Research Article

An Early Control Algorithm of Corporate Financial Risk Using Artificial Neural Networks

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Based on DL theory, this paper discusses and studies the early warning of enterprise financial risks in detail. And put forward a new enterprise financial risk early-warning model. The purpose is to enable enterprises to better analyze the changing trend of financial data, make correct decisions by managers and investors of enterprises, and promote the stable development of national economy and enterprises. This model is based on the early-warning theory of enterprises, based on the financial statements, business plans, and other relevant accounting information of enterprises, using accounting, finance, and marketing theories, adopting the methods of ratio analysis, comparative analysis, factor analysis, etc., to warn the financial risks of enterprises. This paper uses a lot of data to train the parameters of the DL financial early-warning model and then verifies the established financial early-warning model. In order to verify the reliability of this model, this model is compared with other two financial early-warning models. The results show that the prediction accuracy of this model is as high as 94%, which is 8~15% higher than that of other models. In this paper, the DL method has been applied to financial risk early warning and achieved good results. It has certain theoretical and practical significance in the field of enterprise financial early warning.

1. Introduction

With the continuous development of China’s economy, the business environment of enterprises is becoming more and more complex [1]. Simultaneously, with the economy under severe downward pressure, there are an increasing number of cases of business problems or even bankruptcy as a result of financial difficulties [2]. The company’s financial crisis will not only put financial investors, creditors, and investors at risk, but it will also set off a chain of events. Financial risk is defined as the uncertainty of capital gains caused by an enterprise’s debt management, or the risks that an enterprise faces when using debt funds to obtain financial leverage benefits [3]. Financial risk, in general, refers to the possibility that nonproduction and operation activities such as fund-raising, investment, capital recovery, and capital distribution will result in economic losses over a specific time period and within a specific range due to the internal and external environment, as well as a variety of unpredictable factors [4]. In general, the occurrence of a financial crisis will follow a pattern. As a result, it is becoming increasingly important for businesses to establish a high-accuracy financial early-warning model in order to prevent and prepare for financial crises before they occur [5]. The traditional linear financial risk early-warning model has been unable to meet the early warning and identification of nonlinear financial risks caused by the backwardness of the Internet network in the era of sharing economy due to the rapid development of Internet information technology and the rise of sharing economy [6]. Exploring the early-warning model of enterprise sharing financial risks in the sharing economy era has become a fundamental requirement for ensuring the financial security of Chinese businesses. It is critical to establish an effective financial risk early-warning system in order to be invincible in the fierce com-
petition, make enterprises develop healthily and orderly, and make preventing financial risks a top priority.

Every business should always consider early-warning signs of a financial crisis or failure in its business process, and once abnormal signs are discovered, it should take steps to avoid or mitigate the damage to the company. Building an effective financial risk early-warning system to forecast the financial operation is critical, regardless of which aspect is examined. The enterprise financial risk early-warning system is a collection of management systems that, with the financial index system at its core, reflects, monitors, and analyzes changes in enterprise operation and financial situation, provides early warning to risks that occur or may occur in each link of the enterprise in real time, and takes effective measures to resolve or prevent them. A diagnostic tool for risk early warning is an enterprise financial risk early-warning system. The higher the sensitivity, the better at preventing and avoiding financial risks. Financial risk early-warning research will aid in the early detection of investment risks, the protection of all stakeholders’ rights and interests, and the restoration of investor confidence. It is also critical to encourage the healthy development of businesses and the smooth operation of the market economy. DL (deep learning) [7–9] has attracted the attention of scholars from all over the world as a hot topic in the field of machine learning, and various high-tech enterprises have established DL research institutes with the goal of applying it to a broader field. DL is a brand-new branch of traditional machine learning whose concept is based on ANN (artificial neural network) research [10–12]. DL is a deep NN (neural network) structure with multiple hidden layers, as opposed to traditional ANN. To better discover the effective feature representation of data, DL combines low-level features to form a more abstract high level to represent attribute categories or features. DL has a greater impact on the representation of complex functional relationships, according to many scholars and examples. The use of DL networks is currently booming, and significant progress has been made in practical application fields. This paper examines the early-warning model of enterprise financial risk in depth using DL theory. The following are some of its innovations:

1. In this paper, DL is used as a tool for early warning of shared financial risks, and the DL network is used to train the early warning of company financial risks, and then, the obtained DL network is verified by a case enterprise. It is different from Z-score model analysis and logistic model analysis methods often used in academic circles in the past, and it has certain theoretical and practical significance.

