\]  

(8)

\(a_{ij}\) represents the importance of \(s_i\) when calculating \(c_t\), and the mathematical expression is

\[
a_{ij} = \frac{\exp(e_{ij})}{\sum_{j=1}^{T} \exp(e_{ij})}
\]  

(9)

\(M\) in formula (9) is the attention function, which can be divided into additive attention algorithm, subtractive attention algorithm, and multiplicative attention algorithm according to different types.

The mathematical calculation expression of the additive attention model is

\[
M(s_i, h_{t-1}) = V^T \tanh(W_a[s_i, h_{t-1}]).
\]  

(11)

The mathematical calculation expression of the subtractive attention model is

\[
M(s_i, h_{t-1}) = s_i^T W_a h_{t-1}.
\]  

(12)

The mathematical calculation expression of the multiplicative attention model is

\[
M(s_i, h_{t-1}) = s_i^T W_a h_{t-1}.
\]  

(13)

As for the loss function, \(w\) loss is used, and the mathematical calculation expression is

\[
W_2(\hat{y}, y) = \sum_{i=0}^{m} \left( y^{(i)} - \hat{y}^{(i)} \right)^2.
\]  

(14)

Subsequent research found that the superresolution image generated by \(W_2\) loss is somewhat blurred than that generated by \(W_1\) loss. \(W_1\) loss is also called the minimum absolute deviation. The mathematical calculation expression is

\[
W_1(\hat{y}, y) = \sum_{i=0}^{m} | y^{(i)} - \hat{y}^{(i)} |.
\]  

(15)

3.1.3. Deep Learning Attention Mechanism. Pay attention to the signal processing function in people’s brain. The information processing of people’s brain will pay full attention to a certain field observed. People’s attention mechanism also deeply affects the attention mechanism of the deep learning model.

In the coder based on the attention mechanism, the mathematical expression of the sequence test formula is

\[
p(y_t, y_{1...t}, c_t) = \text{soft} \max(f(h_t, c_t)).
\]  

(7)

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\]  

(15)
3.2. Enterprise Performance Calculation Algorithm for Cross-Border E-Commerce Enterprises

3.2.1. Enterprise Performance Calculation and Evaluation. The importance of each indicator can be recorded through the dispersion coefficient, and the performance index of cross-border e-commerce enterprises can be constructed. The mathematical expression is

\[ F = 1 - \sqrt{\frac{(1 - W_i)^2 + (1 - D_i)^2 + (1 - Q_i)^2}{3}}. \]  \hspace{1cm} (16)

In formula (15), \(D_i\) represents the value in the \(i\)th dimension, which represents the performance of a pilot city of cross-border e-commerce in this dimension. The larger \(D_i\) represents the better performance, and \(\omega_i\) represents the weight given to an indicator, \(0 \leq \omega_i \leq 1\). The larger the value, the greater the weight. Otherwise, the smaller the weight.

It can be calculated by using the discrete coefficient method, which can objectively and accurately show the index importance of overseas Internet sales enterprises in each city. The mathematical expression of the discrete coefficient is

\[ CV_i = \frac{Stdev_i}{Average_i}, \]  \hspace{1cm} (17)

The mathematical expression of each index of the discrete coefficient is shown as follows:

\[ \omega_i = \frac{CV_i}{\sum_{i=1}^{n} CV_i}, \]  \hspace{1cm} (18)

In order to evaluate the functional change index of overseas Internet sales enterprises in various cities, the initial efficiency index, service efficiency, and development efficiency are indispensable. The three indexes are expressed in \(W_i, D_i\), and \(Q_i\), respectively, and the mathematical expression is as follows:

\[ W_i = 1 - \sqrt{\frac{\sum_{i=1}^{n} (W_i - \omega_i)^2}{\sum_{i=1}^{n} \omega_i}}, \]  \hspace{1cm} (19)

\[ D_i = 1 - \sqrt{\frac{\sum_{i=1}^{n} (D_i - \omega_i)^2}{\sum_{i=1}^{n} \omega_i}}, \]  \hspace{1cm} (20)

\[ Q_i = 1 - \sqrt{\frac{\sum_{i=1}^{n} (Q_i - \omega_i)^2}{\sum_{i=1}^{n} \omega_i}}. \]  \hspace{1cm} (21)

According to formulas (18), (19), and (20), the total performance index of cross-border e-commerce enterprises in each city is

\[ F = 1 - \sqrt{\frac{(1 - W_i)^2 + (1 - D_i)^2 + (1 - Q_i)^2}{3}}. \]  \hspace{1cm} (22)

F in formula (21) is the total performance index for calculating the operation of overseas Internet sales enterprises about each city. It is calculated from \(W_i, D_i\), and \(Q_i\) when the value of \(F\) is larger, and it means that a city’s cross-border e-commerce enterprise has more operating profits in this year; that is, the total performance value is higher. On the contrary, when the value of \(F\) is lower than that of a city’s cross-border e-commerce enterprise, it means that the total performance value is lower.

