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Research on Financial Early Warning Indicator System Constructed by LSTM Recursive Algorithm in Enterprise Capital Chain Risk Control Empowered by Digital Transformation

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ABSTRACT
In order to improve the accuracy of enterprise financial risk early warning and realize the risk control of enterprise capital chain under digital transformation, this paper adopts the Long Short-Term Memory (LSTM) neural network algorithm to establish the enterprise financial risk early warning model. First analyze the enterprise financial risk early warning indicators, use factor analysis for indicator screening, determine the indicator weights through the Delphi method and the improved hierarchical analysis method, and select the indicators with high importance to construct the enterprise financial risk early warning feature samples. Then after LSTM neural network training, the enterprise financial risk early warning model is obtained, and the model is evaluated for performance and practical use. The experiment proves that the accuracy of the LSTM neural network model on the training set and test set is 91.48% and 88.62% respectively, which indicates that the model can effectively predict the enterprise financial risk. By comparing with the commonly used enterprise financial risk warning algorithms, the algorithm in this paper has the highest warning accuracy, shorter prediction time, and better warning performance in dealing with large-scale enterprise samples. This study provides an effective financial risk early warning method for enterprises, which can help them better carry out capital chain wind control in the process of digital transformation.

Keywords: factor analysis, hierarchical analysis method, LSTM neural network, financial early warning

1. Introduction

In today's rapid development of digital economy, enterprises are facing an increasingly complex business environment, and financial risks are showing new features and trends [1]. Traditional financial risk early warning methods are often based on historical data and static models, which are

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difficult to adapt to the current rapidly changing market environment [2-3]. Digital transformation has brought new opportunities and challenges for enterprise financial risk management, and how to use digital technology to build a more intelligent and efficient financial risk early warning system has become an urgent problem for enterprises [4-6].

In the face of the new changes brought by digital transformation, the traditional financial risk early warning model has exposed many limitations, which are reflected in the single source of data, static early warning indicators, simplified analysis methods, obvious lag of early warning results, and lack of intelligence and automation of the early warning process, etc., while the construction of an intelligent financial risk early warning system can significantly improve the accuracy and timeliness of the risk identification [7-10]. In terms of data collection, the intelligent system can integrate multi-source data, including financial data, operational data, market data, and external environment data, to form an all-round data perspective [11-13]. This comprehensive data collection can capture risk signals that are difficult to detect by traditional methods. In terms of data processing, intelligent systems use machine learning and deep learning algorithms to quickly process massive amounts of data and identify potential risk patterns and anomalies [14-17]. This efficient data analysis capability greatly improves the accuracy of risk identification. Moreover, the real-time monitoring function of the intelligent system makes the risk identification more timely, and the system can monitor all kinds of indicators 24 hours a day without interruption, and trigger the early warning mechanism as soon as an abnormality is detected, so that the enterprise is able to take countermeasures at the early stage of risk occurrence [18-21]. More importantly, the self-learning ability of the system enables the risk identification model to be continuously optimized to adapt to the changing business environment and maintain a high degree of sensitivity and accuracy, and this continuous improvement ensures the long-term effectiveness of risk identification [22-25].

Literature [26] examined the main features of digital transformation and business growth, i.e., the impact of digital transformation on business growth as well as the growth process, and developed a financial early warning model based on convolutional neural networks with a view to assisting companies in their digital transformation plans. Literature [27] analyzed digital transformation based on the introduction of non-financial indicators based on financial indicators, and constructed a logistic regression financial risk early warning model based on the digital transformation of several manufacturing enterprises and companies in the same industry by extracting six principal components to provide guidance for the digital transformation of enterprises. Literature [28] integrated deep learning techniques such as back propagation neural networks to enhance the risk early warning system and improve the accuracy and efficiency of the financial risk prediction model, emphasizing that the algorithm outperforms the baseline model in several metrics. Literature [29] proposed a blockchain-based enterprise financial risk prevention and early warning system for the challenges faced by SMEs in financing, which reveals that the financing activities of commercial banks and SMEs are based on the trust endorsement of the core enterprises in the supply chain through application analysis. Based on the financial data of listed companies, literature [30] establishes an independent index system within the framework of profitability, solvency, and operating ability, verifies the effectiveness of the system, which has a very high prediction accuracy, and aims to define a generalized financial risk early warning model applicable to all enterprises. Literature [31] discusses the necessity of enterprise financial management innovation under digital transformation and puts forward suggestions, emphasizing the need for enterprises to make use of information technology to optimize financial decision-making and reduce financial risks by innovating the financial management model, laying the foundation for the healthy development of enterprises. Literature [32] examined the relationship between digital transformation and the financial performance of manufacturing enterprises, and the results show that digital transformation has a positive impact on the financial performance of enterprises, and at the initial stage of digital transformation, the profitability of enterprises decreases, and with the deepening of the digitalization process, the profitability and return on total assets will gradually increase.

Literature [33] emphasizes the importance of financial management for the sustainable development of enterprises, and for the problems that cannot be solved by traditional methods, it explores the early warning model of association rule mining and time series analysis, and analyzes the financial risk of enterprises by combining data mining technology, in order to assist enterprises in formulating reasonable investment strategies. Literature [34] explored the formation mechanism of enterprise financial risk based on the value chain perspective, combined with system dynamics ideas, and revealed that the financial risk situation can be changed by adjusting the value chain structure by constructing a financial risk evolution monitoring model and a financial dynamic early warning simulation model. Literature [35] adopts chaotic particle swarm optimization algorithm to optimize the back propagation neural network, and builds an early warning model for financial management of enterprise circular economy, which verifies that the model has high prediction accuracy, fast convergence speed, significantly higher than other models, and has the potential to be applied in the financial management of enterprises. Literature [36] introduces the concept of enterprise financial risk, proposes a financial risk early warning model based on evidence theory, and takes a number of enterprise companies as the research object, revealing that the model can effectively improve the prediction accuracy of the company's intelligent financial decision-making system, and reduce the subjective factors and information loss in the process of risk assessment. Literature [37] analyzed the impact of digital transformation on corporate breach risk based on data from listed companies, emphasizing the inverted u-shaped relationship between the degree of digital transformation and corporate breach risk, which is supported by the three dimensions of motivation, opportunity, and management attitude. Literature [38] explored the financial risk early warning mechanism of real estate companies, based on the financial risk assessment and analysis of BP neural network model, which verified its effectiveness in early financial risk detection and revealed that this model has significant advantages for corporate financial risk early warning. The above study examined the financial early warning of enterprises in the context of digital transformation from the perspectives of convolutional neural network, logistic regression, time series analysis, chaotic particle swarm optimization algorithm, etc., and verified the effectiveness of these methods in this field, which showed excellent prediction accuracy and laid the foundation for the sustainable development of enterprises.