2. Based on DL, this paper constructs an early-warning model of enterprise financial risk. From the perspective of financial early warning, the concept of enterprise financial management is integrated, the characteristics of enterprise financial data are studied, the level of enterprise accounting informatization construction is improved, and the methods and ways of extending the postevent analysis of financial distress to the pwarning are explored.

Based on the actual situation and the literature research of experts and scholars, this paper can get an index system based on the DL method, and several macro indexes are added in the index selection, which makes the accuracy of the model higher.

The specific parts introduced in this paper include the following:

The first section, the introduction, explains the entire text and provides background information, research content, research methods, and research innovations, among other things. The literature review is the second section. The related literatures at home and abroad are summarised and explained in this section, as well as the research ideas for this paper. The method section is covered in the third section. The related concepts, applications, and algorithms of DL and financial risk are discussed in detail in Sections 3.1 and 3.2, which are the research bases for enterprise financial early warning in this paper. Section 3.3 develops and implements a DL-based early-warning model for corporate financial risks, as well as the methods and steps for implementation. The experimental analysis section of the fourth section conducts numerous experiments, trains and evaluates the performance of the financial risk early-warning model, and analyzes the results. The conclusion and research prospects are presented in the fifth section. This section summarises the entire text and concludes the research. This paper examines the research’s flaws and proposes some research topics for the future.

2. Related Work

Sun and Lei introduced the cash flow index into the established model, compared the linear probability model to the logistic model, tested it with the company’s financial situation, and found that the linear probability model is slightly more accurate [13]. In the study of Ouyang et al., an empirical study of the logistic model with the random effect of cross-sectional data was conducted, and it was discovered that the effect of this operation is better and that the addition of nonfinancial indicators can improve the early-warning effect [14]. The enterprise financial risk early-warning system was investigated and established by Fletcher and Abbas. It integrates key projects involving enterprise financial risks and strives to improve the system’s practicability and value in order to achieve true risk early warning and prevention effectiveness [15]. Song et al. built an enterprise financial risk early-warning model; the theoretical framework of methodology integrates text mining and DL [16]. Cui et al. based their findings on a new perspective, proposed a dynamic modelling method for financial risk early warning that incorporates convolutional NN and long-term and short-term memory networks, and conducted empirical research using publicly traded service companies as samples [17]. Li and colleagues introduced a genetic algorithm to the BP network, which encoded topology, threshold, and other parameters into chromosomes as a whole. To improve the accuracy of model prediction, the appropriate parameters and topology are determined through sample training [18]. According
to Duprey and Klaus, as the output node of the NN model, the method of cluster analysis was used to divide the financial situation of enterprises into five categories. Simultaneously, the rough set theory is used to screen the indicators as the network’s input node. The model’s prediction accuracy is greater than 90%, indicating that the expected effect was achieved [19]. For early warning of financial crises, Wang et al. used the univariate financial risk early-warning model. It finally determined the predictable indicators by dividing 25 businesses into two groups based on bankruptcy and nonbankruptcy and distinguishing them with separate financial ratios [20]. Restrepo et al. are a group of people who work in the restaurant industry. The field of financial crisis early warning was studied using a logistic model. The multivariate linear model can only predict whether or not a financial crisis will occur, but not how likely it will be. The probability of a financial crisis in an enterprise at a specific time is calculated using logistic discriminant analysis [21]. Gietzen discovered that, when compared to the NN financial early-warning method, the decision tree method is easier to understand, has higher precision, and has a simpler generation mode, but its results are unstable and may suffer from overfitting [22]. Amico et al. successfully conducted univariate analysis with four indicators of debt guarantee rate, asset liability rate, asset return rate, and asset safety rate on 40 companies that failed in operation and an equal number of companies that did not fail in operation and achieved good results [23]. Given that the duration of the financial crisis may have an effect on the binary model’s early-warning effect, Colasante and Riccetti developed a multiple regression early-warning model to conduct research on financial crisis early warning. Finally, the goal of the first mock exam is to determine whether this model can significantly improve crisis prediction ability [24]. Crona and colleagues compared the two methods of decision tree and logistic regression in the context of financial early-warning research and discovered that the decision tree method is better for short-term financial early warning, while the logistic regression method is better for long-term financial early warning [25].

