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Construction of recursive neural network-based prediction model for corporate financial indexes in digital financial environment

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Abstract With the continuous change of the global economy and the increasingly fierce competition in the market, the financial risks faced by enterprises are increasingly complex and diverse. This paper constructs a LSTM neural network financial risk early warning model for enterprises based on recursive neural network. 130 listed companies were selected as the research object, and 28 financial indicators and 2 non-financial indicators were obtained as the research samples. Then the 30 financial early warning indicators were downscaled using factor analysis to extract the principal component factors. The principal component factor scores are input to the LSTM network, the relevant parameters of the network are set, and the network is trained to complete the construction of the enterprise financial risk early warning model. The training results of this paper's model show that the model tends to be balanced after three hundred iterations, and the fit of the model is better, and the loss value is only 0.12. The empirical results of the model's financial risk prediction show that this paper's model has a better performance than the traditional prediction models, such as Random Forest, in terms of the prediction of corporate financial risk. The application of LSTM neural network to the financial warning of enterprises has obvious advantages.

Index Terms Financial Risk Early Warning, LSTM Neural Network, Factor Analysis, Principal Component Factor

I. Introduction

In the era of rapid development of digital finance, digital technology is deeply integrated with the real economy, empowering the transformation and upgrading of traditional industries, and giving rise to new industries, new businesses, and new models [1], [2]. As an important component of the national economy, enterprises vigorously develop emerging businesses and inject new power for high-quality development through digital transformation, playing an important role in the digital wave [3]-[5]. Financial indicators are important tools for measuring the financial status and past business performance of an enterprise, and analyzing them can help assess the competitive strength and future growth potential of an enterprise [6]. For example, the revenue growth rate of a company reflects the company's sales performance, while the profit growth rate reflects the company's profitability, in addition to a number of other financial indicators such as net interest rate, gross margin, dividend yield, and return on assets [7]-[9]. These indicators can help investors to assess the company's profitability, efficiency and risk aspects, through which the growth of the company can be predicted [10], [11]. With the continuous development of deep learning algorithms, numerous learning algorithms have been widely used in various classification and quantitative prediction problems. Deep learning algorithms can extract valuable information and patterns from massive data and use them to analyze financial indicators, which can more accurately predict the future growth of enterprises and provide reference for many investors in the market [12]-[15].

In this paper, the selection of enterprise financial risk early warning indicators is carried out from the aspects of financial and non-financial indicators, and 30 indicators are selected from the aspects of solvency, operating ability, enterprise growth ability, cash flow ability and profitability to complete the construction of enterprise financial risk early warning indicator system. Subsequently, factor analysis was applied to screen the indicators so that they could meet the needs of LSTM neural network training. Since recurrent neural networks have defects in dealing with long-term dependence problems, this paper constructs a deep LSTM neural network containing forgetting gate, input gate and output gate, balances the network's control of historical and real-time information through gating units, and optimizes the performance of the early warning model by adding Dropout and BN layers to the early warning model. The utility of the model in this paper is verified with empirical comparison experiments.

II. Construction of an early warning indicator system for enterprise financial risk

II. A.Factor analysis

Factor analysis is applied to extract a smaller number of indicators that are not correlated with each other from a larger number of original evaluation indicators, which retains most of the information of the original indicators and at the same time serves the purpose of dimensionality reduction of the indicators. The main steps of factor analysis are as follows.

Step 1: Variable standardization: Standardize the original data, in order to unify the scale and order of magnitude of different variables, so as to facilitate the subsequent analysis.

Step 2: Find the correlation coefficient matrix of each variable, and then derive the cumulative contribution rate of the characteristic root of the matrix, determine the suitable common factor and name it according to the contribution rate, and the goal of common factor selection is to represent the majority of the information of the original evaluation indexes with as few common factors as possible, so as to minimize the loss of information. That is:

$$x_i = \mu_i + a_{i1}F_1 + a_{i2}F_2 + \cdots + a_{ik}F_k = a_{ik}F_k + \mu_i, k \le i, i = 1,2,\cdots,20 \tag{1}$$

Where: x_i indicates the content of the selection of evaluation indicators; $a_{ik}\left(k \le i\right)$ indicates the common factor of each indicator, also known as the factor loading; μ_i indicates the factor unique to each indicator.

