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A Shared Financial Risk Warning Strategy Based on Deep Learning

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Abstract. The financial sharing center also carries certain service risks while providing high-quality accounting services. To address such issue, this article proposes a financial sharing risk warning model based on deep learning. We have adopted a new perspective to construct a shared financial risk indicator system for enterprises, integrating important information in financial indicator data with gain information in annual report text. Then, an optimized algorithm is introduced to optimize the parameters of the deep learning model, and the model is used to mine historical financial data from multiple periods. Finally, using the relevant financial data of a listed company in Tai' an DBS, as the testing sample, a neural network model is constructed by deep learning as a research tool. The selected early warning indicator data is imported into Matlab to train a deep learning neural network, to predict whether a company is in financial crisis. The experimental results show that the risk prediction algorithm based on deep learning can accurately predict the financial data trends of enterprises, which significantly improves the model's generalization ability, and its prediction performance is better than traditional single objective optimization algorithms.

Keyword: shared financial risk; warning strategy; deep learning; LSTM; CNN; index system

1. Introduction

The financial sharing model has played a huge role in achieving the goals of unified enterprise financial accounting, comprehensive and centralized prevention and control of business risks, and reducing enterprise costs and expenses. With the continuous development of construction enterprises and finance themselves, financial functions have gradually shifted towards the direction of industry finance integration, process control, and decision support. In order to further improve the risk management mechanism, standardize the defense line management process, refine risk control, effectively enhance the risk prevention ability of enterprises, effectively prevent the occurrence of major and important risk events, and fully leverage the role of the financial sharing center as the "economic monitoring center, risk blocking center, and data integration center", a quality management and financial risk warning linkage system of the financial sharing center should be established to empower the protection of enterprise value [1,2]. From the current use of sharing platforms, the promotion of financial sharing mode in the construction industry has the soil for sustained growth and growth. The centralization, standardization, informatization, and sharing of financial management on shared platforms have maximally compensated for the drawbacks of traditional financial management models in construction enterprises.

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With the expansion of the shared platform's functions it can analyze and study the original real data, identify potential risks and problems, and promptly solve them; It can predict or plan management direction in advance through real-time real data; It is possible to integrate platform resources to strengthen data communication, verification, support, and sharing among various departments of the enterprise. In recent years, with the continuous development of deep learning technology, it has been widely applied in various fields. The advantage of deep learning lies in gradually learning through multiple networks, extracting complex and effective features [3], with higher prediction accuracy and generalization ability. At present, there is relatively little research on the application of deep learning in financial risk prediction. Meanwhile, it should be noted that the selection of parameters can also have a significant impact on the predictive performance of the model [4]. At present, the optimization methods for model parameters mainly include cross validation, grid search, and intelligent optimization algorithms. Marso and Merouani [5] used the CSA algorithm to optimize the weights of the feedforward neural network, and the results showed that the prediction performance of the model was significantly improved, reaching over 90%.

This article delves into the concept and potential risks of shared finance based on actual situations, and points out the potential risk influencing factors and corresponding requirements of the current shared finance center. In the construction process of the financial indicator system, primary and secondary indicators for shared financial risks were proposed from the perspectives of the enterprise's debt paying ability, profitability, development ability, operating ability, and cash flow, which were used to combine them for comprehensive evaluation. On this basis, common deep learning algorithms and their applications in risk warning analysis were discussed, with a focus on conducting in-depth research on LSTM and CNN models. Then, taking the possible financial risks of a listed company as an example, LSTM and CNN are combined to mine time series, and important features in financial indicators are output through training to obtain potential financial risk factors. The experimental results show that the shared financial risk warning strategy designed in this article can explore the interrelationships in massive financial data, and performs better in indicators such as accuracy and AUC value.