Based on the in-depth discussion of previous related literature, this paper puts forward and constructs a new enterprise financial risk early-warning model by using the DL method. This paper introduces the theoretical basis of financial early warning and then analyzes the path of forming enterprise financial risk and the relationship between financial risk and financial distress by expounding the definition and characteristics of enterprise financial risk. It also describes the definition of the company’s financial distress and expounds the related concepts of financial early warning. Then, through DNN (deep neural network), the features are abstracted layer by layer, and the feature dimensions are reduced. Finally, the output layer can be set as two variables: financial health and financial risk. And select the samples used in the research, use some specific principles of index selection to select appropriate financial indicators, establish the final financial index system, and list the calculation formulas of indicators, which will lay a solid foundation for the next research. Train the DL network with sample enterprise data, and test the prediction accuracy of the constructed DL network with test samples to obtain the DL network model with early-warning ability. The experimental results show that the prediction accuracy of the model is about 94%, and the closer to the occurrence time of financial distress, the higher the accuracy of the early-warning results.

3. Methodology

3.1. DL. ANN, abbreviated as NN, is a large-scale distributed parallel processor composed of neurons. The theory of ANN is established and developed on the basis of human brain analysis. It can process parallel information like the human brain. DL is the product of the development of NN in a certain period of time. It is a deep machine learning model. DL is based on ANN theory and is a frontier field of ANN [26]. With the advent of the era of big data and the vigorous development of artificial intelligence, more and more scholars begin to turn their attention to DL, a new tool. “DL” consists of two words: depth and learning. “Depth” means a deep-seated NN with multiple hidden layers, and “learning” refers to feature learning, which plays an indispensable role in DL. As a special manifestation of machine learning, DL can learn the characteristics of things by itself and mainly studies NN. DL is a kind of machine learning. It mainly processes a large amount of data through the deep network with multiple hidden levels and learns the features through training, rather than other methods to determine the features through people, which makes DL perform better in recognition efficiency and accuracy.

The advantage of DL is that its model has good expression ability and can better classify and characterize objectives and behaviors when dealing with complex problems. Therefore, it can help us better learn complex functional relationships. Through the mutual transformation between nonlinearity, DL develops from low level to high level. Without relying on manual work, DL can learn independently, find data characteristics, and learn to express complex functions. The trained DL network can analyze the input data to identify the characteristics represented by the input layer and finally form the output layer through implicit multilayer assignment and feedback. DL framework is a set of solutions developed for DL with independent architecture, unified style template, and reusability. It usually has the characteristics of high cohesion, strict standardization, scalability, maintainability, and high versatility, which can reduce the writing of a large number of repetitive codes. DNN has strong fault tolerance. In NN, information is stored in a distributed way, and the damage of a few neurons will not have a devastating impact on the NN system, which has a strong self-associative memory function. The DNN model is shown in Figure 1.

DL gives NN the ability of self-learning. People can input a lot of unlabeled data when applying DL. The DL network can be trained layer by layer, abstract the characteristics of data, and then judge the data and draw corresponding conclusions. Nonlinear mapping is a universal feature of natural things, and the human brain is a typical nonlinear phenomenon. The neurons in DNN generate
Financial risks can not be avoided but can be identified in advance, so as to prevent further deterioration of financial risks and eventually turn into financial crisis. The generalized financial risk refers to the uncertainty that the expected income is lower than the preset target in the daily production and operation activities of enterprises due to external factors or their own reasons, which affects the continuous and good operation of enterprises and thus has a bad influence on the development of enterprises. Financial risk has the following characteristics: gradual, objective, sudden, predictable, controllable, complex causes, and dual nature. Financial crisis is related to financial risk, and the evolution of financial risk in a bad direction will eventually lead to financial crisis. Therefore, to prevent financial crisis, we should pay attention to financial risks.