Step 3: Do the orthogonal rotation of the factor loading matrix with the highest variance [16], and then according to the obtained value against the actual meaning, so as to determine the specific meaning of each common factor, which facilitates the subsequent analysis. In the calculation process, let the orthogonal matrix Q be:

$$Q = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{2}$$

Thus, x_i can be expressed as:

$$x_i = a_{ik}F_k + \mu_i = a_{ik}\left(QQ^T\right)F_k + \mu_i = \left(a_{ik}Q\right)Q^T F_k \tag{3}$$

Let $B = \left(a_{ik}Q\right)$, which is known as the rotated factor loading matrix, then by rotation, the variable is divided into two parts consisting of different factors b_1 and b_2, stipulating the requirement that the variance of each of the two columns of data is maximized.

Step 4: Set the public factor weights. Because the way of expert scoring has subjectivity and other shortcomings, this paper adopts the factor variance contribution ratio as the weight of the common factor.

Step 5: Multiply the weight of the common factor with the score of the common factor and then sum up, so as to get the final comprehensive evaluation score.

II. B.Sample Selection and Data Preprocessing

II. B. 1) Sample selection and data sources

This paper takes listed companies in the automobile manufacturing industry between 2019 and 2023 as the research object, which is categorized in accordance with the industry standards of the Securities and Exchange Commission. In order to ensure the accuracy and reliability of the research results, the outliers and missing values of relevant variables are excluded. On this basis, 130 automobile manufacturing companies were selected to obtain 28 financial warning and 2 non-financial warning indicators. The financial data of these companies mainly come from the Cathay Pacific database, while the processing of the data is done with the help of SPSS software. For model development, Matlab was chosen as the main framework tool.

II. B. 2) Standardized treatment methods

After standardization, data with different scales and units can be transformed into uniform scale data, thus effectively eliminating the differences in scales between different variables and significantly improving the comparability of data. Commonly used standardization methods mainly cover minimum-maximum standardization and Z-score standardization.

In this paper, the Z-score standardization method [17] is used to process the data of financial early warning indicators. Specifically, Z-score standardization is a data processing method that standardizes data by subtracting its mean from the original data and dividing the difference by its standard deviation. This method is effective in processing data so that it conforms to a standard normal distribution, i.e., a mean of 0 and a standard deviation of 1.

The formula for Z-score standardization is as follows:

$$z = \frac{x - \mu}{\sigma} \tag{4}$$

where x represents the original data, μ represents the mean of the data, and σ represents the standard deviation of the data. Through the Z-score standardization process, it can make the distribution of the data more concentrated and effectively eliminate the influence of the scale between different variables, and this process is extremely beneficial to the subsequent model training and prediction work. This paper uses SPSS software to standardize the initial financial data.

II. B. 3) Sample pre-categorization

The specific details of the sample pre-categorization in this paper are shown in Table 1. I1: net profit after deduction ⩾ 0, I2: return on net assets ⩾ 20%.

Table 1: Factors used to identify the extent of financial alert

Interval	L1	L2	One of the things that correspond to L1 and L2	Marking
Safety alert interval	✓	✓		1
Mild warning interval			✓	2
Severe warning interval				3

Table 2: Company's financial risk warning index system

Primary indicator	Secondary indicator	Symbol
Solvency	Mobility ratio	A1
	Speed ratio	A2
	Cash ratio	A3
	Asset ratio	A4
	Interest rate	A5
	Equity ratio	A6
Operational capacity	Total asset turnover	A7
	Turnover of current assets	A8
	Inventory turnover	A9
	Receivable turnover	A10
	Fixed asset turnover	A11
Enterprise ability	Revenue growth	A12
	Net profit growth rate	A13
	Total asset growth rate	A14
	Capital accumulation rate	A15
	Fixed asset growth rate	A16
Cash flow capacity	Net profit	A17
	Company cash flow 1 yuan	A18
	Total cash recovery	A19
Profitability	Asset returns	A20
	Return on equity	A21
	Operating rate	A22
	Operating margin	A23
	Cost margin	A24
	Total asset profit rate	A25
Risk capacity	Financial leverage	A26
	Operating lever	A27
	Integrated lever	A28
Non-financial indicators	Equity structure	A29
	Audit opinion	A30

