Construction and Empirical Study of a Financial Risk Early Warning Model for Enterprises

Mei Zhang*

Xi'an Eurasia University, Xi'an, Shanxi, 710002, China

*Email: 13891835816@163.com

Abstract. This study aims to develop and validate a financial risk early warning model for enterprises based on a deep neural network. By extracting key financial and non-financial indicators, the model leverages deep learning algorithms to predict financial risk in enterprises. Data from selected Chinese listed companies from 2015 to 2020 were processed with feature selection and standardization before being fed into the deep neural network model. Cross-validation and multiple evaluation metrics were used to assess model performance. Experimental results demonstrate that the model performs excellently in terms of accuracy, precision, and recall, showing high capability in financial risk identification. The study identifies debt-to-asset ratio and net profit margin as significant influencing factors. This model provides an effective tool for financial risk early warning, with substantial practical implications for enterprise risk management and decision-making.

Keywords: Enterprise financial risk, Deep neural network, Early warning model, Feature selection, Prediction

1 Introduction

Financial risk early warning is crucial for ensuring the stable operation of enterprises and the healthy development of capital markets. With the intensification of economic globalization and market competition, enterprises face increasingly complex external environments, making financial risk factors more diverse and harder to predict. Traditional financial risk early warning models, such as the Z-Score and Logistic regression, are based on linear assumptions[1], which limit their ability to capture the nonlinear relationships in financial data[2], thus affecting predictive accuracy.

In recent years, machine learning methods have been introduced to the field of financial risk early warning. Models such as Support Vector Machines (SVM), Decision Trees, and Random[3] Forests have gained attention for their ability to handle nonlinearity and high-dimensional data[4]. However, these models may encounter challenges in computational efficiency and parameter selection when dealing with large-scale data and complex features[5].

Deep learning, a frontier technology in artificial intelligence, has shown superior performance in financial risk early warning due to its strong feature-learning and

H. Sun et al. (eds.), *Proceedings of the 2025 10th International Conference on Social Sciences and Economic Development (ICSSED 2025)*, Advances in Economics, Business and Management Research 332,
https://doi.org/10.2991/978-94-6463-734-2_10

nonlinear fitting capabilities. Deep neural networks (DNNs) can automatically extract deep features from data[6], adapting well to the high dimensionality and complexity of financial data. Studies have shown that deep learning models can significantly improve the accuracy of financial risk prediction.

Additionally, non-financial indicators, such as corporate governance structure, management characteristics, and macroeconomic conditions, have substantial impacts on an enterprise's financial health[7]. Integrating these non-financial factors into risk warning models can enhance the comprehensiveness and accuracy of predictions. Previous research has attempted to combine financial and non-financial indicators, yielding some positive results[8], though there remains room for improvement in model effectiveness and interpretability.

This study aims to construct a financial risk early warning model for enterprises that integrates deep learning with traditional statistical methods. By incorporating both financial and non-financial indicators, and leveraging deep neural networks to enhance model performance while maintaining interpretability, this research seeks to provide a novel approach and practical reference for financial risk early warning, contributing to advancements in the field of financial risk management.

2 Model Construction

The data used in this study were obtained from the publicly available financial statements and authoritative industry reports of selected Chinese listed companies from 2015 to 2020. Specifically, the data include key financial indicators from balance sheets, income statements, and cash flow statements, as well as indicators on corporate governance structure, management turnover, and macroeconomic environment. A sample of 300 listed companies was selected from industries such as manufacturing, finance, services, and others.

The sample selection followed these criteria: first, companies listed on the Chinese securities market with publicly available and transparent financial information were chosen; second, companies of different sizes and from various industries were included to ensure representativeness and diversity; finally, companies with complete financial data were selected to support subsequent analysis and modeling. The industry distribution of the sample is presented in Table 1.

Table 1. Comparison of Physical Education Integration in Different Regions

Industry Category	Number of Companies	Percentage (%)
Manufacturing	100	33.3
Finance	80	26.7
Services	70	23.3
Others	50	16.7
Total	300	100

2.1 Variable Selection

A variety of financial and non-financial indicators were selected as feature variables. The primary financial and non-financial indicators, along with their definitions and expected impact directions, are listed in Table 2.

The financial indicators include debt-to-asset ratio, current ratio, net profit margin, total asset turnover, and revenue growth rate. Non-financial indicators comprise corporate governance structure, management turnover frequency, and macroeconomic environment indicators. Corporate governance structure is represented by board size and the proportion of independent directors, reflecting governance quality; management turnover frequency assesses management stability; macroeconomic environment indicators, such as GDP growth rate and industry prosperity index, reflect the impact of external economic conditions on enterprises.

Significant variables correlated with financial risk were selected through correlation analysis, with redundant features removed. Principal Component Analysis (PCA) was employed for dimensionality reduction, transforming high-dimensional data into a lower-dimensional space to retain key information and enhance model training efficiency.

