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Enterprise Risk Early Warning Model Based on Recurrent Neural Network

Xiaokui Zhao*

Qinghai Normal University, Qinghai, China

304918110@qq.com

**corresponding author*

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Abstract: The establishment of a safe and effective recurrent neural network enterprise risk early warning model is conducive to the effective risk assessment of bank loans, provides a reliable guarantee for the risk management of various enterprises, and meets the actual needs of current investors for risk control. In order to solve the shortcomings of the existing research on the enterprise risk early warning model of RNN, this paper discusses the functional equation of RNN and the concept of non-functional requirements of enterprise risk early warning. The parameter settings and sample data of the risk warning model application are briefly introduced. And design and discuss the structure of enterprise risk early warning model about cyclic neural network. Finally, the accuracy rate of the enterprise risk early warning model designed in this paper about enterprise health, mild enterprise risk and severe enterprise risk is analyzed. , recall rate and true negative rate for experimental data analysis, in which the model's early warning accuracy rate for enterprise health is 0.96% to 0.98%, the early warning recall rate for mild enterprise risks is as high as 0.98%, and the early warning rate for severe enterprise risks is as high as 0.98%. The true negative rate is as high as 0.93%, thus verifying the reliability of the enterprise risk early warning model based on the recurrent neural network.

1. Introduction

With the continuous development and popularization of technologies such as computers and the Internet, as well as more and more mature technologies such as data mining, computer languages and algorithms, and neural networks, the use of neural networks and other technologies is conducive to the healthy development of the financial industry.

Nowadays, more and more scholars pay attention to the research of various technologies and platforms in enterprise risk early warning, and through practical research, they have also achieved certain research results. Kim S aims to raise awareness of enterprise risk management by promoting the active participation of employees in the company's decision-making process, using a qualitative approach. Promote various early warning methods of enterprise risk management policies, such as the introduction of computer technology for early warning of enterprise risk management. And through the system or customized model to realize the early warning of enterprise risk management and data collection of the risk types of enterprise risk management. These include top management's goals for implementing a full enterprise risk management early warning. The research results are also used in the development of early warning system for mechanical enterprise risk management [1]. In order to identify the risk problems in corporate finance, Saari S proposed that the use of early warning system and prediction model for corporate risk early warning identification is beneficial to ensure the healthy development of corporate finance. Therefore, the main purpose of the Saari S study is to verify the predictive power of a model of financial crisis in the manufacturing sector developed under the Slovakian economic conditions. In order to test the prediction accuracy of the model, the confusion matrix operation curve is used to analyze the experimental data. The experimental results show that the prediction ability of the model developed in a certain enterprise field is far superior to that of other models, and the results confirm that The highest predictive power of bankruptcy prediction models was used in the same economic conditions and corporate domains in the early stages of development [2]. Trofimova N examines the impact of CER performance on corporate management risk by controlling sample companies for the potential relationship between CER and corporate management risk. The empirical results show that CER performance has an impact on corporate management risk, and research on CER can reduce the Risks in business management. In addition, companies with economic interest-oriented CERs have certain relationships with employees and the environment, and therefore have lower corporate management risks. Moreover, after classifying the risk of sample companies according to national legal sources, Trofimova N found that common law countries have CER firms are associated with higher firm management risk [3]. Although the existing research on enterprise risk early warning is very rich, the research on enterprise risk early warning model of recurrent neural network is still insufficient.

Therefore, in order to solve the existing problems in the research on the enterprise risk early warning model of the cyclic neural network, this paper firstly introduces the functional equation steps of the cyclic neural network and the concept of the non-functional requirements of the enterprise risk early warning, and then discusses about the cyclic neural network. The parameter settings and sample data for the application of the enterprise risk early warning model of the cyclic neural network are finally designed. The validity of the proposed application of recurrent neural network to enterprise risk early warning model.

2. Enterprise Risk Early Warning about Recurrent Neural Network

2.1. Recurrent Neural Network

Recurrent neural network is a kind of neural network that takes enterprise risk early warning sample data as input and performs regression or classification tasks [4]. Its main mathematical model formulas are:

(1) Recurrent Neural Network Risk Warning

T represents the enterprise risk weight from the hidden layer to the output layer [5]. The value of w depends on the current sample data input f, while the enterprise risk weight R is the weight of the last sample data as the hidden layer [6]. Usually the state of the recurrent neural network unit at time x is expressed as formula (1):

$$g_x = k(w(x-1), f(x), R, T) \tag{1}$$

Among them, g represents the enterprise risk warning state of the recurrent neural network, and k represents the activation function, usually the tanh function [7]. The recurrent neural network usually outputs enterprise risk early warning indicators [8]. It is defined as a linear function formula (2):

$$z_x = k(T_{w_x}) = \lg_{(x)} + m \tag{2}$$

Among them, l and m respectively represent the enterprise risk weight coefficient [9]. The enterprise risk value is usually output directly after the softmax function [10].