II. C.Design of financial risk early warning indicator system

II. D.Principles of financial risk early warning based on recurrent neural networks

II. D. 1) Design Principles of LSTM Neural Networks

LSTM neural network [18] evolved from recurrent neural network. In recurrent neural networks [19], its spatial architecture consists of input, hidden and output layers, which can produce outputs in which each time node has a connection relationship with the next hidden node.

However, recurrent neural networks encounter huge difficulties in dealing with long term dependencies and produce the problem of gradient vanishing or gradient inflation, to solve the above problems researchers proposed LSTM neural network. LSTM neural network controls the degree of influence of real time information on the historical information by adding gating units, which allows the neural network model to retain and transmit the information over long periods of time.

LSTM has forgetting gates, input gates and output gates. LSTM neural network includes a memory store and three gating settings inside each neuron, the memory store records the neuron state, the input gates and output gates are used to receive and output parameters and correction parameters and the forgetting gates are used to control the extent to which the previous state of the unit is forgotten.

The computational principle of which forgetting gate, input gate and output gate is shown in the following equation:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{6}$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{7}$$

In the above calculation, h_{t-1} is the output of the LSTM neuron at moment $t-1$, $[h_{t-1}, x_t]$ denotes the joining of the two vectors into a longer vector, W_f, b_f, and f_t each denote the weights, bias tops, and states of the forgetting gates to the input sequence, W_i, b_i, and i_t are the weights, bias tops, and states of the input gates, and similarly W_o, b_o, and o_t denote the weights, bias tops, and states of the output gates; and σ denotes the activation function of the output. The computational principle of LSTM neuron output h_t is shown in the following equation:

$$\tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right) \tag{8}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{9}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{10}$$

In the above expression, $\tilde{C}_t$ is the instantaneous state of the input feature at moment t, the current unit state is C_t, $\tanh$ is the activation function of the output feature, and h_t is the output of the current unit. When calculating the current unit state, the product of the previous unit state and the oblivion gate state is used to add the product of the current unit state and the input gate state. In this way, the current memory C_t and the long-term memory C_{t-1} can be combined to form a new unit state C_t. The control of the forgetting gate allows the network to store all previously filtered moments of information, while the control of the input gate prevents irrelevant content from being entered into the storage.

From the above, it can be seen that the LSTM neural network can deal with data with long-term dependence. Financial distress of enterprises is the performance of objective financial risk accumulated to a certain extent, financial early warning is through the characterization of financial data with long-term dependency relationship, so as to predict the probability of financial distress of enterprises in the next year.LSTM neural network can achieve this goal, using the idea of deep learning, through the construction of a deep LSTM neural network model, it can be carried out. Corporate financial early warning.

II. D. 2) Programming steps for LSTM neural networks

In this paper, we complete the LSTM neural network programming based on Python platform as follows.

Step 1: Set hyperparameters. Determine the dimension of hidden vector, learning rate, input and output data dimension according to the input and output.LSTM neural network requires the input data to be 3D tensor, so it needs to reconstruct the dataset.

Step 2: Define the input and output placeholder nodes. That is, determine the placeholders in Tensor Flow for the input and output data of the network layer.

Step 3: Define the network structure.The performance of the LSTM neural network depends greatly on the number of neurons in the hidden layer, but there is no specific formula for calculation. The usual practice is to take 32 as the base number and adjust it according to the training results, usually a multiple of 2, to find the number of hidden layer neurons with the best training effect. Network computation statements need to be written in the platform for generating the output states of the LSTM units during computation.

Step 4: Define the weights and biases of the fully connected layers. It is used to convert the LSTM unit state output into the category unnormalized probability.

Step 5: Define the activation function.

Step 6: Define the loss function.

Step 7: Define the training optimizer and optimization operation. Usually the stochastic gradient descent algorithm is used for optimization, the most important thing is to determine the appropriate number of batches, within a certain range, the larger the number of batches, the more accurate the direction of its gradient descent.