2. Theoretical Basis for Sharing Financial Risk Warning and Deep Learning

2.*1 Shared Financial Risks*

The risks of enterprises can be divided into operational risks and financial risks, among which financial risks specifically refer to the risks faced by enterprises in their financial activities and governance during production and operation. The definition of financial risk in the theoretical community can be divided into two levels: narrow and broad. The narrow view of financial risk refers to the risk of bankruptcy or significant changes in common stock returns caused by the use of liabilities for enterprises; The broad view holds that financial risk refers to the uncertainty that exists in the entire financial activity process of a company, which may lead to inconsistency between the actual returns and expectations of the company. The broad sense of financial risk is a complex concept with multiple variables and levels, which is closer to the overall risk of the enterprise and ultimately reflected in the financial statements of the enterprise [6]. After clarifying the warning level of the financial risk of the enterprise, the enterprise should refer to the results of the warning, combine with the actual situation of the company and internal and external data information, efficiently and comprehensively use contemporary comprehensive management professional skills and models, and analyze the reasons through internal discussions, expert consulting services, and other models. After studying and analyzing the main factors that contribute to financial risks, accelerate the adoption of appropriate emergency strategies to reduce losses caused by financial risks. After comprehensively handling this warning, it is necessary to promptly and quickly implement a warning and notification of financial and accounting risks. The notification should identify the causes of financial risks, risk response measures, economic losses caused by risks, including analysis of their impact on the enterprise. Finally, a financial and accounting risk warning and filing database of the company should be established to provide reference for the company in the event of similar or similar situations in the future.

2.2 Deep Learning

Deep learning (also known as deep structure learning or hierarchical learning) is part of a broader series of machine learning methods based on artificial neural networks. Learning can be supervised, semi supervised, or unsupervised. Deep learning architectures, such as deep neural networks, deep confidence networks, recurrent neural networks, and convolutional neural networks, have been applied in fields such as computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection, and board game programs. Their results can be comparable to those of human experts. In certain cases, it is superior to human experts. Multilayer neural networks contain many nonlinear transformations and are good at distinguishing complex patterns in data [7]. They are used to solve problems in machine vision, natural language processing, speech recognition, and other fields. Deep learning can classify or predict nonlinear data with an appropriate number of parallel and nonlinear steps. A deep learning model performs hierarchical learning on input data, with each layer extracting features from the output of the previous layer.

Deep learning inherits the hierarchical structure of artificial neural networks, as shown in Figure 1.

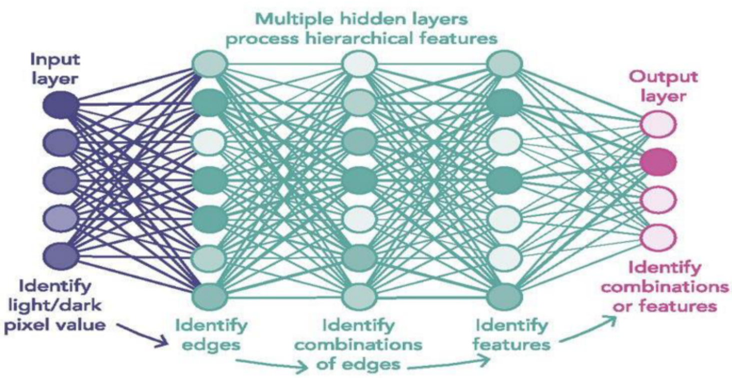


Figure 1. Deep learning neural network.

It simulates the connections between neurons in the human brain by constructing multi-layer neural networks. Each layer of neural network contains multiple neurons, which transmit and process information through a combination of weights and activation functions. Through the stacking of multi-layer networks, deep learning can learn more complex feature representations and abstract concepts, thereby improving the performance and expression ability of the model. The inspiration for this hierarchical structure of the network comes from the organization of artificial neural networks, but deep learning has improved and optimized the network structure and training algorithms, resulting in significant results in various tasks.

3. A Shared Financial Risk Warning Model Based on Deep Learning

3.1 *Selection of Shared Financial Indicators*

The financial risk early warning model has two core tasks: firstly, the selection of early warning model algorithms; Secondly, the construction of an early warning indicator system. The former is the application of prediction algorithms, while the latter is the deep mining of financial risk warning information. Both factors simultaneously affect the accuracy of predicting financial distress of listed companies. Therefore, the effectiveness of financial risk warning models not only depends on the generalization ability of the model algorithm, but also on the selection of model input variables [8]. On the basis of existing research, this article provides 15 alternative financial indicators from five aspects of a company's debt paying ability, profitability, development ability, operating ability, and cash flow indicators. In order to truly and completely reflect the profitability and financial risk situation of the enterprise, this article introduces non-financial indicators such as corporate governance structure on the basis of financial indicators, and finally establishes an indicator system as shown in Table 1. Although some of the indicators may be highly correlated, deep learning neural networks can better capture the complex relationships and nonlinear patterns between variables. Therefore, when selecting financial indicators, it is important to include as much information as possible to help neural networks better understand and predict data.

