Design of Financial Risk Assessment System for Listed Companies: A Perspective Based on Deep Learning

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Abstract. Financial risk assessment is very important for the development of enterprises. It can detect potential risks in advance, help enterprises to rationally plan funds, optimize resource allocation, reduce losses, and ensure stable operation. Aiming at the problems of traditional financial risk assessment methods relying on subjective experience and single data dimension, this study develops a deep learning-driven framework for evaluating financial risks in publicly traded firms. Drawing upon the historical financial data of A-share listed companies, this study constructs a risk assessment system through a neural network model based on deep learning, effectively captures the temporal correlation of financial indicators, and introduces interdisciplinary analysis methods to reduce the subjective bias in traditional assessment. The experimental results demonstrate that the MAE of the model is about 0.3, and the evaluation accuracy is 97%. The accuracy and stability of the risk classification show promising advantages in terms of the traditional methods. The research results provide a new technical path and theoretical support for data-driven enterprise risk quantitative management.

Keywords: Listed companies; financial risks; deep learning.

1. Introduction

With the intensification of global economic uncertainty and the complexity of financial risks, the scientific and forward-looking nature of the financial risk assessment system of listed companies has become the focus of academic and practical circles. Traditional evaluation methods are based on expert experience and statistical models [1-2]. The former relies on subjective judgment, which leads to significant heterogeneity of evaluation results [3]. The latter is limited by linear assumptions and data distribution constraints [4]. Both are difficult to cope with the nonlinear interaction effects of multidimensional risk factors [5]. Machine learning improves the prediction accuracy through automatic feature screening and nonlinear modeling capabilities, but there are technical barriers to the fragmented processing of multimodal data [6-8]. Considerable headway has been made in the ongoing research on financial risk assessment for listed corporations [9-10]. However, there is still an opportunity for more in-depth exploration. An urgent need is to use available information components to represent the status of corporate financial risks [11-12].

Based on deep learning technology, this paper focuses on three dimensions: multi-modal data alignment, interpretable model design, and model processing accuracy. By introducing the Pearson formula, random seed partition method, and neural network model (Keras framework in TensorFlow library), the traditional model and deep learning are combined [13-14]. To these points, the system design constructs a dynamic evaluation system that integrates structured financial data, unstructured text, and real-time streaming data. The purpose of this paper will focus on providing listed companies with a risk assessment solution that combines predictive efficiency and risk management adaptability and on helping financial risk prevention and control transform from “passive response” to “active governance”.

2. Data Processing

2.1. Data Sources & Index Selection

The data of this paper are selected from the wind database, the financial statement data of A-share listed companies from 1991 to 2023. Due to the strict supervision of the securities supervision department, the financial statements of listed companies have been strictly audited, so the information disclosure is relatively perfect. Therefore, this paper starts with listed companies. Since very large enterprises, such as large commercial banks, large securities firms, and the real estate industry, with their heavy asset industries, can have occasional impacts on the model structure, this study further screens the listed company data in accordance with the national standards for small and medium-sized enterprises. Ultimately, 45,619 sample data from the manufacturing, service, and transportation industries that meet the criteria of having annual revenue below 100 billion yuan or fewer than 2,000 employees are selected.

The selection of financial risk assessment indicators in this study is drawing on the fundamental principles of accuracy, systematicness, scientificity, operability, and comprehensiveness in the construction of the indicator system. Combined with the company's debt-paying ability, operation ability, development ability, and profitability, ten indicators, including return on assets, net profit margin of total assets (ROA), return on equity (ROE), debt-to-asset ratio, net profit growth rate, owner's equity growth rate, effective tax rate, main business profit, net profit, and sustainable growth rate, have been selected.

2.2. Data Cleaning

Data cleaning is to improve the quality of data sets used in subsequent research and identify and correct incomplete or erroneous data in data sets. Under normal circumstances, the original data set will be disturbed by many factors in the whole process from generation and storage to extraction. Therefore, there will be problems such as data loss, significant outliers of samples, and data inconsistency, which makes the original data set unable to be directly applied to the modeling process. The data cleaning in this paper mainly processes the missing values, repeated values, and data with null values of the original data, which is the preparatory work for the subsequent model construction.

2.3. Index Analysis

Fig. 1 is the characteristic correlation matrix heat map, which is drawn according to the data of the selected type as the numerical value. Each cell in Fig. 1 represents the correlation coefficient of a feature pair. A deep color represents a high degree of correlation, whereas a pale color suggests low correlation or the absence of correlation. In this paper, the Pearson correlation coefficient is used to measure, and the coefficient's value spans from -1 to 1, where -1 denotes a perfect negative correlation, 1 indicates a perfect positive correlation, and 0 signifies the absence of linear correlation. The values in the cell of Fig. 1 only represent the correlation between two related features. However, in practice, a feature may be affected by multiple other features, so these values are only used as preliminary estimates of the data. In the following part, the complex relationship between data will be evaluated more accurately through a deep learning neural network, and the model will be trained to learn more accurate evaluation criteria.