Step 8: Train the network. Determine whether the algorithm reaches the optimal prediction, if not, return to the first step to adjust the hyperparameters.

III. LSTM-based financial risk early warning model

III. A. Data pre-processing

III. A. 1) Data standardization

The early warning indicator system constructed in this paper is composed of indicators with different meanings, and there is the problem of inconsistency in the scale and order of magnitude. If they are directly brought into the model for training, it will affect the training speed and accuracy of the model. Therefore, it is necessary to standardize the sample data. In this paper, Z-score standardization is chosen to process the data, and the original data are processed by calculating the mean and standard deviation of each index data, so as to ensure that the numerical range of each index data is consistent to the greatest extent possible.The part of the data after Z-score standardization is shown in Table 6.

Table 6: Partial data on the standardized processing of the data

Company number	A1	A2	A3	A4	A5	A6	A7
A	-0.42617	-0.51150	-0.28065	0.03487	1.46008	0.0162	-0.05412
B	-0.43396	-0.47932	-0.31999	0.12082	1.52171	0.05969	-0.05871
C	-0.45222	-0.44041	-0.30921	-0.02591	1.49196	0.06036	-0.05469
D	-0.44334	-0.47081	-0.27408	0.03008	1.56081	0.07744	-0.02328
E	-0.47137	-0.45004	-0.30099	0.07780	1.49866	0.11399	-0.05003
F	-0.45839	-0.47607	-0.28459	0.05579	1.48997	0.12845	-0.01012
G	-0.49083	-0.51208	-0.23425	0.02022	1.47176	0.04698	0.00469
H	0.44391	-0.4860	-0.30852	0.08640	1.51518	-0.07765	0.04041
I	0.40467	-0.52349	0.24532	0.03138	1.48898	0.05274	-0.02250
J	0.43953	-0.51966	0.25856	0.02596	1.5207	0.10215	0.01042
K	0.45750	-0.51618	-0.26174	0.08687	1.48347	-0.11236	0.05663
L	0.54527	-0.46118	0.23770	0.04291	1.51154	0.00198	0.06103
M	-0.48321	-0.48117	-0.27879	0.06073	1.49321	0.11254	0.06362
N	-0.52658	-0.49183	-0.24912	0.08153	1.47099	0.04687	-0.0782
O	-0.43490	-0.45908	-0.25514	0.03546	1.48961	0.03670	-0.05524

III. A. 2) Data equalization process

In the study of predicting the financial risk situation of enterprises, the most important thing is to be able to effectively identify the financial crisis category of enterprises with higher financial risk. When there is a large imbalance in the sample data categories, it will make the prediction model more inclined to predict the sample categories with a larger number, resulting in poor early warning effect for the categories with a smaller number, thus reducing the prediction effect of the early warning model.

In this paper, we choose to use the VAE algorithm to equalize the unbalanced sample data so that the sample ratio of non-ST firms with low financial risk to ST and *ST firms with high financial risk in the sample data reaches 1:1.The Loss curve of the VAE model training is shown in Fig. 2, and the model was trained for 250 rounds to achieve convergence.

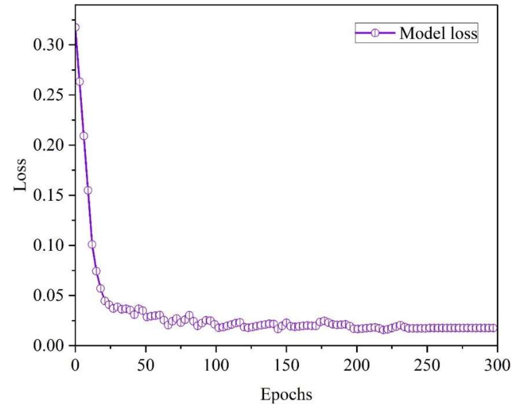

Figure 2: VAE model training loss changes

By training the VAE model finally 150 new samples are generated, the distribution of the original and new samples is shown in Figure 3, the distribution of the generated samples is roughly the same as the distribution of the original samples, so they can be put into the model as a small number of class samples for training.