The last step is the fitting of enterprise risk warning results, which is also based on the time axis [11]. Using the input and output to establish an enterprise risk early warning model, the formula (3) is as follows:

$$g^{(x)} = k(mF^{x-1} + rg^{(x-1)} + Tz^{(x-1)}) \tag{3}$$

Among them, each RNN enterprise risk early warning calculation introduces the enterprise risk early warning of the previous moment [12]. The recurrent neural network regards this part as the actual enterprise risk input, and finally obtains an enterprise risk early warning model [13].

2.2. Enterprise Risk Warning

(1) Non-functional requirements of enterprise risk early warning model design In the process of building an enterprise risk early warning model based on recurrent neural network [14]. Among them, the real-time push, ease of use and scalability of the model are the three non-functional requirements that the model in this paper focuses on [15].

(2) Real-time push

After the risk information occurs, the model needs to analyze and process immediately, and push the relevant analysis results to the users [16]. This requires that the entire early warning process, from risk identification, classification to practice, is stable and controllable at every step [17].

(3) Ease of use

The model is mainly used by financial practitioners. In order to improve the usability of the model, the implementation of the model shields users from technology-related content as much as possible. Users do not need to be exposed to technology-related knowledge, but only need to register the financial entities they care about. The early warning function of the model [18].

(4) Scalability

In the big data scenario, in order to support the calculation of massive data, the design of the system and the selection of components need to ensure that all modules support horizontal expansion as much as possible.

3. Investigation and Research on Enterprise Risk Early Warning Model of Recurrent Neural Network

3.1. Parameter Setting of Enterprise Risk Early Warning Model of Recurrent Neural Network

The sample of enterprise risk status enters the network from the input layer, and is then transmitted to the output layer after being calculated by the hidden layer. The weight adjustment process of forward propagation and back propagation repeats in a loop until the output error reaches an acceptable level, or reaches the threshold of the number of learning times. There are 2387 training samples. In order to ensure that each data can be learned at least twice, the loop the parameter settings of the neural network enterprise risk early warning model are shown in Table 1:

Table 1. Parameter settings

Parameter item	Parameter value
Input layer	3 Neurons
Hidden layer	5 Neurons
Output layer	1 Neurons
Learning rate	0.055
Network Error Accuracy	0.01
Number of iterations	2000

3.2. Sample Data of Enterprise Risk Early Warning Model Based on Recurrent Neural Network

According to the classification of the manufacturing industry by a website and the sample enterprise data of the database, among the listed companies in the manufacturing industry, 100 sample companies are selected as the early warning research. According to the risk status of these sample companies, 298 companies are divided into two groups: training companies and test companies, which can not only effectively train the network, but also test the accuracy of the neural network model. The specific classification is shown in Table 2 below:

Table 2. Sample data

Early warning indicators	Training samples	Test sample	Total
Corporate health	78	56	134
Mild corporate risk	67	35	102
Severe corporate risk	38	24	62
Total	183	115	298

4. Application Research on Enterprise Risk Early Warning Model of Recurrent Neural Network

4.1. Design of Enterprise Risk Early Warning Model about Recurrent Neural Network

The main function of the enterprise risk early warning model design of the recurrent neural network in this paper is to identify the risk information existing in the enterprise risk data, which mainly includes the processing of the enterprise risk sample data in the input layer, the hidden layer and the output layer of the recurrent neural network. , identification training and enterprise risk classification training to finally obtain enterprise risk early warning data. The construction process of the entire enterprise risk early warning model is shown in Figure 1:

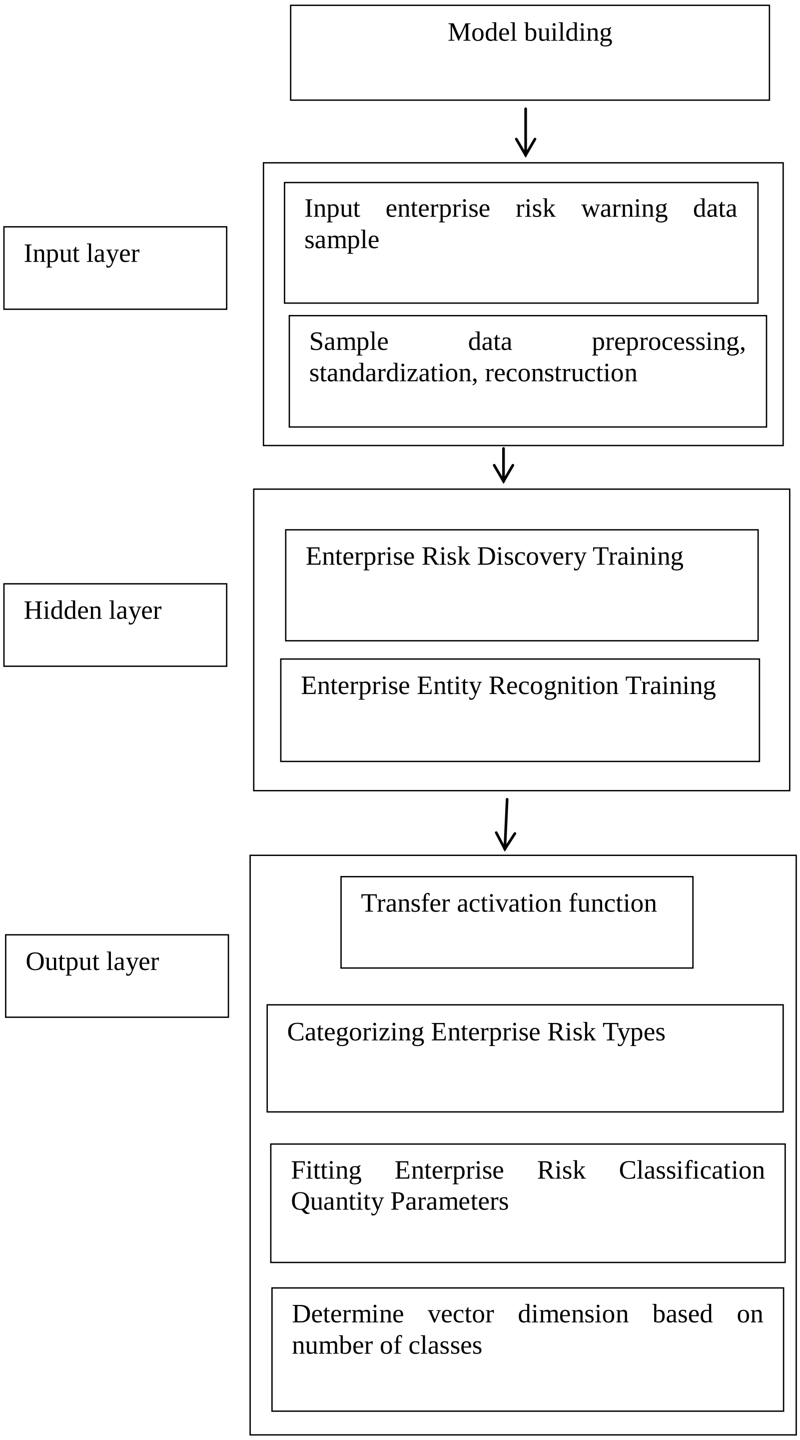

Figure 2. Enterprise risk early warning model of recurrent neural network

The main process design of the enterprise risk early warning model using the recurrent neural network is as follows:

(1) In the input layer, the sample data of the input layer is determined by analyzing the early warning indicators of enterprise risk. Therefore, according to the analysis results of the early warning indicators of enterprise risk, the early warning indicators of the selected enterprise risk

sample data are optimized, and the sample data is standardized and reconstructed, and finally enters the hidden layer.

(2) Hidden layer, the specific design of this paper adopts the method of trial and error, trains the network with different numbers of neurons, conducts enterprise risk discovery training and enterprise entity identification training, and compares the training results.

(3) Output layer. When using a recurrent neural network model for enterprise risk classification, binary numbers are the most commonly used formulas, which have the advantage of clearly classifying the results of different patterns. Usually, in the specific processing, the result matrix of each mode is output first, and then the output value is obtained. The previous model classifies the risk status of manufacturing sample enterprises into three states. Therefore, the dimension of the vector must be determined according to the number of classifications of the evaluation results. The vector (1,0,0) indicates that the risk status of the enterprise is healthy, the 1) Indicates a severe corporate crisis, which is used as the output layer of the neural network.

(4) Transfer the activation function and select the gated recurrent unit as the nonlinear activation function

(5) Setting of training parameters, in order to achieve better fitting effect, adjust the learning times of the model to a maximum of 2000 iterations. When the error drops to 1-6, the model stops training and inputs the results.