On the basis of constructing the financial early warning indicator system, this paper builds an enterprise financial risk early warning model based on LSTM recursive algorithm, which provides a digital tool for realizing the enterprise capital chain wind control. Firstly, taking listed companies in the manufacturing industry as the research object, the initial selection of indicators is based on enterprise financial data. Then, the factor method and the improved hierarchical analysis method are used to screen and assign the indicators, and the financial risk early warning indicator system is constructed. Then, the data of enterprise financial early warning indicators are imported into the LSTM model for financial risk prediction, and the enterprise financial risk early warning thresholds are effectively set. Finally, in order to verify the effectiveness of the model, the trained model is compared with other models, and Company A is selected as a specific research object to analyze the prediction accuracy and warning results.

2. The construction of the index system of the enterprise financial early warning model

In order to realize the financial early warning in the wind control of enterprise capital chain under the empowerment of digital transformation, this chapter, on the basis of the preliminary selection of enterprise financial early warning indicators, screens the indicators through correlation test and factor analysis, and determines the weights of the indicators by combining the Delphi method with the improved hierarchical analysis method, and ultimately constructs the indicator system of the enterprise financial early warning model, which lays the foundation of the establishment of the model.

2.1. Selection of model samples

In this paper, 16 listed companies were selected to be ST or *ST for the first time in 2023, and 30 companies were ST or *ST for the first time in 2022, while 46 financially normal companies were selected in 2022 as a comparison, for a total of 92 listed companies, and the data of the sample indexes of the financially abnormal companies are all from the first two years of being ST or *ST, and the data of the sample indexes of the financially normal companies are from 2020. The selected companies all belong to the manufacturing industry, Class C of CSRC's industry classification standard, for the following reasons:

1) The selected samples are all listed companies in China, and the China Securities Regulatory Commission requires the stock exchange to implement special treatment (ST) for stock trading of listed companies with "abnormal conditions", which is preceded by "ST" in the abbreviation, and such stocks are called ST shares. "Abnormal conditions" here include "abnormal financial conditions" and "other abnormal conditions".

2) The guidelines for defining financial crises are different due to the different industries in which they operate. The manufacturing industry is the leading sector of China's economic growth and the foundation of economic transformation. Listed companies in the manufacturing industry account for most of the listed companies in China, in order to avoid the complexity of the problems caused by industry factors, the selection of listed companies in the manufacturing industry as a sample better reflects the discovery of the actual problems of the enterprises in this industry, and better establishes the financial early warning model especially for the manufacturing industry.

3) Once a company's annual report for the fiscal year T-1 is available, it is almost certain that the company will be treated as special due to “abnormal financial condition”. Therefore, the predictive information used in this paper is all publicly available information two years before the special treatment, thus effectively controlling the impact of the time of information acquisition on the predictive ability of the model.

2.2. Construction of the model indicator system

2.2.1. Selection of financial early warning indicators. The financial statements of a listed company are a comprehensive reflection of the company's financial position, operating performance and development trend, and are a comprehensive and reliable first-hand source for investors to understand the company's situation. Financial statements contain a large amount of financial data, using which many meaningful financial ratios can be calculated to understand various aspects of business management. This paper refers to a large number of literature, from the enterprise solvency, asset operation ability, enterprise growth ability and enterprise profitability of the four aspects of the selected 22 financial indicators, so as to get the preliminary construction of the financial early warning indicator system as shown in Table 1.

Table 1. The preliminary construction of financial early warning index system

Primary index	Symbol	Secondary index
Solvency of enterprise	X1	Current ratio
	X2	Quick ratio
	X3	Cash ratio
	X4	Asset-liability ratio
	X5	Interest cover
	X6	Equity ratio
Operational capacity of assets	X7	Turnover of total assets
	X8	Current asset turnover
	X9	Inventory turnover
	X10	Accounts receivable turnover rate
	X11	Turnover rate of fixed assets
Enterprise growth ability	X12	Revenue growth rate
	X13	Net profit growth rate
	X14	Growth rate of total assets
	X15	Rate of capital accumulation
	X16	Growth rate of fixed assets
Enterprise profitability	X17	Return on assets
	X18	Return on equity
	X19	Gross operating margin
	X20	Operating profit margin
	X21	Profit rate of cost expense
	X22	Net profit rate on total assets

2.2.2. Relevance test for financial early warning indicators. When applying the factor analysis method, the primary consideration is the correlation between the indicator variables, and the factor analysis method is not suitable when the correlation is weak. Therefore, before factor analysis, KMO test and Bartlett's test of sphericity are conducted to assess the degree of correlation between indicators. The results of the correlation test are shown in Table 2.

Based on the results in Table 2, it can be seen that the value of the KMO test is 0.725, which is greater than 0.6, indicating that there is a correlation between the selected risk warning indicator variables. In the Bartlett's test of sphericity, the statistic is 11,472.853, which corresponds to a significance level of 0.000, which is less than 0.050, indicating that the risk warning indicators from the sample of 92 listed manufacturing companies are statistically significant. Therefore, all indicator variables passed the KMO test and Bartlett sphericity test and can be factor analyzed.

Table 2. KMO and Bartlett's test of sphericity

A measure of adequacy of the Kaiser-Meyer-Olkin sample		0.725
Bartlett's sphericity test	Approximate chi-square	11472.853
	df	448
	Sig.	0.000

2.2.3. Factor analysis of financial early warning indicators:

1) Factor analysis. Factor analysis [39] is a branch of multivariate statistical analysis technique, which refers to the study of statistical techniques for extracting common factors from groups of variables, and its main purpose is to condense the data.