From the perspective of financial early warning, the financial risks of enterprises are not limited to the category of fund-raising activities [30]. Improper investment activities, operation activities, and distribution activities may also expose enterprises to risks. Once the financial risk loss exceeds the limit that the enterprise can bear, it will form a financial crisis for the enterprise. The causes of financial risk turning into financial crisis are complicated, which may be caused by various comprehensive factors. Generally speaking, the causes of enterprise financial risks can be divided into two categories: internal causes and external causes. External reasons include ① market changes, ② changes in macroeconomic environment, ③ exchange rate change, and ④ inflation. Internal reasons include ⑤ business reasons. Poor business management may eventually lead to financial crisis. Poor management of enterprises may be caused by internal or external factors. ⑥ Management reasons: the management of enterprises affects all aspects of enterprises, so poor management will inevitably lead to financial crisis. ⑦ Governance reasons: at present, the governance of domestic companies is complicated and mixed, so the governance reasons will also become one of the important reasons for the financial crisis. Financial early-warning control is to monitor the daily business activities of enterprises, focusing on abnormal business fluctuations and financial crisis. The classification of the financial risk identification system and early-warning model is shown in Figure 2.
Through historical data of enterprises, financial risk early warning can judge the degree of financial risk faced by enterprises and whether it will cause financial crisis. Because the causes of financial crises are complex and sudden, it is critical for businesses to provide early warning of financial risk. Financial early warning can help enterprises prepare for a rainy day by predicting problems and preventing them before they occur, ensuring that their financial management activities are always safe and reliable. Financial risk early warning is critical in determining whether the enterprise financial crisis occurs at all. It is beneficial for businesses to identify operational problems early on, avert a crisis, and contribute to the long-term viability of their operations. Financial risk early warning is a type of monitoring that involves keeping track of changes in financial data. Enterprises should always be aware of and assess the risk of a financial crisis. Because financial risk does not appear out of nowhere, it will go through a storage, accumulation, evolution, and manifestation process that has some foreshadowing and predictability. Enterprises must establish and improve a financial risk early-warning system in order to prevent and avoid financial crises.

3.3. Design and Implementation of Enterprise Financial Risk Early-Warning Model Based on DL. Deep learning is a model with a multilayer network hierarchy, and deep features can be learned by constructing a deep nonlinear network model with multiple hidden layers. Network representation of data at different levels and more advanced or abstract data representation of sample data can be obtained through analysis of multiple hidden layers. The original intention of the development of the DL network is to identify features by self-study of the network, instead of artificially determining more effective features, which can greatly reduce the difficulty of work and improve the accuracy.

The scale and nature of businesses influence the characteristics of the financial risk early-warning system as a whole. It can be run by a whole department or by a few posts in various production, sales, or functional departments. To begin, this paper selects the sample enterprises and financial indicators, as well as the data that goes with them, before splitting the samples into two parts for training and testing. The selected financial index data is also preprocessed, or normalized, to ensure the accuracy of the training results. DNN propagates the signal forward, then transmits the error backward, constantly correcting the weights and deviations between layers in NN during the transmission process. Select the sigmoid function as the neuron-to-neuron transfer function in NN, and adjust the error and weight. Using a deep learning network, features are abstracted layer by layer to reduce feature dimension, and the final output layer can be set as one of two variables: financial risks or no financial risks. The DL algorithm corrects the weight and deviation of each neuron layer by determining which neuron layer’s error function drops the fastest. The following is how the iteration is calculated:

$$X_{k+1} = X_k - a_k b_k.$$  \hspace{1cm} (1)

Among them, $X_k$ represents the weight and local difference value of the network, $X_{k+1}$ represents the weight and deviation value after iterative calculation, $a_k$ represents the speed of NN learning, and $b_k$ represents the gradient of the
error function. NN adopts the forward way to pass the input samples (such as Equation (2)) to the neural network for training.