4.2. Application of Enterprise Risk Early Warning Model of Recurrent Neural Network

After the training and learning of the recurrent neural network, it is necessary to test the effect of the enterprise risk early warning model of the recurrent neural network. The actual situation is compared and sorted, and the accuracy, recall and true negative rate of the recurrent neural network enterprise risk early warning model are tested. The data collation results are shown in Table 3:

Table 3. Accuracy, recall and true negative rate data of the early warning model

Project	Recall	Accuracy	True negative rate
Corporate health	0.986	0.978	0.967
Mild corporate risk	0.985	0.957	0.998
Severe corporate risk	0.949	0.916	0.935

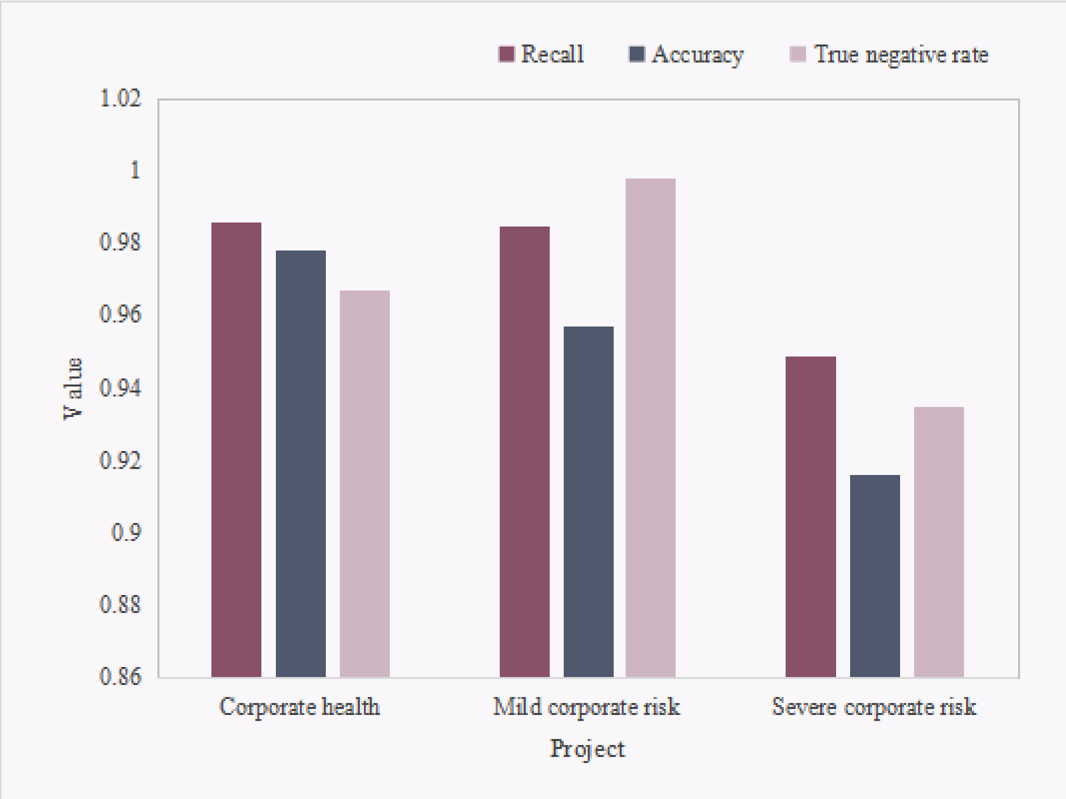

Figure 2. Comparison of accuracy, recall and true negative rate of early warning models

From the data curves of the accuracy, recall and true negative rate of the RNN enterprise risk early warning model tested in Figure 2, it can be seen that in the enterprise health test sample in the sample data, the RNN's early warning accuracy, recall The detection rate and the true negative rate reached 0.978%, 0.986% and 0.867%, respectively, while the accuracy, recall and true negative rate of early warning of the recurrent network in mild enterprise risks reached 0.957%, 0.985% and 0.998%, respectively. , and the accuracy rate, recall rate and true negative rate of the loop network for the sample data of severe enterprise risk reached 0.916%, 0.949% and 0.935% respectively, of which the true negative rate in the early warning of mild enterprise risk reached the highest. 0.99%.

5. Conclusion

Therefore, in order to enrich the research on the enterprise risk early warning model of RNN, this paper first briefly introduces the functional equation of RNN and the concept of non-functional requirements of enterprise risk early warning, and then discusses the enterprise risk early warning model of RNN. Based on the analysis and discussion of the construction technology, the parameter setting and sample data of the enterprise risk early warning model of the recurrent neural network are investigated and designed. Secondly, design and analyze the structure of the enterprise risk early warning model of the RNN, and finally analyze the experimental data for the application of the RNN enterprise risk early warning model designed in this paper. The final experimental results verify the enterprise risk of the RNN in this paper. Advantages of early warning models.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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