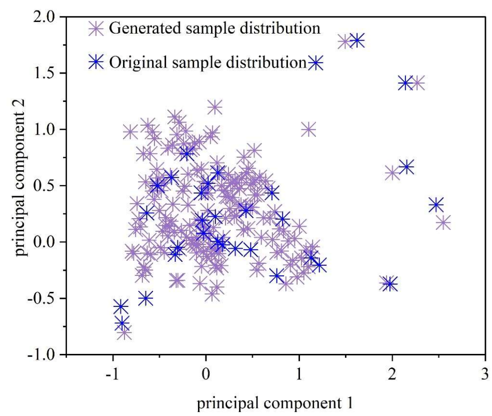

Figure 3: The distribution of the original sample and the new sample

III. B. Financial risk identification model construction based on LSTM

III. B. 1) Modeling

In the LSTM neural network model, the gradient in the back propagation will produce the multiplication effect, which leads to the gradient disappearance and overfitting and other problems, when the model is too fit, it will lead to the weakening of the model's generalization ability, in order to solve the problem, this paper in the construction of the model to add a Dropout layer, in the training, the Dropout will be set up for the neuron in each layer of the deactivation probability, neural network The neural network will eliminate all neurons according to the set deactivation probability, forming a simplified neural network structure, the simplified neural network can alleviate the overfitting problem to a certain extent, and the addition of the BN layer can solve the problem of gradient disappearance generated by the neural network in the backpropagation. In addition, the LSTM model will have the problem of incomplete short-term feature portrayal when recognizing the input boundary information, this paper invokes the hidden state to increase the fully connected structure to enhance the depth of the LSTM layer; different input samples are different in the ability to extract the feature vectors, and the attention mechanism is introduced into the extraction of the residual module of different depths, and the magnitude is processed before doing the mean value processing to get the final weights, then the related problems can be solved effectively.

So this paper adds Dropout and BN layers when constructing the LSTM neural network model, and also adds the residual module and introduces the attention mechanism, so as to optimize the neural network, this paper through a large number of experiments, and finally constructs the four-layer LSTM neural network model for solving the problem of the financial distress identification model with the best training effect, and the structure of the neural network model constructed in this paper is shown in Fig. 4.

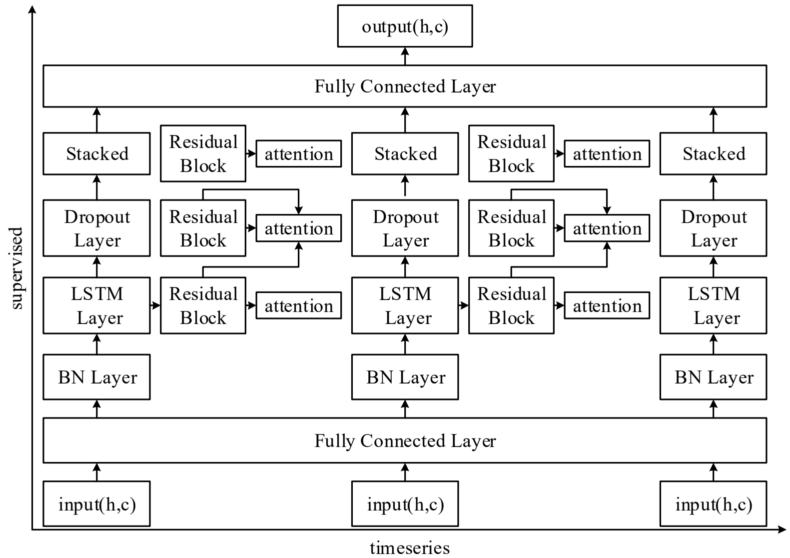

Figure 4: Neural network structure

(1) Input layer: according to the financial distress identification index system of listed companies constructed in this paper, a total of 25 indicators constitute the input layer of the LSTM neural network, and the input layer of the LSTM neural network model is the three-dimensional data, which consists of three dimensions: samples, time step, and features.