4. Experimental Analysis of Enterprise Performance Evaluation of Cross-Border E-Commerce Enterprises Based on Deep Learning Model

4.1. Development Trend and Current Situation of China’s Overseas Internet Sales Enterprises. The development of cross-border e-commerce enterprises can be roughly divided into four stages. From the stage of the Golden Customs project, with the progress of Internet technology, a networked overseas trade has been built, and the networking of overseas e-commerce trading enterprises has been realized. The early 21st century is the embryonic period of Internet development, so Internet + commercial sales have become a new and popular business model. Therefore, most enterprises have established overseas trade websites. After 2007, the network transaction mode was in the initial stage of development. During this period, various e-commerce enterprises developed rapidly, and the development of e-commerce enterprises penetrated from cities to rural areas. In this period, the development of e-commerce enterprises was divided into two modes: step into e-commerce mode and desktop e-commerce mode.

As shown in Figure 2, the transaction development of cross-border e-commerce enterprises in China shows an increasing trend. From 2014 to 2017, the development scale of cross-border e-commerce enterprises was 12 million, 18 million, 26 million, and 48 million, respectively.

As shown in Figure 3, the growth range of overseas Internet sales enterprises users’ development scale from 2014 to 2017 has remained at 35% or above, and the growth range of overseas Internet sales enterprises users’ development scale reached 85.61% in 2017.

Figure 4 shows the growth scope direction of overseas Internet sales transaction performance from 2014 to 2017.

Figure 5 shows the transaction mode of overseas Internet sales enterprises in 2017.

4.2. Performance Analysis and Evaluation Process of Overseas Internet Sales Enterprises

4.2.1. PMO and Bartley Ball Test. To be able to use the analysis method, the basis is the correlation between each key factor, so the first step in the experimental analysis is to screen the selected factor indicators. If there is no correlation between the 12-factor indicators mentioned below, the analysis method cannot be used. PMO
statistics and Bartley ball test statistics are selected in the selection of analysis methods.

As shown in Table 1, test results that kmo is greater than nig and nig is less than 0.05, indicating that the factor analysis method can be applied to the processing of experimental sample content.

4.2.2. Extracting Factor Indicators and Factor Flipping.

As shown in Table 2, the first column of the table is the 12-factor indicator, and the second column is the initial value. fV_he closer the result value of the extracted data is to 2, it means that this can be well explained by the extracted co-factor indicators. From the data in the third column of the table, it can be seen that all data values are declining, so it can be explained that the analysis method effectively explains the changes in performance indicators.

Table 3 shows the explanation table for the variance of the overall sample in 2017.

As shown in Figure 6, the data in the table show a very prominent decline in slope, indicating strong credibility. Therefore, the screening and extraction of these four-factor indicators can correctly explain the transformation of cross-border e-commerce enterprise performance.

By flipping the matrix, the value of each variable on a common factor indicator is larger; that is, the load is larger, and the load on other common factor indicators is relatively small; that is, for each common factor indicator, the load on some variables is larger, and the load on other variables is smaller, highlighting the relationship between each common factor indicator and those variables with a larger load.

As shown in Table 4, from the flipped factor index matrix in 2017, it can be seen that the load rate of the four-factor statistics and Bartley ball test statistics are selected in the selection of analysis methods.

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Table 1: PMO and Bartley ball measure in 2017.

<table>
<thead>
<tr>
<th>PMO capacity</th>
<th>Approximate chi-square test</th>
<th>Bartley ball test</th>
<th>Nig</th>
</tr>
</thead>
<tbody>
<tr>
<td>429</td>
<td>160.89</td>
<td>78</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Table 2: Variance table of common factor indicators in 2017.

<table>
<thead>
<tr>
<th></th>
<th>Initial</th>
<th>Extract</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3.50</td>
<td>0.943</td>
</tr>
<tr>
<td>B</td>
<td>4.50</td>
<td>0.965</td>
</tr>
<tr>
<td>C</td>
<td>5.50</td>
<td>0.628</td>
</tr>
<tr>
<td>D</td>
<td>4.50</td>
<td>0.724</td>
</tr>
<tr>
<td>E</td>
<td>2.00</td>
<td>0.982</td>
</tr>
<tr>
<td>F</td>
<td>2.00</td>
<td>0.822</td>
</tr>
<tr>
<td>G</td>
<td>2.00</td>
<td>0.641</td>
</tr>
<tr>
<td>H</td>
<td>2.00</td>
<td>0.690</td>
</tr>
<tr>
<td>I</td>
<td>2.00</td>
<td>0.682</td>
</tr>
<tr>
<td>J</td>
<td>2.00</td>
<td>0.610</td>
</tr>
<tr>
<td>K</td>
<td>2.00</td>
<td>0.831</td>
</tr>
<tr>
<td>L</td>
<td>2.00</td>
<td>0.787</td>
</tr>
</tbody>
</table>

Table 3: Explanation of overall variance in 2017.