Table1. Shared financial indicator system

Index type	Index name	Variable
Solvency	Tangible Net Worth Ratio	X1
	Current ratio	X2
	Quick ratio	X3
Profitability	Net profit margin	X4
	Gross profit margin	X5
	Return on assets	X6
Development capability	Operating revenue growth rate	X7
	Net profit growth rate	X8

Business capability	Total asset growth rate	X9
	Accounts receivable turnover rate	X10
	Inventory turnover rate	X11
	Fixed asset turnover rate	X12
Cash flow indicators	Cash flow ratio from operating activities	X13
	Free cash flow	X14
	Cash flow return rate	X15
Internal control and risk management	State share ratio	X16
	Senior shareholding ratio	X17
	Ratio of circulating shares	X18
EVA	Total assets EVA	X19
	Net asset EVA	X20

3.2 Improvement of Deep Learning Algorithm

By comprehensively considering the advantages of LSTM (Long Short Term Memory) network and CNN (Convolutional Neural Network) network, and deeply integrating them, a more powerful deep learning model can be obtained. The LSTM network performs well in processing sequence data and is able to capture long-term dependencies. However, CNN has advantages in processing images and spatial data, as it can extract local features and spatial relationships. Integrating LSTM and CNN can fully leverage their respective advantages. The common method used in this article is to use CNN as the input layer of LSTM to extract local features of the input sequence. This can help LSTM networks better understand the spatial relationships in sequence data [9]. The LSTM CNN network structure design diagram is shown in Figure 2. By designing the LSTM-CNN network structure, long-term dependencies and local features can be considered simultaneously when processing sequence data, thereby improving the performance and effectiveness of the model.

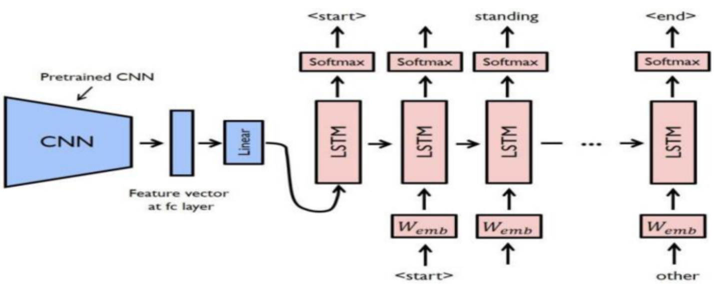


Figure 2. The structure of LSTM-CNN.

The gate functions in LSTM include input gate, forget gate, and output gate. The input gate determines how much information input at the current moment will be remembered. Through the control of these gate functions, LSTM can flexibly capture long-term dependencies in the time series, thereby better predicting future temporal changes. The calculation formula of LSTM has been improved as follows:

$$\mathrm{i}_{\mathrm{t}} = \sigma(W_{xi}x_{\mathrm{t}} + W_{hi}h_{\mathrm{t\text{-}1}} + b_i) \tag{1}$$

$$f_{\mathrm{t}} = \sigma(W_{xf}x_{\mathrm{t}} + W_{hf}h_{\mathrm{t\text{-}1}} + b_f) \tag{2}$$

$$\sigma_{\mathrm{t}} = \sigma(W_{x0}x_{\mathrm{t}} + W_{h0}h_{\mathrm{t\text{-}1}} + b_0) \tag{3}$$

$$\tilde{c}_t = \tanh(W_{xc}x_{\mathrm{t}} + W_{hc}h_{\mathrm{t\text{-}1}} + b_c) \tag{4}$$