(2) Implicit layer: the implicit layer is an important part of the LSTM neural network model, and the implicit layer can significantly improve the efficiency and accuracy of the neural network model. The hidden layer refers to the dimension of the input data between each structural layer within the network, and the training of the neural network model is also a layer-by-layer dimensionality reduction process, where the input data is gradually abstracted after each layer of processing, and the prediction results are finally obtained. The research problem of this paper, i.e., whether the listed company is in financial distress is a more abstract problem, which needs to be combined with a variety of characteristics of the enterprise's financial situation to make judgments, and finally get the conclusion of whether the enterprise is in financial distress.

There is no conclusion about the determination of the number of neurons contained in the hidden layer, the determination of the number of neurons in the hidden layer is mainly through the debugging of the system, to find out the best number of neurons in the hidden layer for this study, this paper through the continuous debugging of the system, to select the best number of neurons, this paper through the debugging to determine the hidden nodes of the LSTM layer contains 64, 512, 512 and 2 neurons each.

(3) Output layer: the output layer of this paper is a two-dimensional data, corresponding to the two results of the financial health of the enterprise and the enterprise in financial distress, in which the financial health of the enterprise is represented by 0, and the enterprise in financial distress is represented by 1. The sample data can be normalized to start the training process, and the final output results are displayed in the “Status” column, which is adjusted to 1 if the output result is greater than 0.5, and adjusted to 0 if it is less than 0.5.

III. B. 2) Training results

Figure 5 shows the accuracy of training, the horizontal coordinate in the figure indicates the number of iterations of the training samples, and the vertical coordinate indicates the training error rate, from the figure, we can see that in the training, with the increase in the number of iterations, the error value of the samples gradually becomes smaller, although there is a local volatility in a small range, but the overall general trend is gradually smaller, in addition, at the beginning of the training, the error rate changes faster, which indicates that the model is in the process of training constantly fine-tuned, and after 300 iterations, the decreasing trend of the loss value becomes flat, indicating that the model is gradually converging to the optimal process, which is finally controlled at about 0.12, indicating that the model has a good fit.

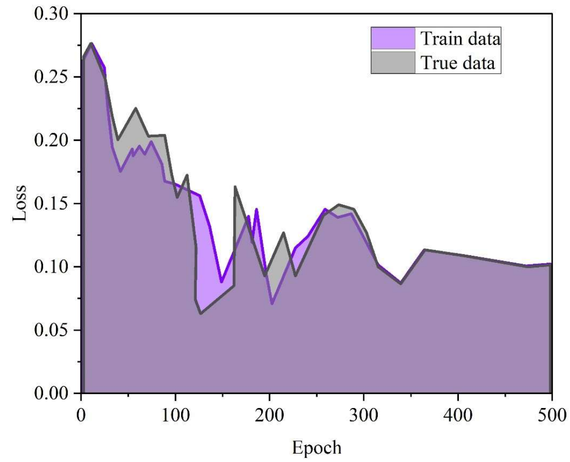

Figure 5: Training result drawing

IV. Empirical study of LSTM-based corporate financial risk prediction

IV. A. Comparative experiments based on stock price and indicator characteristics

With the continuous development of financial science and technology, the research mode based on computer thinking has gradually provided new research ideas and methods to the research in the field of finance, therefore, we innovatively use stock price time series data and LSTM neural network model to conduct a set of experiments to try to corporate financial distress, in order to make a preliminary comparison with the financial indicator characteristics, this experiment is mainly through three sets of experiments The comparison is made by inputting stock price time series data, price and financial indicator - current ratio, and price and multi-indicator data, respectively, to preliminarily verify the validity of the stock price characteristics in predicting whether the enterprise will ST, and whether the combination of multi-indicator and price will improve the accuracy of the prediction. The results of the comparison experiment are shown in Table 7.

LSTM-CP is a standard LSTM model using closing price metrics, LSTM-CPLR is a standard LSTM model using closing price as well as liquidity ratio metrics, and the model in this paper is a standard LSTM model using price class metrics as well as 30 corporate earnings metrics. Experimental comparisons are conducted through four categorization assessment metrics, including: accuracy (Acc), precision (Pre), recall (Rec), and F1 value. The final classification results are expressed in the form of mean ± standard deviation, and the classification results are shown in Table 7.