The basic idea of factor analysis is to group the original variables according to the magnitude of their correlation, so that the correlation between variables within the same group is high, while the correlation between variables in different groups is low. Each group of variables can be represented by a common factor. The general model of factor analysis, with n samples, each sample has p observations, which p indicators have a strong correlation, the model of factor analysis can be expressed as:

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \ldots + a_{1m}F_m + \varepsilon_1 \\ X_2 = a_{21}F_1 + a_{22}F_2 + \ldots + a_{2m}F_m + \varepsilon_2 \\ \ldots\ldots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \ldots + a_{pm}F_m + \varepsilon_p \end{cases} \tag{1}$$

Introducing factor analysis into the early warning analysis of financial distress of listed companies is to find out the main factors through the study of the internal structural relationship of the correlation matrix of the original indicators, so that the main factors are linear combinations of the original indicators, so that not only the main information of the original indicators is retained, but also the main factors are not correlated with each other, which meets the premise assumptions of the LSTM recursive algorithm. At the same time, factor analysis allows multiple indicators to be downscaled, so that the number of independent variables is reduced on the basis of reflecting the information contained in the original variables to the maximum extent possible, which solves the problem of insufficient sample size.

2) Extraction of principal components. For the 22 financial indicators that entered the secondary screening, using the financial data of 92 ST and normal listed companies, SPSS28.0 was used to conduct a factor analysis, and the resulting factor contribution ratio is shown in Table 3.

This analysis from the results of the selection of cumulative contribution rate of 91.494% or more of the factors as the main component factors, can be derived from the main component factors for 6, that is, these 6 main component factors contain the original indicators of 91.494% of the amount of information, can be used to replace the original 22 financial indicators with these 6 main components.

Table 3. Contribution rate of factors

	Initial eigenvalue			Extract the sum of squared loads			Rotating load sum of squares		
Principal component	Total	Percentage of variance	Cumulative /%	Total	Percentage of variance /%	Cumulative /%	Total	Percentage of variance /%	Cumulative /%
1	5.906	23.756	23.756	5.906	23.756	23.756	5.121	18.251	18.251
2	4.078	19.905	43.661	4.078	19.905	43.661	3.924	17.384	35.635
3	3.824	15.852	59.513	3.824	15.852	59.513	3.635	16.157	51.792
4	2.847	13.534	73.047	2.847	13.534	73.047	3.221	15.262	67.054
5	1.975	10.792	83.839	1.975	10.792	83.839	2.563	13.605	80.659
6	1.379	7.655	91.494	1.379	7.655	91.494	2.044	10.835	91.494
7	0.965	3.893	95.387						
8	0.798	1.949	97.336						
9	0.515	1.095	98.431						
10	0.464	0.824	99.255						
11	0.393	0.432	99.687						
12	0.103	0.313	100.000						

In order to explain these six principal component factors, it is also necessary to obtain the factor loadings of the 22 raw financial warning indicators on these six principal component factors, i.e., the correlation coefficients between the raw indicators and the principal component factors. In order to get the factor loadings, this paper uses the variance maximization method in orthogonal rotation method for transformation. The factor loading matrix is shown in Table 4.

From the orthogonal rotated factor loading matrix, the following conclusions can be obtained:

In factor 1, there are five variables with large contribution are: return on net assets, gross operating profit margin, operating profit margin, cost and expense margin, and net profit margin of total assets, which reflect the profitability of the enterprise.

In Factor 2, the 2 variables with greater contribution are current ratio and quick ratio, reflecting the solvency of the enterprise.

In Factor 3, the 2 variables with greater contribution are total asset turnover, current asset turnover, inventory turnover, accounts receivable turnover, and fixed asset turnover, all of which represent the firm's operating ability.

In factor 4, the contribution of net profit growth rate and total assets growth rate is much larger than other indicators, which reflect the growth ability of the enterprise.

In Factor 5, the largest contribution is the gearing ratio, which reflects the solvency of listed manufacturing companies.

In factor 6, the largest contributor is the growth rate of operating income, which also reflects the growth ability of the company.

Table 4. The preliminary construction of financial early warning index system

Variable name	Principal component						
	1	2	3	4	5	6	7
X1	0.174	0.923	-0.165	-0.013	-0.088	0.063	-0.024
X2	0.153	0.948	-0.119	-0.024	-0.044	0.034	0.016
X3	0.102	0.818	0.014	-0.008	-0.035	-0.004	-0.026
X4	-0.383	-0.572	0.305	0.077	0.936	0.005	0.053
X5	0.116	-0.013	-0.023	0.052	0.003	0.735	0.078
X6	-0.041	-0.142	0.002	-0.027	0.474	-0.015	-0.014
X7	0.197	-0.187	0.866	0.023	-0.062	0.132	-0.081
X8	0.172	-0.368	0.738	0.056	-0.169	0.012	-0.065
X9	0.035	-0.023	0.709	-0.037	0.298	-0.083	0.218
X10	-0.005	-0.001	0.602	0.014	-0.098	-0.012	0.082
X11	0.047	0.122	0.642	0.004	0.188	0.182	-0.075
X12	0.014	0.033	0.003	-0.018	0.016	-0.106	0.775
X13	0.063	-0.005	0.049	0.943	-0.013	-0.117	0.168
X14	0.188	-0.028	0.024	0.934	-0.037	-0.008	0.102
X15	0.526	0.058	0.025	0.431	-0.159	0.028	-0.008
X16	0.037	-0.044	-0.002	0.544	0.027	-0.012	0.011
X17	0.433	0.157	0.097	0.083	-0.106	0.121	-0.032
X18	0.878	-0.007	0.061	0.014	0.005	-0.083	0.003
X19	0.854	0.329	-0.271	0.121	-0.251	0.008	-0.043
X20	0.949	0.073	0.055	0.014	0.028	-0.046	0.032
X21	0.929	0.212	0.017	0.061	-0.025	0.024	0.004
X22	0.884	0.189	0.129	0.055	-0.104	0.117	-0.023

Through correlation test and factor analysis, finally we got 16 representative indicators. These 16 indicators can basically reflect the company's situation from all aspects. The finalized indicator system is shown in Table 5.