$$c_t = f_t \Theta c_{t-1} + i_t \Theta \tilde{c}_t \tag{5}$$

$$h_t = \mathrm{o}_t \Theta \tanh(c_t) \tag{6}$$

where x_{t} is the $\mathrm{t_{th}}$ input sequence element values, c is the cell status which control the information transmission; i means how information is saved for x_{t} by the input gate; f is the cell status from c_{t-1} to c_t at previous hour, decided by the forgotten gate; o is the output transmitted by c_{t} decided by the output gate; $h_{\mathrm{t\text{-}1}}$ is the hidden layer status at time $t-1$; W_{xi}, W_{xf}, W_{x0}, W_{xc} are corresponding weigh vector of input gate, output gate, forgotten gate and cell status; b_i , b_f , b_0 and b_c are the offset of input gate, output gate, forgotten gate and cell status; σ is the sigmoid activation function; $\tanh$ is the hyperbolic tangent activation function; Θ is vector element multiplication

In CNN layer, the features are extracted from output sequence content and we set 32 convolutional kernel whose size is (3,3). Relu is taken as activation function. Subsequently, the output of LSTM is integrated and dimensionally reduced through a fully connected layer, and finally, the prediction results for year T are classified and output through Softmax.

4. Empirical Analysis

From the perspective of statistical analysis of economic issues, we construct statistical analysis models and explore the results reflected by statistical data from statistical analysis variables or indicators. This article selects samples from the Guotai' An database and collects case studies to analyze the necessary indicators and variables, such as income, profit, liabilities, etc. Data preprocessing: includes steps such as data cleaning, missing value processing, feature selection, and standardization to ensure that the dataset contains financial indicators and corresponding risk labels. After the investigation is completed, if errors found in the data cannot be corrected, or if some data does not meet the requirements of the investigation and cannot be remedied, it is necessary to filter the data. Divide the 98 companies under the total sample into two groups, namely the test sample for judging the accuracy of the model and the training sample for establishing a deep learning shared financial risk warning model. Select appropriate features or perform feature engineering to provide important information about the task to the model and determine the architecture of the model, including the number of layers, nodes, and activation functions. Then we establish the model using the selected LSTM-CNN algorithm, defining the structure, number of layers, activation function, etc. of the model. Import sample data in MATLAB. Finally we use the deep learning toolbox to establish and train the model, and the data is normalized by Mapminmax function as

$$f(x)=\frac{y_{\max}-y_{\min}}{x_{\max}-x_{\min}}(x-x_{\min})+y_{\min} \tag{7}$$

where $y_{\min}$ and $y_{\max}$ is the minimum and maximum by data convertion, which are set as -1 and 1 in this paper; $x_{\min}$ and $x_{\max}$ are the minimum and maximum of each sample. Such function can normalized the data to are interval like [-1, 1]. After processing the data can be directly used to the training of financial alarming. For example, the processed data in year T+1 is depicted in figure 3:

Income Statement						
Revenue	**66,132**	**73,558**	**79,716**	**84,438**	**97,103**	**111,669**
Cost of Goods Sold (COGS)	26,884	27,511	29,488	31,760	40,783	45,784
Gross Profit	**39,248**	**46,047**	**50,228**	**52,678**	**56,320**	**65,885**
Expenses						
Marketing, Advertising & Promotion	12,689	13,369	12,882	14,138	15,537	17,867
General & Administrative	5,670	5,649	6,172	6,391	7,000	7,000
Depreciation & Amortization	10,165	9,635	9,265	9,006	4,203	4,512
Interest	1,400	840	840	840	1,344	1,344

Normalized Grid for 19-20 (for Reference)

Step	B	B+15	B+30	M	M+15	M+30	M+45	M+60	M+75	DOC
1	51,215	52,868	54,518	56,165	57,828	59,472	61,131	61,952	63,620	64,452
2	53,609	55,339	57,066	58,790	60,531	62,251	63,988	64,847	66,593	67,464
3	56,003	57,810	59,614	61,415	63,234	65,030	66,845	67,742	69,566	70,476
4	58,397	60,281	62,162	64,040	65,937	67,809	69,702	70,637	72,539	73,488
5	60,791	62,752	64,710	66,665	68,640	70,588	72,559	73,532	75,512	76,500
6	63,185	65,223	67,258	69,290	71,343	73,367	75,416	76,427	78,485	79,512

Figure 3. Financial data cleaning results in year T+1.