From the experimental results, we can see that the separate stock price time series data feature has a better effect on the prediction of financial distress of enterprises, which proves the effectiveness of this feature in prediction. And after adding the current ratio indicator feature, the overall prediction result of the model is slightly decreased. After adding the full combination of indicators, the effect gained further improvement over the effect of a single type of feature alone. This also shows that a single indicator may be one-sided, and a combination of indicators can describe the financial status of the enterprise more comprehensively from multiple dimensions. This also validates the conclusion that our addition of the form of feature data makes the model's prediction effect better than that of a single type of feature data.

Table 7: Model experimental data comparison

Model	Acc	Pre	Rec	F1
LSTM-CP	81.89±0.38	88.42±0.27	90.65±0.33	0.89±0.05
LSTM-CPLR	81.21±0.28	88.23±0.24	90.21±0.34	0.89±0.00
This model	81.94±0.95	90.68±0.19	91.26±0.94	0.91±0.01

IV. B. Multi-model comparison experiments based on structured features

This set of experiments adds SVM, random forest and logistic regression models as comparisons to the first set of experiments, comparing the traditional models and the models used by most scholars with our proposed deep learning model, and the inputs are still stock price time series data and indicator portfolio data, and the experimental results are shown in Table 8.

This comparison experiment adds Random Forest model and Logistic Regression model, the experiment of two types of indicators corresponds to RF-CP-INDICATOR and Logistic-CP-INDICATOR, respectively, and adds a column Cont for ranking. From the table, it can be seen that the results of Random Forest are similar to SVM, and from the Rec indicator, it can be seen that the ability to discriminate between ST and non-ST of the stock will be lost under the condition of sample imbalance. Therefore, these two models are not applicable when the experimental data are unchanged, and it should be noted that in the individual indicators Random Forest works better, but in the relatively important Pre indicators it is the LSTM model that dominates. Through this set of experiments, we demonstrated that the prediction model based on recurrent neural network has higher accuracy compared with the traditional model, with an average accuracy of 82.95%.

Table 8: Comparison of experimental data results of multimodel experiments

Model	Acc	Pre	Rec	F1	Cont
SVM-CP-INDICATOR	81.25±0.00	86.03±0.00	100.00±0.00	0.92±0.00	0
RF-CP-INDICATOR	81.39±0.00	89.65±0.00	100.00±0.00	0.89±0.00	0
Logistic-CP-INDICATOR	80.05±0.00	89.01±0.00	88.01±0.00	0.85±0.00	2
This model	82.95±0.91	90.59±0.12	89.24±0.95	0.87±0.02	1

V. Conclusion

This paper explores and examines the corporate financial risk early warning model based on LSTM, and the research conclusions obtained are in the following three aspects:

(1) In terms of sample data processing, for the uneven and non-standard problems of sample data in this paper, the VAE algorithm and Z-score standardization are used to preprocess the data, and the data before and after preprocessing are brought into the model for training and testing respectively, and the model converges after 250 rounds of training, and the distribution of the generated samples is more or less the same as that of the original samples, which indicates that the LSTM-based enterprise financial risk early warning model is more effective in predicting the financial risk of enterprises after the data are preprocessed with the method of this paper. This indicates that after applying the method of this paper to preprocess the data, the prediction effect of the LSTM-based enterprise financial risk early warning model is better.

(2) The recursive neural network-based prediction model in this paper is compared with several traditional prediction models, and the experimental results show that the LSTM-based neural network model proposed in this paper has a higher prediction accuracy, and the average prediction accuracy of the model in this paper reaches 82.95%.

(3) Through the LSTM-based financial risk early warning model for enterprise financial risk prediction, timely detection of risk and early intervention and adjustment, can avoid the enterprise to reduce the enterprise in the face of risk, brought about by the loss of interests, the model of this paper is applied to the practice, not only can help enterprises to escape from the financial predicament, but also to help the regulatory agencies to maintain the stability of the order of the capital market.

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References

[1] Luo, S. (2022). Digital finance development and the digital transformation of enterprises: based on the perspective of financing constraint and innovation drive. Journal of Mathematics, 2022(1), 1607020.