Table 5. Finalization of the financial early warning indicator system

Primary index	Symbol	Secondary index
Solvency of enterprise	Y1	Current ratio
	Y2	Quick ratio
	Y3	Asset-liability ratio
Operational capacity of assets	Y4	Turnover of total assets
	Y5	Current asset turnover
	Y6	Inventory turnover
	Y7	Accounts receivable turnover rate
	Y8	Turnover rate of fixed assets
Enterprise growth ability	Y9	Revenue growth rate
	Y10	Net profit growth rate
	Y11	Growth rate of total assets
Enterprise profitability	Y12	Return on equity
	Y13	Gross operating margin
	Y14	Operating profit margin
	Y15	Profit rate of cost expense
	Y16	Net profit rate on total assets

2.2.4. Determination of weights of financial early warning indicators:

1) Scoring by experts. After the preliminary determination of the above evaluation index system, using the Delphi method [40], the importance of the relevant factors of each indicator to consult the expert opinion on the importance of each indicator on the degree of prediction of financial warning alert scoring. The Likert 5-point system is used, that is, the degree of influence from low to high is expressed by 1, 2, 3, 4, 5 points respectively: 1 point represents not important at all, 2 points represents relatively unimportant, 3 points represents the general degree, 4 points represents relatively important, and 5 points represents very important.

2) Calculation of weights. In this paper, the improved hierarchical analysis method [41] is used for the calculation of weights. The specific steps of the improved hierarchical analysis method are as follows:

Step1: Build a comparison matrix $C=\left[c_{ij}\right]$. Take $c_{ij}=1$ when indicator i is more important than indicator j, $c_{ij}=0$ when indicator i is equally important as indicator j, and $c_{ij}=-1$ when indicator i is less important than indicator j.

Step2: Establish the sense judgment matrix $S=\left[s_{ij}\right]$. Where $s_{ij}=d_i-d_j$ and $d_i=\sum_j c_{ij}$.

Step3: Build an objective judgment matrix $R=\left[r_{ij}\right]$. where $r_{ij}=p^{s_{ij}/s_m}$, $s_m=\max_{i,j} s_{ij}$, p is the range of user-defined scalar extension values, e.g. $p=5\ or\ 7$. In this calculation, take $p=5$.

Step4: Normalize any column element of R that is the weight vector.

According to the above steps, the weights of the financial warning indicators are finally obtained as shown in Table 6.

Table 6. The weight of financial early warning index

Primary index	Weight	Secondary index	Weight
Solvency of enterprise	0.25	Y1	0.310
		Y2	0.432
		Y3	0.258
Operational capacity of assets	0.25	Y4	0.189
		Y5	0.095
		Y6	0.433
		Y7	0.189
		Y8	0.094
Enterprise growth ability	0.25	Y9	0.335
		Y10	0.353
		Y11	0.312
Enterprise profitability	0.25	Y12	0.254
		Y13	0.254
		Y14	0.152
		Y15	0.216
		Y16	0.124

3. Early warning model construction of enterprise financial risk based on LSTM recursion

This chapter constructs an enterprise financial risk early warning model based on LSTM on the basis of the constructed financial early warning index system, and evaluates the performance and practical application of the model.

3.1. *Long and Short-Term Neural Network (LSTM) Models*

Typically, general recurrent neural networks suffer from a fatal core problem. The network increases the likelihood of gradient bursting or dispersion with a gradual increase in the time interval. In order to solve this problem, the threshold mechanism is introduced, by utilizing the properties of the threshold mechanism can be achieved by external control to control the speed of the accumulation of the amount of information, and has the functional role of forgetting part of the accumulated information. The model used in this paper is the long and short-term memory neural network [42].

Improvement of motivation analysis: in a simple recurrent neural network, if defined:

$$\xi = W^T \cdot diag\left(\sigma'\left(S_{j-1}\right)\right) \tag{2}$$

Then there is:

$$\prod_{j=k+1}^{t}\left(W^T \cdot diag\left(\sigma'\left(S_{j-1}\right)\right)\right) \to \xi^{t-k} \tag{3}$$

If the spectral radius of ζ, $\|\xi\|<1$, tends to infinity when the time difference $(t-k)$, then Eq. (3) diverges and leads to the so-called gradient explosion problem of the system. On the contrary, if $\|\xi\|<1$, it will lead to the problem of gradient dispersion as the time difference expands infinitely. In order to avoid gradient explosion or gradient dispersion, the core is to set the spectral radius of ξ to $\|\xi\|<1$ without loss of generality, and if W is set to be the unit matrix, and at the same time the spectral paradigm of $\sigma'\left(S_{j-1}\right)$ is also set to be 1, i.e., the original model's hidden relationship degenerates to:

$$s_t = \sigma\left(U \cdot x_t + W \cdot s_{t-1} + b\right) \xrightarrow{\text{Degradation}} s_t = U \cdot x_t + s_{t-1} + b \tag{4}$$

But there is a problem with such a form, which creates a lack of nonlinear activation properties. Therefore, an improvement is made for this problem by introducing a new state, denoted as c_t, for the nonlinear transfer of information, i.e.:

$$\begin{cases} c_t = c_{t-1} + U \cdot x_t \\ s_t = \tanh\left(c_t\right) \end{cases} \tag{5}$$

where $\tanh(\cdot)$ is the nonlinear activation function. With the increase of time t, the accumulation of r_t will become larger and larger, in order to cope with and deal with this problem, a mechanism is carried out to introduce, i.e., the threshold mechanism, to fundamentally control the speed of the accumulation of information, and at the same time, the introduction of the threshold mechanism is also able to achieve the effect of partial amnesia, which leads to the introduction of the long and short-term memory neural network as shown in Figure 1.

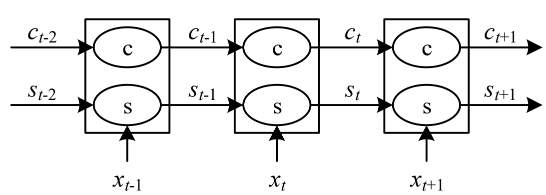

Fig. 1. Recurrent neural network structure after adding new states

Long and short-term memory neural network construction:

As can be seen from Figure 1, the new long and short-term neural network mainly relies on the state C to control the long and short-term changes of information. The long and short-term memory neural network structure includes the following two points:

With respect to the state C, how many components of c_{t-1} are retained in c_t through the forgetting gate, and how much of the punishment in x_t is retained in c_t through the input gate.

With respect to the state S, the output gate determines how many components of the output n_t are output into s_t via the control unit c_t.