Figure 4 shows the mean square error diagram of the training group model. From it, it can be seen that the root mean square error of the model is decreasing, reaching the set target error of 0.1. This means that the model gradually learns the patterns and patterns of the data during the training process, and can make more accurate predictions or classifications. If the proportion of positive and negative samples of financial risk is imbalanced, such as having fewer positive samples and more negative samples, the model may tend to predict more negative samples, leading to misjudgment of the financial risk of the enterprise. By adjusting the prediction threshold of the model, the probability of misjudgment can be controlled. In practical applications, the occurrence of misjudgment is inevitable, as early warning models are based on statistics and probability. We can regularly evaluate the performance of the model and iterate and improve it based on the evaluation results, in order to detect and correct misjudgment issues as early as possible and improve the performance of the model.

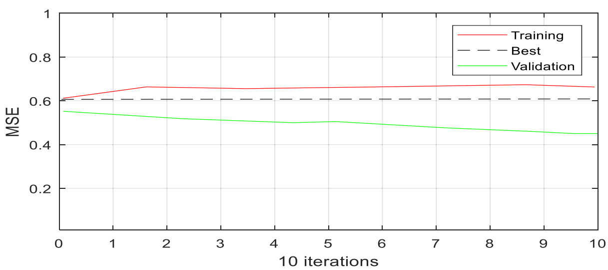
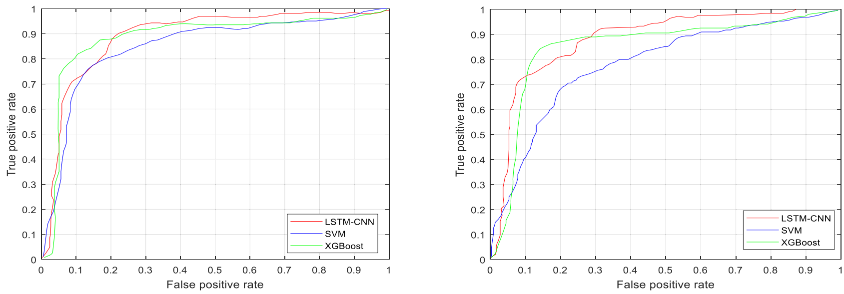


Figure 4. Root mean square error graph of the model.

When using the LSTM-CNN model for sample prediction, randomly partitioning data may have a certain impact on the performance of the model. Deep learning models typically require a large amount of data to train and leverage their advantages. If there is less available financial indicator data, traditional machine learning models may be more suitable for handling this situation. In the risk warning based on financial indicator data, this experiment used 20 financial indicators, all of which are mature features constructed by relevant research. Therefore, when comparing the comprehensive performance with traditional machine learning models, poor performance may occur if computational resources are limited. However, in large-scale datasets and complex pattern recognition tasks, our algorithm can still achieve excellent prediction performance through further analysis. From Figure 5, it can be seen that the accuracy of deep learning in year T+2 is higher than other algorithms in the same period, and the learned features of the financial normal group are more complete than those of the learned financial crisis group.



（a）ROC curve of randomly partitioned data （b）ROC curve of partitioned data by year

Figure 5. Comprehensive prediction performance comparison by on ROC curve in year T+2.

5. Conclusion

Deep learning models can automatically extract and represent advanced features of data by learning the features in the data. In shared financial risk warning, deep learning models can learn the complex relationships between financial indicators and discover hidden patterns and patterns. Based on this, this article introduces a deep neural network in deep learning to alert companies to shared financial risks. Due to the excellent performance of CNN and LSTM in processing time series data. In shared financial risk warning, the combination of these models can be used to analyze the time dependence and trend of financial data, thereby more accurately predicting future risks. We have integrated and improved these two algorithms by applying models trained in other fields to shared financial risk warning through transfer learning, in order to accelerate the training process of the model, improve its performance and generalization ability. The dataset testing results on MATLAB indicate that this scheme outperforms traditional machine learning models and other deep learning models in terms of accuracy and AUC values, and can effectively improve the effectiveness of financial risk warning.

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