\[ X_k = [X_{k1}, X_{k2}, \cdots, X_{kl}] \]  \hspace{1cm} (2)

Then, the input of neuron \( i \) in the first hidden layer is expressed as

\[ u^f_i = \sum_{h=1}^{H} W_{hi}X_{kh}. \]  \hspace{1cm} (3)

The output of neuron \( i \) in the first hidden layer is expressed as

\[ v^f_i = f\left( \sum_{h=1}^{H} W_{hi}X_{kh} \right). \]  \hspace{1cm} (4)

The input of neuron \( p \) in the output layer is represented as

\[ u^p_p = \sum_{j=1}^{l} W_{jp}v^f_j. \]  \hspace{1cm} (5)

The output of neuron \( p \) in the output layer is represented as

\[ y_{kp} = v^p_p = f\left( \sum_{j=1}^{l} W_{jp}v^f_j \right). \]  \hspace{1cm} (6)

Assume that the relevant financial indicators are set as \( X \), and assume that there are \( N \) financial indicators. Let \( X_1, X_2, \cdots, X_n \) be the independent variable, financial risk be set to \( Z \), and the value of \( Z \) is between 0 and 1. Predict the probability of financial risk occurring.

\[ \sum(Z_i) = f\left( \beta_1x_1 + \beta_2x_2 + \cdots + \beta_p x_p \right). \]  \hspace{1cm} (7)

When \( Z = 0 \) and \( Z = 1 \), \( Z \) is not sensitive to changes in \( X \), and \( X \) needs a large change to cause a weak change in \( Z \). Small changes in \( Z \) will have large changes in \( \partial(\beta) \), which will change the function.

\[ \frac{\partial \theta(Z)}{\partial Z} = \frac{1}{Z} + \frac{1}{1-Z}. \]  \hspace{1cm} (8)

Available:

\[ \theta Z = 1n\left( \frac{Z}{1-Z} \right) = X^T \beta. \]  \hspace{1cm} (9)

Due to

\[ 1n\left( \frac{Z}{1-Z} \right) = X^T \beta \Rightarrow \frac{Z}{1-Z} = e^{X^T \beta} \Rightarrow Z = \frac{e^{X^T \beta}}{1 + e^{X^T \beta}}. \]  \hspace{1cm} (10)

Obtain

\[ Z = \frac{e^{X^T \beta}}{1 + e^{X^T \beta}}. \]  \hspace{1cm} (11)

The construction of an early-warning index system is the most basic premise and the most important link of effective financial early warning, which has a key influence on the effectiveness of the shared financial risk early-warning model. Finally, this paper selects 5 first-level indicators and 18 second-level indicators that can reflect the overall financial situation of the company for follow-up empirical analysis, as shown in Table 1. These indicators are effective indicators screened out based on previous studies. Because the DL method has a self-learning ability, this paper selects as many indicators as possible to describe the sample enterprises, hoping to show the enterprise situation more comprehensively.

The training of the DL network is the most important premise of the network application, and the effect of training determines the effect of specific application. Firstly, set the training parameters and determine the number of hidden layers and variables in each layer. In order to obtain a good network model, it is necessary to continuously train and test, adjust the relevant step length and times in time to improve the accuracy of the test, determine the number of hidden layers and training parameters of the network through training, and give an early warning to the constructed network. Its network training is divided into two stages. ① The unsupervised layer-by-layer training method is used to train the network, so as to obtain the parameters of each layer and the overall network. ② The supervised training method is used to fine-tune the parameters of the DL network and describe the features in more detail, so as to realize the ultimate goal of early warning. Because the input value can be reproduced by the output value, the encoded data is another characteristic expression of the input value. This algorithm can realize unsupervised learning without an artificial training network. After training the first layer, take the output value of this layer as the input value of the next layer, and so on. In this way, DNN can learn the characteristics of input values. In DL model training, each training corresponds to an accuracy rate, that is, each training effect will show different convergence, so it is necessary to train many times and select the best training result. This paper uses Matlab to normalize the data. The mathematical expression of this function is as follows:

\[ f(x) = \frac{y_{max} - y_{min}}{x_{max} - x_{min}} (x - x_{min}) + y_{min}, \]  \hspace{1cm} (12)

where \( y_{max} \) and \( y_{min} \) are the maximum and minimum values obtained by transforming the data, which are 1 and -1, respectively, in this paper, indicating that the data is transformed to \([-1, 1]\). \( x_{max} \) and \( x_{min} \) represent the maximum and minimum values for each sample.