<table>
<thead>
<tr>
<th>Component</th>
<th>Initial value of test sample</th>
<th>Product acquisition and input</th>
<th>Product rollover &amp; input</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Initial</td>
<td>Standard deviation (%)</td>
<td>Final (%)</td>
</tr>
<tr>
<td>A</td>
<td>3.87</td>
<td>29.7</td>
<td>29.7</td>
</tr>
<tr>
<td>B</td>
<td>3.41</td>
<td>26.2</td>
<td>55.9</td>
</tr>
<tr>
<td>C</td>
<td>1.69</td>
<td>13.0</td>
<td>69.0</td>
</tr>
<tr>
<td>D</td>
<td>1.01</td>
<td>7.8</td>
<td>76.8</td>
</tr>
<tr>
<td>E</td>
<td>0.85</td>
<td>6.7</td>
<td>83.4</td>
</tr>
<tr>
<td>F</td>
<td>0.78</td>
<td>5.9</td>
<td>89.4</td>
</tr>
<tr>
<td>G</td>
<td>0.44</td>
<td>3.4</td>
<td>92.7</td>
</tr>
<tr>
<td>H</td>
<td>0.40</td>
<td>3.1</td>
<td>95.7</td>
</tr>
<tr>
<td>I</td>
<td>0.26</td>
<td>1.9</td>
<td>97.7</td>
</tr>
<tr>
<td>J</td>
<td>0.17</td>
<td>1.3</td>
<td>99.1</td>
</tr>
<tr>
<td>K</td>
<td>0.08</td>
<td>0.6</td>
<td>99.7</td>
</tr>
<tr>
<td>L</td>
<td>0.02</td>
<td>0.2</td>
<td>99.9</td>
</tr>
</tbody>
</table>

Figure 6: Broken stone of overseas Internet sales enterprises in 2017.
Table 4: 2017 turnover component matrix.

<table>
<thead>
<tr>
<th>Component</th>
<th>Profit rate of total assets</th>
<th>Return on shareholders’ equity</th>
<th>Basic income</th>
<th>Gross profit margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.92</td>
<td>1.05</td>
<td>1.30</td>
<td>1.06</td>
</tr>
<tr>
<td>B</td>
<td>1.96</td>
<td>1.12</td>
<td>1.05</td>
<td>1.05</td>
</tr>
<tr>
<td>C</td>
<td>1.77</td>
<td>1.09</td>
<td>1.13</td>
<td>1.06</td>
</tr>
<tr>
<td>D</td>
<td>3.01</td>
<td>3.22</td>
<td>3.03</td>
<td>3.75</td>
</tr>
<tr>
<td>E</td>
<td>4.17</td>
<td>4.17</td>
<td>4.93</td>
<td>4.21</td>
</tr>
<tr>
<td>F</td>
<td>2.03</td>
<td>2.27</td>
<td>2.84</td>
<td>2.13</td>
</tr>
<tr>
<td>G</td>
<td>1.08</td>
<td>1.15</td>
<td>1.75</td>
<td>1.17</td>
</tr>
<tr>
<td>H</td>
<td>1.07</td>
<td>1.76</td>
<td>1.28</td>
<td>1.12</td>
</tr>
<tr>
<td>I</td>
<td>1.09</td>
<td>1.56</td>
<td>1.25</td>
<td>1.53</td>
</tr>
<tr>
<td>J</td>
<td>1.18</td>
<td>1.23</td>
<td>1.11</td>
<td>1.70</td>
</tr>
<tr>
<td>K</td>
<td>1.19</td>
<td>1.83</td>
<td>1.14</td>
<td>1.23</td>
</tr>
<tr>
<td>L</td>
<td>1.83</td>
<td>1.29</td>
<td>1.02</td>
<td>1.02</td>
</tr>
</tbody>
</table>

Table 5: L-means clustering results.