[2] Li, R., Rao, J., & Wan, L. (2022). The digital economy, enterprise digital transformation, and enterprise innovation. Managerial and Decision Economics, 43(7), 2875-2886.

[3] Sun, C., Zhang, Z., Vochozka, M., & Vozňáková, I. (2022). Enterprise digital transformation and debt financing cost in China's A-share listed companies. Oeconomia Copernicana, 13(3), 783-829.

[4] Guo, B., Feng, Y., & Lin, J. (2023). Digital inclusive finance and digital transformation of enterprises. Finance Research Letters, 57, 104270.

[5] Liu, M., Li, H., Li, C., & Yan, Z. (2023). Digital transformation, financing constraints and enterprise performance. European Journal of Innovation Management.

[6] Bogićević, J., Domanović, V., & Krstić, B. (2016). THE ROLE OF FINANCIAL AND NON-FINANCIAL PERFORMANCE INDICATORS IN ENTERPRISE SUSTAINABILITY EVALUATION. Ekonomika, 62(3).

[7] Barker, J., Gajewar, A., Golyaev, K., Bansal, G., & Conners, M. (2018, April). Secure and automated enterprise revenue forecasting. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 32, No. 1).

[8] Okeke, N. I., Bakare, O. A., & Achumie, G. O. (2024). Forecasting financial stability in SMEs: A comprehensive analysis of strategic budgeting and revenue management. Open Access Research Journal of Multidisciplinary Studies, 8(1), 139-149.

[9] Nazarov, A., & Zhogova, E. (2023). Forecasting the Financial Performance Dynamics of a Present-Day Industrial Enterprise in Today's Market. Sustainable Development and Engineering Economics, (4), 21-34.

[10] Wang, Z. (2025). Construction of Enterprise Financial Performance Evaluation System. Asia Pacific Economic and Management Review, 2(2).

[11] Bojnec, Š., & Žampa, S. (2021). Subsidies and economic and financial performance of enterprises. Journal of Risk and Financial Management, 14(11), 505.

[12] Lazcano, A., Herrera, P. J., & Monge, M. (2023). A combined model based on recurrent neural networks and graph convolutional networks for financial time series forecasting. Mathematics, 11(1), 224.

[13] Di Persio, L., & Honchar, O. (2017). Recurrent neural networks approach to the financial forecast of Google assets. International journal of Mathematics and Computers in simulation, 11, 7-13.

[14] Popa, D. C. S., Popa, D. N., Bogdan, V., & Simut, R. (2021). Composite financial performance index prediction–a neural networks approach. Journal of Business Economics and Management, 22(2), 277-296.

[15] Lin, Y. F., Huang, T. M., Chung, W. H., & Ueng, Y. L. (2020). Forecasting fluctuations in the financial index using a recurrent neural network based on price features. IEEE Transactions on Emerging Topics in Computational Intelligence, 5(5), 780-791.

[16] Paul, P. H. (2024). Advancing Hybrid Optimization Frameworks for Groundwater Inverse Problems: Parallel Computing and Modern Techniques. *TK Techforum Journal (ThyssenKrupp Techforum)*, 2024 (2). 1-6.

[17] Zhirong Gao,Lixin Ding,Qiming Xiong,Zhongyi Gong & Chengyi Xiong. (2019). Image Compressive Sensing Reconstruction Based on z-Score Standardized Group Sparse Representation.. IEEE Access,7,90640-90651.

[18] Hongyu Yan,Jianbo Li,Benjia Chu & Zhihao Xu. (2025). HT-STNet: a hierarchical Tucker decomposition and spatio-temporal LSTM network for accurate and efficient shared mobility demand forecasting on sparse data. Applied Intelligence,55(7),631-631.

[19] Chen Yongfa,Xu Xinzhou,Li Ziqian,Wang Zhengyu & Schuller Björn. (2025). Data-driven motion estimation for cable-driven end-effectors through parallel 1D-convolution and recurrent neural networks with attention. Proceedings of the Institution of Mechanical Engineers,239(8),2994-3005.