When the dimension of the hidden layer of the deep network decreases layer by layer, fewer features can be used to represent the input value, and finally, abstract features can
| Variable type           | Variable name                      | Code | Definition                                                                 |
|------------------------|------------------------------------|------|-----------------------------------------------------------------------------|
| Development capacity    | Total asset growth rate            | X1   | Total assets at the end of the period/total assets at the end of last year  |
|                        | Net profit growth rate             | X2   | Net profit/shareholders’ equity                                             |
|                        | Operating income growth rate       | X3   | Growth in operating income/total operating income in the previous year      |
|                        | Liquidity ratio                    | X4   | Total current assets/total current liabilities                              |
| Solvency               | Currency ratio                     | X5   | Closing balance of cash and cash equivalents/current liabilities            |
|                        | Asset-liability ratio              | X6   | Total liabilities/total assets                                              |
|                        | Receivable turnover ratio          | X7   | Sales revenue/average accounts receivable balance                          |
|                        | Inventory turnover                 | X8   | Cost of sales/average inventory balance                                     |
| Operating capacity      | Current asset turnover             | X9   | Main business income/average balance of current assets                      |
|                        | Turnover of total assets           | X10  | Main business income/average total assets                                  |
|                        | Return on assets                   | X11  | (total profit + interest expenses)/total average assets                    |
|                        | Net profit margin of total assets  | X12  | Net profit/total average assets                                             |
| Profitability           | Rate of return on common stockholders’ equity | X13 | Net assets at the end of the period/net assets at the end of last year-1     |
|                        | Operating profit rate              | X14  | Operating profit/total business income                                      |
|                        | Earnings per share                 | X15  | (gross profit for the current period – dividends on preferred stock)/total share capital at the end of the period |
| Human capital capability| Executive performance compensation | X16  | Salary payable by senior executives                                        |
|                        | Director performance compensation | X17  | Employee remuneration payable by directors                                  |
|                        | Production staff performance pay   | X18  | Salary payable by production staff                                         |
be obtained inside the network. This is the first step of unsupervised step-by-step training. The feature representation obtained in the first layer is used as the input of the SDAE (Stack Denoising Automatic Encoder) network structure of the second layer. According to the same method of the first layer, the feature representation of the second layer is obtained, and the weight and deviation of the SDAE model of the second layer are obtained. There is evaluation of the DL financial early-warning model with root mean square error. The calculation principle is shown in the formula:

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}. \]  

Its range is \([0, +\infty)\), and the larger the error between the predicted value and the true value, the larger the value. Through training, the system parameters of the DL data network are bidirectional, including those that continuously identify features from bottom to top, and those that reproduce input values from top to bottom. Compared with the traditional NN, there are only parameters identified from bottom to top, and there are fewer levels, so DNN is more accurate. In order to obtain a better early-warning index system of enterprise shared financial risk, continuous training and testing are needed to determine the network parameters suitable for enterprise shared financial risk early warning. The vibration sample data is input into the first SDAE. By training layer by layer, the problem of easily falling into local convergence is overcome. Every SDAE is greedily trained to ensure the realization of local optimum. BPNN is used in the output layer to fine-tune the previous layers of networks, and the classification results are output.