Table 2. Variable Names, Definitions, and Expected Impact Directions

ariable Name	Definition or Formula	Expected Impact
Debt to Asset Ratio	Total Debt / Total Assets	Positive
Current Ratio	Current Assets / Current Liabilities	Negative
Net Profit Margin	Net Profit / Revenue	Negative
Total Asset Turnover	Revenue / Total Assets	Negative
Revenue Growth Rate	(Current Revenue - Previous Revenue) / Previous Revenue	Negative
Board Size	Total Number of Board Members	Positive/Negative
Proportion of Independent Directors	Number of Independent Directors / Total Board Members	Positive
Management Turnover Frequency	Number of Management Changes	Positive
GDP Growth Rate	Annual GDP Growth Rate	Positive
Industry Prosperity Index	Prosperity Index released by Industry Association	Positive

2.2 Model Construction

A deep neural network (DNN) was used to construct the financial risk early warning model. The DNN model consists of an input layer, two hidden layers, and an output layer, utilizing ReLU and Sigmoid activation functions to achieve accurate financial risk prediction for enterprises.

The DNN model structure is designed as follows: (1) The input layer contains all financial and non-financial indicators processed through feature engineering, with a total of 10 input nodes. (2) The hidden layers include two layers, each with 64 nodes, and use the ReLU (Rectified Linear Unit) activation function to enhance the model's nonlinear representation capabilities. (3) The output layer consists of a single node, using the Sigmoid activation function to handle binary classification, outputting the probability of financial risk presence in an enterprise.

Binary crossentropy was selected as the loss function, and the Adam optimizer was used to accelerate model convergence. During model training, the batch size was set to 32, and the number of epochs was set to 100. Early stopping was applied to monitor loss changes in the validation set, preventing the model from overfitting to the training data.

3 Empirical Study

Model evaluation is a critical step in verifying the performance of the early warning model. The selected evaluation metrics include accuracy, precision, recall, F1 score, ROC curve, and AUC.

Accuracy measures the proportion of correctly predicted samples among the total samples. Precision assesses the proportion of correctly predicted positive samples among all samples predicted as positive. Recall indicates the proportion of actual positive samples that were correctly identified by the model. The F1 score, which is the harmonic mean of precision and recall, reflects the model's accuracy and coverage. The ROC curve shows the model's performance across different thresholds, providing a visual assessment of its classification ability, while the AUC quantifies the area under the ROC curve; the closer the AUC is to 1, the better the model's classification performance.

To enhance the reliability of model evaluation, K-fold cross-validation was applied. The dataset was divided into K subsets, with each subset used as the validation set once while the remaining K-1 subsets served as the training set. This process was repeated K times, and the average performance across all iterations was calculated as the model's overall performance metric. This method effectively minimizes the impact of data partitioning randomness, thereby improving the stability of evaluation results.

3.1 Experimental Results

The DNN model performs excellently across all evaluation metrics, achieving an accuracy of 90.0%, precision of 88.0%, recall of 85.0%, F1 score of 86.5%, and an AUC of 0.93. This indicates the model's high accuracy and stability in predicting financial risk in enterprises. Figure 1 illustrates that the DNN model's ROC curve significantly outperforms the random guess diagonal, with an AUC of 0.93, demonstrating the model's strong classification capability across various thresholds. Table 3 further shows that the DNN model performs well in predicting both positive and negative classes, accurately identifying 40 positive samples, with only 5 false positives and

10 false negatives, while correctly classifying 95 true negative samples. This reflects the model's high prediction accuracy and low misclassification rate., while its ROC curve is shown in Figure 1. The trend predictions of financial indicators for three enterprises are depicted in Figure 2.

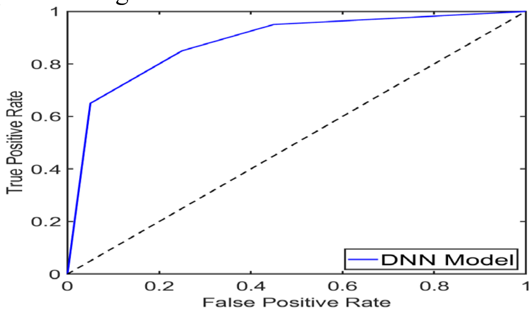

Fig. 1. ROC Curve of the DNN Model

Table 3. The confusion matrix for the DNN model

Actual\predicted	Predicted Positive	Predicted Negative
Actual Positive	True Positive: 40	False Negative: 10
Actual Negative	False Positive: 5	True Negative: 95

Feature importance analysis reveals that the key factors influencing financial risk include debt-to-asset ratio, net profit margin, and corporate governance structure, with importance scores of 0.35, 0.30, and 0.25, respectively. Secondary factors are revenue growth rate, current ratio, and total asset turnover, with scores between 0.07 and 0.10. Management turnover frequency, proportion of independent directors, GDP growth rate, and industry prosperity index have relatively minor impacts, with importance scores between 0.01 and 0.05.