The core design of the long and short-term memory network consists of an input gate, a forgetting gate and an output gate. The performance states of its three gates are as follows:

1) Input gate. The main purpose of this gate is to determine how many components of the input x_t are retained in c_t, which is realized by the formula:

$$\begin{cases} i_t = \sigma\left(I_i \cdot x_t + W_i \cdot s_{t-1} + V_i \cdot c_{t-1}\right) \\ \tilde{c}_t = \tanh\left(U_c \cdot x_t + W_c \cdot s_{t-1}\right) \end{cases} \tag{6}$$

Here i denotes "$input$", where i_t is the input to the input gate at the moment of t, through which the corresponding $\tilde{c}_t$ times in the input are retained, i.e., after the input gate is passed, the retained c_t in the The components $i_t \otimes \tilde{c}_t$, where the symbol "$\otimes$" denotes the multiplication of corresponding elements in the corresponding vector.

2) Oblivion Gate. The purpose of this gate is to use the control unit c_t to determine how many components of the output o_t are output to the hidden layer s_t. First, after the input gate and the forgetting gate the state C, i.e., c_t realizes Eq:

$$f_t = \sigma\left(U_f \cdot x_t + W_f \cdot s_{t-1} + V_f \cdot c_{t-1}\right) \tag{7}$$

Here f is an abbreviation for "forget".

3) Output Gate. This gate determines how many components of the output o_t are output to the hidden layer s_t by means of the control unit r_t. First, after the input gate and the forgetting gate the state C, i.e., r_t realizes Eq:

$$r_t = i_t \otimes \tilde{c}_t + f_t \otimes c_{t-1} \tag{8}$$

where the first term is the component retained in r_t after the input gate, and the second term is the component retained in r_t after the forgetting gate. Second, to determine how many components of r_t are retained in s_t, the output realizations of the formulas are given first:

$$o_t = \sigma\left(U_o \cdot x_t + W_o \cdot s_{t-1} + V_o \cdot c_t\right) \tag{9}$$

Here, it represents the state of the output layer at the moment of t. Finally, through the output gate, the hidden layer retains the following components:

$$h_t = o_t \square \tanh\left(c_t\right) \tag{10}$$

To summarize, the structural design flow of the whole network with the change of time is shown in Fig. 1. The network has been successfully applied to handwritten character recognition, language recognition, machine translation, image generation and analysis and other fields. This paper takes the financial indicators of listed companies in the manufacturing industry as the basis to further analyze the early warning model about the financial risk of listed companies in the manufacturing industry.

3.2. *Model training process and results*

3.2.1. Training process. The training of LSTM neural network is divided into three stages. In the first stage, the output value of each neuron is calculated in the forward direction. In the second stage, the error term of each neuron is computed in the reverse direction.The LSTM neural network error values are propagated backward in two directions: first, chronological backward propagation, which refers to the computation of the LSTM error value at each moment in turn, taking the current moment as the base. Second, the error values are passed to the previous layer of the network. In the third stage, the gradient of each weight is computed based on the corresponding error value.The LSTM needs to learn

8 sets of parameters, i.e., the weights and bias terms of each of the cell states, forgetting gates, input gates, and output gates. In the Spyder development platform of Anaconda3, the dataset is loaded with sample data preprocessed and each feature distribution curve is plotted separately. In this paper, 16 indicators are used for financial early warning, and this paper only shows the feature distribution curves of the first 5 indicators in T-2 years under the single step dimension as shown in Figure 2.

Sample characteristics distribution chart can be more intuitive understanding of the value domain of the collected sample data, by observing the distribution curve of each feature, you can query the existence of abnormal data from its fluctuations. The curve with smoother fluctuation indicates that the range of fluctuation of the value domain of the data is not large, and the abrupt peak indicates that the financial data of the listed company corresponding to this value is quite different from that of the majority of the companies, which should be emphasized.

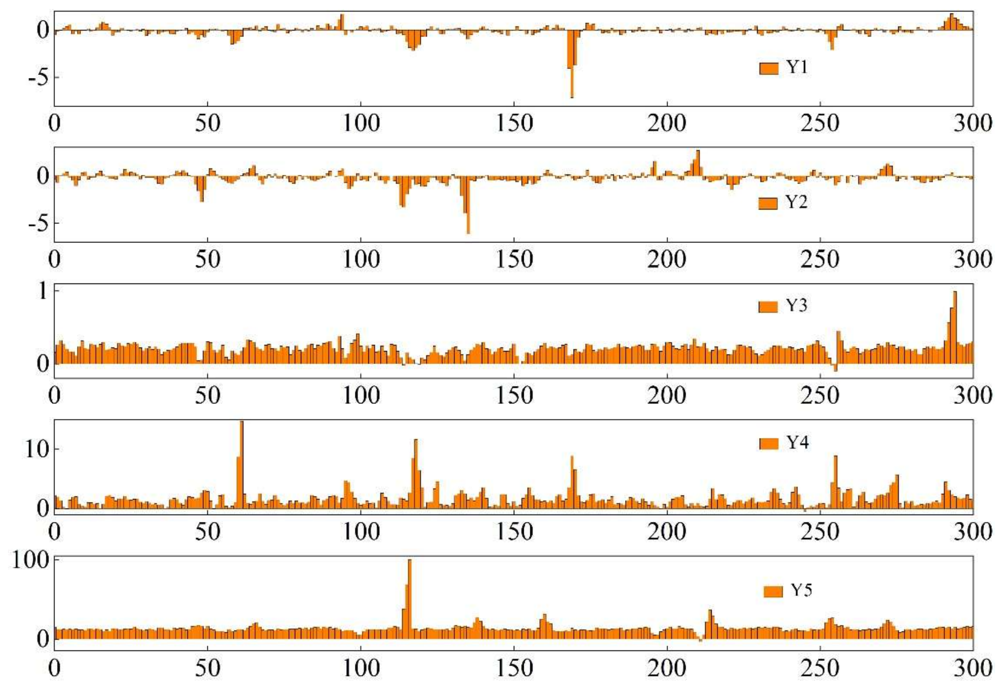

Fig. 2. Feature distribution of the first five indicators

Since the LSTM neural network layers must specify the shape of the inputs, and the inputs to each LSTM layer must be three-dimensional. So it is necessary to reconstruct the input data, reorganize the input data into [Sample, Time Step, Feature] format. Next, the training set and test set are determined, the input variables and output variables are determined according to the training set and test set, and the input variables are transformed according to the input format of LSTM. In the financial early warning model based on LSTM neural network constructed in this paper, the number of neurons in the hidden layer of the four LSTM layers are 50, 512, 512, and 2, respectively, and there is one neuron in the output layer. The loss function uses the mean absolute error MAE, i.e., the absolute value of the difference between the predicted value and the actual value is summed up, which presents the average magnitude of the deviation of the predicted value without considering the positive or negative direction of the deviation. Stochastic gradient descent with adaptive moment estimation Adam is used to do the optimization and dynamically adjust the learning rate for each parameter.The LSTM layer uses the sigmoid function as the activation function, with a learning rate of 0.01, 300 iterations, and a batch size of 64.