4. Result Analysis and Discussion

The financial risk early-warning system’s operation principle is to gather initial information through production, sales, and other business and functional departments and then identify and evaluate the risks that businesses may face. The financial risk early-warning model is used to assess the likelihood of businesses facing financial risks based on the changes in various factors. The financial risk early-warning system should track an enterprise’s entire production and operation process, compare the current production and operation situation to the enterprise’s predetermined objectives, plans, and standards, forecast the enterprise’s operating conditions, identify deviations, and analyze the causes and existing problems of the deviations. Give a warning when financial key factors endangering the enterprise appear, and allow the enterprise managers to formulate countermeasures as soon as possible to minimise financial losses. The total sample of 200 companies is divided into two groups in this paper: a test sample to judge the model’s accuracy and a training sample to establish DL’s shared financial risk early-warning model. In total, there are 155 training samples and 45 test samples. Matlab software is used to programme, and 155 training samples of 18 financial risk early-warning index data are fed into the programme. There are 155 training samples to choose from. After much debugging, the best training times and training batches, namely, 1200 training times and 121 training batches, were finally determined. The activation function is the sigmoid function, which has a learning rate of 0.02, 180 iterations, and 60 batches. The police situation is divided into warning intervals in this paper, as shown in Table 2.

According to the above operation method, the sample data is divided into a test group and a training group. Theoretically, there is a positive correlation between the number of nodes in the hidden layer and the nonlinear mapping relationship between input and output errors. The more dimensions of hidden layers, the higher the accuracy of nonlinear mapping between input and output. However, this is not the case. When the dimension of the hidden layer is too large, the noise between training samples also has memory ability, which weakens the ability of extracting information from samples and increases the training time, which may lead to overfitting of the model. Figure 3 shows the root mean square error of training samples.

At the beginning of training, the root mean square error of the middle curve decreases very quickly, which shows that the algorithm is performing local fine-tuning. After 240 times, the training error decreases slightly, which shows that the solution trained by the fine-tuning algorithm has become the optimal process.

Different indicators have different dimensions, and the data units of various indicators are inconsistent and vary in different ranges. In the calculation process, the larger order of magnitude index will completely cover the role of the smaller order of magnitude index. In order to make the DNN model achieve very good results in data training and reduce variance, we normalize the original data. In this paper, Matlab software is used for data processing and training of the DL network. By constantly adjusting the training parameters, different training results can be obtained by changing the parameters and repeated until the most satisfactory results are obtained. The same normalization method is applied to test samples. Then, the normalized data can be used for network training. In order to verify the performance of this algorithm, we compare the methods in literature [16] and literature [17] with this method, and the recall rate of the algorithm is shown in Figure 4. The errors of different algorithms are shown in Figure 5.

According to the data in Figure 4, the recall rate of this algorithm is higher than the other two algorithms, and the error of this algorithm is lower than that of the comparison algorithm. This result verifies the view that the performance of this algorithm is better. Compared with other algorithms, it has certain advantages.

In this section, the selected indicators are not screened by factor analysis and other methods, because the DL network itself has the ability of self-learning features, and even features can be learned from unlabeled data if the amount of data is large enough. This is the advantage of the DL network. In this paper, the average absolute error MAE is used as the loss function, that is, the absolute value of the difference between the predicted value and the actual value is summed up, showing the average deviation range of the
predicted value without considering the positive and negative directions of the deviation. Considering the characteristics of the disclosure system of listed companies’ annual reports, the time period studied in this paper is mainly the first two years of being processed, and the data of the first three years are also investigated to reflect the predictive ability of the data of the first three years and the changing trend of the company’s financial situation. And because of the limited data of listed companies, training with unlabeled data cannot get good results. Therefore, this chapter selects as many indicators as possible to train the network, so as to avoid removing important characteristic indicators by artificial processing errors. In this way, training with labeled data can make up for the problem of less sample data to some extent. Figure 6 shows the training effects of different algorithms.

It can be seen that with the increase of training times, the prediction error rate of the network is getting lower and lower. This error rate reflects the accuracy of the network in predicting the training sample data. And because of the limited data of listed companies, training with unlabeled data cannot get good results. Therefore, this chapter selects as many indicators as possible to train the network, so as to avoid removing important characteristic indicators by artificial processing errors. In this way, training with labeled data can make up for the problem of less sample data to some extent. Figure 6 shows the training effects of different algorithms.