<table>
<thead>
<tr>
<th>Performance aggregation</th>
<th>Experiment label</th>
<th>Transmission trend</th>
<th>Number of experimental trainings</th>
<th>Number of simulated samples</th>
<th>Inspection quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>62.8</td>
<td>1</td>
<td>[0, 0, 0, 1]</td>
<td>124</td>
<td>105</td>
<td>19</td>
</tr>
<tr>
<td>68.4</td>
<td>2</td>
<td>[0, 1, 0, 0]</td>
<td>113</td>
<td>101</td>
<td>12</td>
</tr>
<tr>
<td>75.6</td>
<td>3</td>
<td>[0, 0, 1, 0]</td>
<td>95</td>
<td>74</td>
<td>21</td>
</tr>
<tr>
<td>89.5</td>
<td>4</td>
<td>[0, 1, 0, 1]</td>
<td>28</td>
<td>20</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 6: Comparison of prediction accuracy of each algorithm.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Softmax iterations</th>
<th>Number of hidden nodes</th>
<th>Number of fine adjustments</th>
<th>Acc (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Softmax classifier</td>
<td>100</td>
<td>Nothing</td>
<td>Nothing</td>
<td>73.3</td>
</tr>
<tr>
<td>Softmax classifier</td>
<td>300</td>
<td>Nothing</td>
<td>Nothing</td>
<td>78.3</td>
</tr>
<tr>
<td>DBN-softmax</td>
<td>300</td>
<td>(31, 21)</td>
<td>200</td>
<td>85.0</td>
</tr>
<tr>
<td>RBMs-softmax</td>
<td>300</td>
<td>(14, 10)</td>
<td>Nothing</td>
<td>76.7</td>
</tr>
<tr>
<td>Paper method</td>
<td>300</td>
<td>(14, 10)</td>
<td>200</td>
<td>88.3</td>
</tr>
</tbody>
</table>

Figure 7: Performance comparison between traditional e-commerce enterprises and integrated deep learning mode.
4.3. Performance Analysis of Cross-Border E-Commerce Enterprises Based on Deep Learning Model. In recent years, global learning models supporting the development of Internet transaction mode have gradually increased. In order to promote in-depth learning, enterprise performance data access a wider range of e-commerce platforms and establish more targeted and accurate forecasts, that is, intelligent forecasts. Practice has proved that the system can generally meet the following requirements: first, data mining, and computer learning become the entrance to complete the operation of data elements; second, according to the results obtained, the relevant knowledge base is established to ensure data input, traffic pre-evaluation, and other building materials.

4.3.1. Overseas Internet Sales Enterprises Data Preprocessing. In the input-output performance evaluation data of cross-border e-commerce companies, variable indicators are used as candidate elements at a level. Because some elements are missing, or most of the data values are 0 or smaller than the performance rating indicators, this part of the indicator data is deleted. The performance in the sampled data is executed as an output variable, and the value of the basic performance data is between 56 and 100. According to the k-way classification, the power value is considered in the fourth type of label, which is represented by 1, 2, 3, and 4. The higher the category label, the better the performance. In different output formats, single output performance is diversified. L-clustering is still used to select training mode. The specific method of grouping samples using the performance category label is to select $l = 4300$ samples near the middle of the course as training examples and other samples as test examples. Refer to Table 5 for detailed data.

As shown in Table 5, L-means aggregation results are displayed.

4.3.2. Effectiveness Analysis of Deep Learning Model. As shown in Table 6, the prediction accuracy of this method before fine-tuning is 76.7%, and after fine-tuning is increased by 11.6%, which reflects the importance of reverse fine tuning to network parameter learning and shows that fine-tuning is effective to optimize the filter mechanism. Combined with the data characteristics of this paper, the prediction accuracy of two RBMs is higher than that of one RBMs, namely DBN softmax, which verifies the feasibility and effectiveness of this model.

Figure 7 shows the comparison between the merits of traditional overseas Internet sales and the merits of the integrated deep learning model from 2014 to 2017.

As shown in Figure 8, the dividend capacity of overseas Internet sales enterprises after integrating the Shendu learning model shows an upward trend. While expanding the sales model, it ensures an increase in profits, and the overall development trend is good.

5. Conclusion

At the beginning of this paper, the research topic and background are put forward. Then, it introduces the theoretical overview of cross-border e-commerce, confirms the research content of this paper, and introduces the six construction principles of overseas Internet sales enterprises performance index system and the construction model framework of overseas Internet sales enterprises performance index model. It is necessary to focus on these six principles and the construction model framework of the

The document contains tables and figures which are not transcribed but are expected to provide visual representation of the data discussed in the text.

Figure 8: Some indicators of profitability of traditional e-commerce enterprise model and integrated in-depth learning e-commerce model.
performance index system to build a correct e-commerce enterprise business model. Then, it introduces the enterprise performance algorithm of cross-border e-commerce enterprises based on the deep learning model, mainly including the deep learning algorithm and the enterprise performance calculation algorithm of cross-border e-commerce enterprises. Finally, the development trend and current situation of China’s overseas Internet sales enterprises and the performance analysis and evaluation process of China’s overseas Internet sales enterprises are experimentally calculated, and the experimental results are sorted out and classified.

**Data Availability**

The experimental data used to support the findings of this study are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest regarding this work.

**References**