3.2.2. Training results. The financial data of the selected manufacturing industry for the years 2020-2024 are inputted into the LSTM neural network model constructed in this paper, and the comparison of the prediction results of the training set and the test set are obtained as shown in Fig. 3 and Fig. 4, respectively.

Combining the data in Fig. 3 and Fig. 4, it can be seen that the LSTM neural network model shows an accuracy of 91.48% and 88.62% in the training set and test set, respectively, which indicates that the LSTM neural network model constructed in this paper has a high degree of accuracy, and it can effectively warn of the financial risks of listed companies in the manufacturing industry.

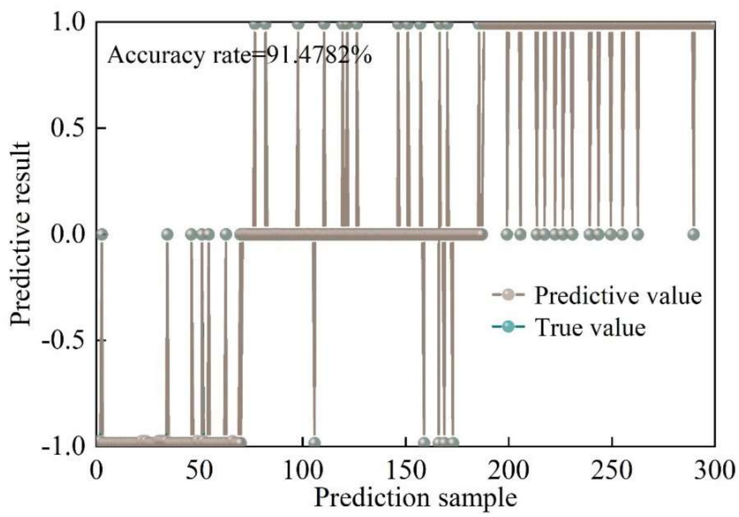

Fig. 3. Comparison of training set prediction results

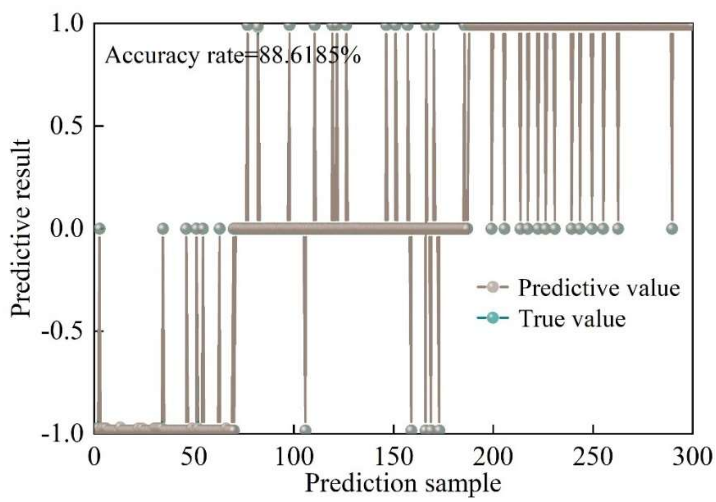

Fig. 4. Comparison of test set prediction results

3.3. Warning accuracy performance of different algorithms

In order to further verify the performance of LSTM neural network in large-scale enterprise financial risk warning, support vector machine (SVM), BP neural network, convolutional neural network and LSTM neural network algorithms are used to analyze the financial risk warning of 1472 alert data of 92 listed enterprises, respectively, and the simulation results of the different algorithms of the performance of the enterprise financial risk warning are shown in Figure 5. As can be seen from the observation, the LSTM neural network algorithm has the highest warning accuracy of about 92%, followed by convolutional neural network, and SVM is the worst. And from the aspect of warning time performance, SVM algorithm is the best, BP and LSTM neural networks are second, and convolutional neural network is the worst. Comprehensive comparison shows that the algorithm in this paper has better performance in dealing with large-scale enterprise sample warning.

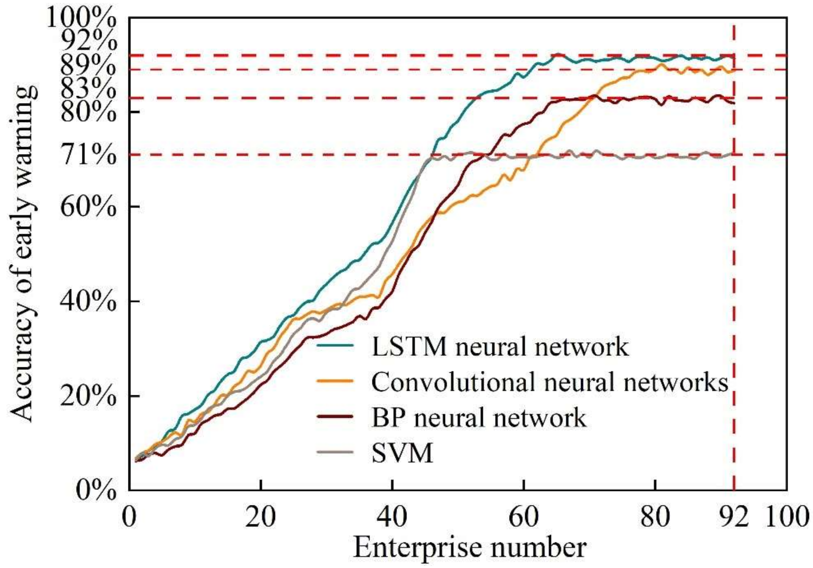

Fig. 5. Performance curves of enterprise financial warning based on different algorithms

3.4. Specific applications of financial risk early warning models

3.4.1. Application of the early warning model for financial risk in Company A. In order to further verify the actual effectiveness of the constructed LSTM financial early warning model, this section selects the financial data of Company A during the period of 2020-2024 as the object of study, uses the index data of Company A during the period of 2020-2023 to carry out financial early warning for the period of 2021-2024, and compares the actual financial situation with the results of risk early warning. According to the risk early warning model constructed in this paper, and the factor score coefficient matrix obtained through factor analysis, with the help of MatlabR2023a, the factor scores are entered in the input layer, and the financial risk prediction results of Company A are obtained after finishing as shown in Table 7.