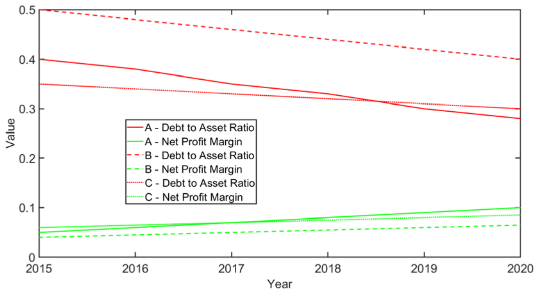

Fig. 2. Financial Indicators Trends of Typical Companies

As shown in Figure 2, the financial indicator trends for the three sample enterprises align closely with the model's predictions, validating its effectiveness in practical applications. For Enterprise A, a decrease in debt-to-asset ratio alongside improvements in net profit margin and corporate governance structure align with the model's risk warning results. For Enterprise B, a continuous decline in financial indicators was accurately flagged by the model as indicating financial risk. Enterprise C's stable financial condition was also correctly identified by the model as a low-risk characteristic

3.2 Results Analysis

The model achieved an accuracy of 90.0%, precision of 88.0%, recall of 85.0%, F1 score of 86.5%, and an AUC of 0.93, indicating high accuracy and stability in identifying financially risky enterprises.

The high precision and recall reflect the model's balanced ability to reduce both false positives and false negatives. The AUC close to 1 suggests excellent discrimination between positive and negative classes across various thresholds. Additionally, the confusion matrix shows the model's effectiveness in accurately identifying both risky and non-risky enterprises, with a low number of false positives and false negatives.

Feature importance analysis reveals that debt-to-asset ratio, net profit margin, and corporate governance structure are the primary factors influencing financial risk, consistent with traditional financial analysis, thereby validating the model's rationality. The inclusion of macroeconomic indicators further enhanced the model's accuracy.

Case analysis demonstrates that the model's financial risk predictions align well with actual outcomes, providing robust support for enterprise management and investment decision-making. Overall, the DNN model exhibits high practicality and reliability, offering an effective tool for financial risk early warning.

4 Discussion

The deep neural network (DNN) model constructed in this study performs well in financial risk early warning but has room for improvement. First, data quality significantly impacts model performance; data biases and missing values may lead to misjudgments. Future work could explore additional data sources or improve data preprocessing techniques to enhance predictive reliability.

Second, the "black box" nature of the DNN model limits interpretability. Integrating more interpretable algorithms or applying post-processing techniques could improve transparency and strengthen trust in management decisions.

Moreover, the model's generalizability may be constrained in varying economic environments. To enhance adaptability, future research could consider transfer learning or adaptive modeling approaches to improve stability across different markets and industry contexts.

Finally, this study focuses on financial and non-financial indicators. Future models could incorporate external factors, such as market volatility, to further improve predictive accuracy and practicality.

5 Conclusion

This study developed a financial risk early warning model based on a deep neural network and conducted empirical validation. The main conclusions are as follows: (1) The model performs excellently in terms of accuracy, precision, and recall, demonstrating its effectiveness in identifying financial risks; (2) Feature importance analysis reveals that debt-to-asset ratio, net profit margin, and corporate governance structure are the primary influencing factors of financial risk; (3) The model provides a reliable tool for predicting financial risk in enterprises. Future research could enhance the model's applicability in decision-making by incorporating more external factors and improving interpretability.

References

1. Song YN, Du HQ, Piao TY, Shi HY. Research on Financial Risk Intelligent Monitoring and Early Warning Model Based on LSTM, Transformer, and Deep Learning. *Journal of Organizational and End User Computing.* 2024, 36(1): 1-24.
2. Che F, Jiang Y, Omar K, El-Kanj N. Enterprise Financial Risk Early Warning System Based on Structural Equation Model. *Applied Mathematics and Nonlinear Sciences.* 2023, 8(1): 671-680.
3. Sun XJ, Lei YL. Research on financial early warning of mining listed companies based on BP neural network model. *Resources Policy.* 2021, 73: 102223.
4. Cheng XJ. An attention embedded DUAL-LSTM method for financial risk early warning of the three new board-listed companies. *Peerj Computer Science.* Mar 2023, 9: 1271.
5. Jia CL, Sun S, Geng Y, Ieee. Financial Risk Early Warning Model Based on Intelligent Data Monitoring. Paper presented at: International Conference on Big Data, Information and Computer Network (BDICN). 2022: 161-164.
6. Feng Q, Chen H, Jiang RH. Analysis of early warning of corporate financial risk via deep learning artificial neural network. *Microprocessors and Microsystems.* 2021, 87: 104387.
7. Ouyang ZS, Yang XT, Lai YZ. Systemic financial risk early warning of financial market in China using Attention-LSTM model. *North American Journal of Economics and Finance.* 2021, 56: 108383.
8. Li CA, Jin KY, Zhong ZQ, Zhou P, Tang KZ. Financial Risk Early Warning Model of Listed Companies Under Rough Set Theory Using BPNN. *Journal of Global Information Management.* 2022, 30(7): 1-18.