It can be seen that with the increase of training times, the prediction error rate of the network is getting lower and lower. This error rate reflects the accuracy of the network in predicting the training sample data. It is also necessary to use the data of test samples, that is, samples that have not participated in network training, to test the prediction accuracy of the network. With the increase of training iterations, the root-mean-square error of training samples decreases continuously, but in a small range, there is local fluctuation. This is because the fine-tuning algorithm is constantly adjusting the network structure, which affects the root-mean-square error. Because only the current nearby locations are searched directionally, the overall trend is that the error is decreasing continuously. Test samples are data independent of training samples, which are used to detect the accuracy of network prediction. In order to verify the practicability and feasibility of the proposed financial risk

| Warning limit       | Comprehensive efficacy coefficient | Illustrate                                                                 |
|---------------------|-----------------------------------|-----------------------------------------------------------------------------|
| Super police situation | ≤55                               | Indicates that the financial risk of the enterprise is extremely high and the financial situation is very poor |
| Severe alarm        | 55–65                             | Indicates that the financial risk of the business is high and the financial situation is poor |
| Moderate alarm      | 65–75                             | Indicates that the financial risk of the enterprise is relatively high and the financial situation is average |
| Mild alarm          | 75–85                             | Indicates that the financial risk of the enterprise is low and the financial situation is better |
| No alarm            | ≥85                               | Indicates that the financial risk of the enterprise is small and the financial situation is good |

Figure 3: Root mean square error of training samples.

Figure 4: Comparison of recall rates of different algorithms.

Table 2: Division of warning interval.
early-warning model, this paper makes experiments on the prediction accuracy of different models. The experimental results are shown in Figure 7.

On the whole, the prediction accuracy of this paper has reached 94%, which is higher than that of other models by 8~15%. The results further prove the validity and practicability of the DL-based enterprise financial risk early-warning model proposed in this paper. The financial early-warning model trained by DNN can have a good financial early-warning effect for the company. Reasonable screening of financial risk early-warning indicators can simplify the structure of the early-warning model and make the structure have faster training speed and stronger stability and explanation. Particularly in the situation where there are great differences in the level of managers in the industry at the present stage of information technology, the stability and conciseness of the early-warning model have higher practicability.

5. Conclusions

Most financial crises are predictable for businesses. It goes through a series of stages, from latent to outbreak, and from quantitative to qualitative change. The financial situation of businesses is characterized by crisis precursors, crisis phenomena, and crisis consequences as a result of this change, and the factors causing these performances are the crisis causes. The monitoring procedure for early warning of a crisis is to keep track of these performances and factors over time in order to grasp first-hand information about how a company’s crisis is changing. The financial risk early-warning system is a systematic mechanism that relies on a number of interconnected and cooperating departments or posts within the organisation to operate in accordance with predetermined goals. First and foremost, it must be compatible with the enterprise’s organisational structure system and integrate with the job responsibilities of various departments. Second, the financial risk early-warning system, as the “defence system” against enterprise financial risk, should perform a variety of tasks such as monitoring, diagnosis,
evaluation, measurement, and reporting. Instead of relying solely on statistics and mathematical analysis, the financial early-warning model based on DL is a nonstatic modelling process that is established by the machine learning method. As a result, the financial early-warning process based on DL’s financial early-warning model is more akin to people learning and thinking.

At present, the research on the enterprise financial risk early-warning system is still in the stage of continuous exploration and innovation. Based on the research at home and abroad, this paper makes an in-depth analysis and discussion on the theory, system construction, system operation mechanism, financial early-warning model, and financial early-warning method of DL. Combined with DL characteristics and internal factors affecting the financial situation of enterprises, this paper establishes a financial early-warning index system including 5 first-level indicators and 18 second-level indicators. The experimental results show that the prediction accuracy of the DL network after sample training is as high as 94%, which is higher than the accuracy of the other two prediction models of 8–15%. The financial early-warning model based on DL in this paper is very inclusive for nonlinear data and missing data. And it has certain practicability and feasibility and can be fully applied to enterprise financial risk early warning. Although the research in this paper has certain value and achievements, there are still many limitations and areas worthy of improvement. The next step will be to further study the construction of financial indicators.

Data Availability

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

Conflicts of Interest

The author does not have any possible conflicts of interest.

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