After comparing the data of 2021-2024 with the actual prediction, it shows that the model has an accurate early warning ability for the financial risk situation of Company A. This shows that the financial risk situation in 2025 and 2026 can be predicted with the help of the model using the financial data in 2024 and before, after the trained LSTM model. By analyzing the results of the predictions for 2025 and 2026, it can be seen that Company A has a slight financial risk and the probability of this slight risk is decreasing year by year. However, in order to ensure the sustainability of the business, these slight risks must be carefully addressed.

Table 7. Financial risk prediction results of Company A

Year	Severe risk	Mild risk	No risk	Actual result	Early warning result
2021	0.14	0.75	0.11	Mild risk	Mild risk
2022	0	0.83	0.17	Mild risk	Mild risk
2023	0	0.74	0.26	Mild risk	Mild risk
2024	0	0.69	0.31	Mild risk	Mild risk
2025	0	0.62	0.38		Mild risk
2026	0	0.51	0.49		Mild risk

3.4.2. Analysis of the results of the early warning of financial risk in Company A. During the period of 2020-2024, it is necessary to select the principal component factor indicators that represent the initial warning indicators in the factor analysis and combine them with the commonly used financial indicators in the financial analysis in order to assess the solvency, operating capacity, corporate growth capacity, and profitability of Company A. The analysis is as follows:

1) Solvency. The solvency of Company A is analyzed from the current ratio, quick ratio and equity ratio respectively, and the changes of Company A's solvency in 2020-2024 are shown in Table 8.

Current ratio: in 2020-2022, the current ratio of company A is maintained in the range of [0.98,1.04], which means that the company's current assets and current liabilities are almost equal, indicating that its short-term solvency is in a relatively balanced state. In 2023, the current ratio decreases slightly to 0.96, which is still close to 1, indicating that there is no significant change in the short-term ability of the company to pay off the short-term debt. In 2024, the current ratio declines to 0.71, below the standard level of 1, which points out that the company's current assets are insufficient to cover its current current liabilities, indicating that its short-term solvency is under pressure.

Quick ratio: the quick ratio of Company A is relatively stable from 2020 to 2024, fluctuating slightly between 0.74 and 0.79, except for a slight drop to 0.74 in 2023, which indicates that the company's short-term debt servicing ability remains relatively stable when inventories are removed.

Gearing Ratio: the gearing ratio of Company A gradually decreases from 67.93% to 63.85% from 2020-2023 showing a gradual reduction in the debt ratio of the company which is due to the reduction in the dependence on debt through earnings growth and increase in assets. The gearing ratio rises to 74.37% in 2024, which indicates that the company's liabilities relative to assets have increased due to an increase in new borrowings or assets growing at a slower rate than liabilities. In conclusion, Company A's solvency shows some pressure in 2024, especially the current ratio decreases to 0.71. Although the quick ratio is relatively stable, an increase in the gearing ratio also indicates that the company is taking on more debt in its financial structure.

Table 8. Company A's solvency from 2020 to 2024

Year	Solvency of enterprise		
	Current ratio	Quick ratio	Asset-liability ratio
2020	0.98	0.79	67.93%
2021	0.98	0.77	67.26%
2022	1.04	0.77	66.98%
2023	0.96	0.74	63.85%
2024	0.71	0.79	74.37%

2) Analysis of operating capacity. The solvency of Company A is analyzed from the indicators of accounts receivable turnover, current asset turnover, fixed asset turnover, inventory turnover and total asset turnover respectively, and the change of Company A's solvency from 2020-2024 is shown in Figure 6.

Accounts receivable turnover ratio: the accounts receivable turnover ratio of Company A grows from 2.63 times to 11.42 times from 2020-2024, which indicates that the company's collection speed is significantly accelerated, thanks to the improvement of credit management and the optimization of customer payment behavior.

Inventory turnover ratio: Company A's inventory turnover ratio was 4.78 times in 2020 and slightly decreased to 4.22 times in 2021. the turnover ratio continued in 2022-2024, reaching 5.8 times in 2024, showing that Company A further optimized its inventory management, accelerated the speed of inventory turnover, and the efficiency of converting inventory to sales was improved.

Current asset turnover ratio: the current asset turnover ratio of Company A was 1.21 times in 2020 and 1.17 times in 2021, showing a slight decrease. The turnover ratio increased to 1.45 times in 2022, indicating that the growth in sales of Company A outpaced the growth of its current assets, suggesting that the company has become more efficient in utilizing its current assets. it further increased to 1.58 times in 2023, a continuous improvement indicates that the company is doing a better job of managing its current assets.This significant increase in Company A's current asset turnover ratio to 2.11 times in

2024 indicates that the company has significantly improved its efficiency in utilizing its current assets during the year.The company's current asset turnover ratio has increased to 1.58 times in 2023, indicating that the company has become more efficient in utilizing its current assets.

Fixed Asset Turnover: Company A has a fixed asset turnover of 2.95 times in 2020. After a slight decline to 2.71 times in 2021, the turnover rate continues to rise in 2022-2024, reaching 4.41 times in 2024, either due to productivity improvements, optimization of the product portfolio or strong growth in market demand.

Total Asset Turnover: 2020 Company A has a total asset turnover of 0.74 times. A slight decrease of 0.7 times in 2021. The turnover ratio improves to 0.82 times in 2022, grows further to 0.89 times in 2023, and increases to 1.09 times in 2024, which is a significant increase and indicates that Company A is able to convert its assets into sales more efficiently.

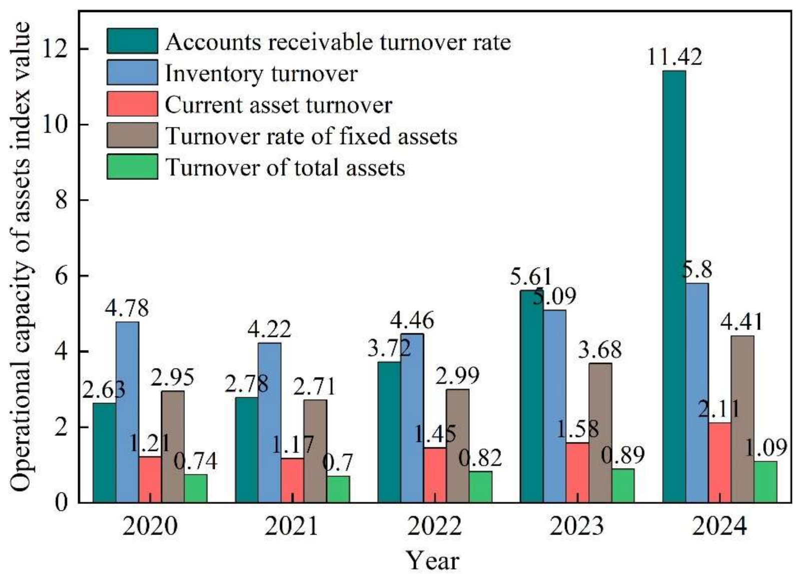

Fig. 6. Analysis of operational capacity indicators of B Company from 2020 to 2024

3) Enterprise growth capacity. The growth capacity of an enterprise refers to the potential of the enterprise to realize the expansion of its scale and strength, and is also called the development capacity. Studying the growth capacity of an enterprise helps to assess whether it has the potential for sustainable growth, and demonstrates the enterprise's future operating strength and development speed. In this paper, the three indicators of Company A's revenue growth rate, net profit growth rate and total assets growth rate are used as research objects to analyze its development potential.

The development ability indicators of Company A from 2020 to 2024 are shown in Table 9.The development ability indicators of Company A are generally positive growth, and all of them declined in 2021, while there is a leaping up in 2024, and its operating income growth rate and net profit growth rate accelerated, and the scale of the company accelerated expansion.

Table 9. Company A's growth ability from 2020 to 2024

Year	Enterprise growth ability		
	Revenue growth rate	Net profit growth rate	Growth rate of total assets
2020	0.25	-0.27	0.10
2021	-0.04	-0.42	0.02
2022	0.25	1.86	0.04
2023	0.40	-0.38	0.49
2024	0.97	3.51	0.69

4) Profitability. The profitability of Company A has been exhaustively analyzed in this paper using five indicators: gross operating margin, net operating margin, net total asset margin, return on net assets and cost and expense margin.

The profitability indicators of Company A for the years 2020-2024 are shown in Figure 7.The trend of changes in the profitability indicators of Company A is similar, with the five selected indicators decreasing in 2021 and 2023, but generally showing an upward trend.

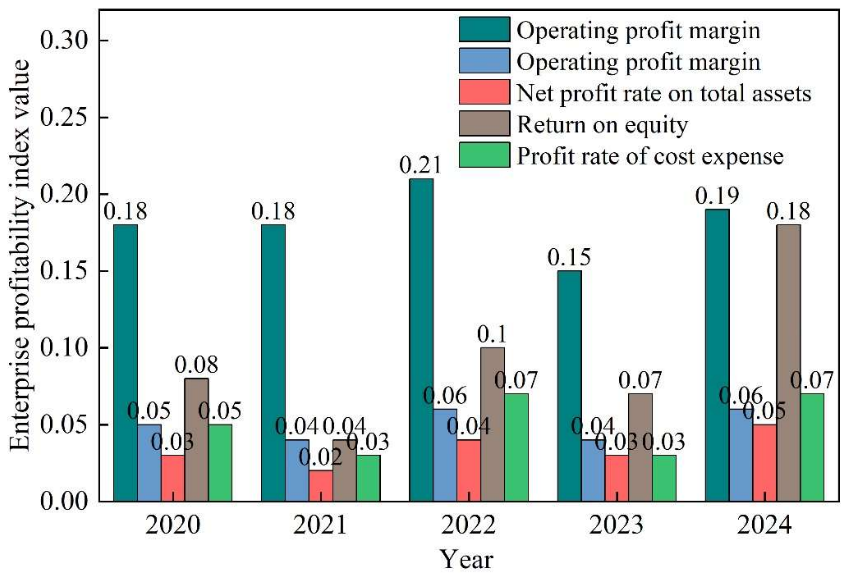

Fig. 7. Company A's profitability indicators for 2020-2024

5) Comprehensive analysis. By analyzing Company A's solvency, operating ability, profitability and development ability, it can be concluded that: Company A's solvency maintains stability, the pressure of repaying current liabilities is obvious, the operating ability maintains stability, the efficiency of capital use has been significantly improved, the profitability has been strengthened, the operating efficiency has been improved, the development ability maintains stability, and the growth rate of operating income has been slightly accelerated.

4. Conclusion

This paper constructs the enterprise financial early warning indicator system, and combines it with LSTM recursive algorithm to realize the construction of enterprise financial risk early warning model, which provides digital tools for the enterprise capital chain wind control.

In this paper, 92 listed companies in the manufacturing industry are selected as research samples, and 22 financial indicators are selected from the four aspects of enterprise solvency, asset operation ability, enterprise growth ability and enterprise profitability by utilizing the data of listed companies in the first two years after they were ST. Six principal component factors were extracted through factor analysis, and the cumulative variance interpretation rate reached 91.494%, which realized the effective interpretation of the enterprise financial warning indicators, and finally obtained the enterprise financial warning indicator system including 16 financial indicators.

The prediction accuracy of the corporate financial risk early warning model based on LSTM neural network reaches 91.48% and 88.62% in the training set and test set respectively, which can effectively realize the financial risk early warning of listed companies in the manufacturing industry. Meanwhile, comparing the commonly used risk warning models such as support vector machine (SVM), BP neural network and convolutional neural network, the model in this paper has the highest prediction accuracy, shorter prediction time and the best overall prediction performance. Finally, the model is applied to the financial risk prediction task of Company A, and the obtained prediction results are consistent with the actual situation. By using the model to predict the financial risk of Company A in the next two years, it can provide more effective financial risk prevention measures for enterprise managers.

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