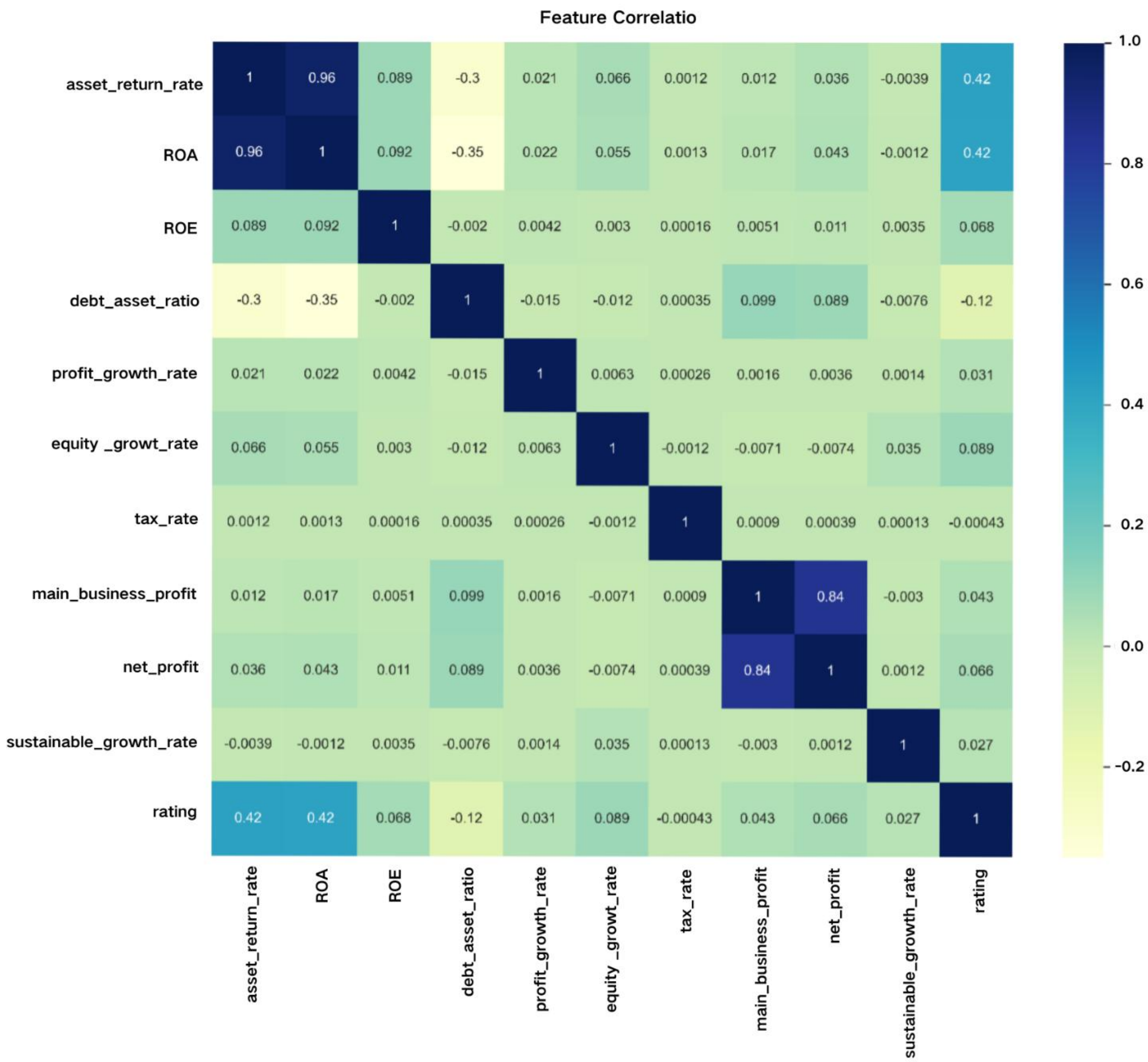

Fig. 1 The feature correlation heat map drawn by the data set

3. Model Construction

In this paper, the Keras framework in the TensorFlow library is used to establish a neural network model. After cleaning the data, 10 index data marked with 0 and 1 labels are used to construct the neural network model. This model is established from the division of training set and test set samples, the choice of activation function and the determination of topological structure, and the results of the model are further analyzed. (1) Sample Division. Table 1 is the specific sample division. The training sample set: 80 % of the samples are randomly selected from 45619 sample data, and the sample size in total that undergoes training is NTrain = 45619 * 80 %=36495. Test sample set: 20 % of the samples are randomly selected from 45619 sample data, and the total number of samples that can be tested is NTest = 45619*20 %=9124. In order to avoid the influence of continuous data segments on model learning, the data set is randomly divided, and the ratio of training samples to test samples is 7:3. At the same time, a fixed random seed is used in the training process, and a fixed starting value (i.e., seed value) is set to ensure that the random number sequence generated each time the program is run is the same, to avoid the influence of different data set divisions on the evaluation results of the model. (2) Activation Function Selection & Topology Determination. The activation function selects the ReLU function to alleviate the gradient disappearance problem. When the input is positive, the gradient is always 1. Fig. 2 is its function image, which alleviates the problem of gradient disappearance in deep neural networks so that the network can propagate the gradient more effectively, so that it is easier to train the model. The model's topology is illustrated in Fig. 3. The input layer is 10 index data, which is expressed as 10 neurons in the network structure. The output layer is the final evaluation score of corporate financial risk, which is divided into 0-10 points, which is expressed as an output neuron in the network structure. By inputting from the input layer and transmitting from one node to another node in the network until reaching the output layer, the first, second, and third layers of this model are all fully connected layers, and the neurons in each layer relate to all neurons in the previous layer to form a dense connection structure. Input 10, output 64, 32, and 1. Finally, through the enterprise 10 evaluation index data, through the neuron transmission, it is concluded that the credit evaluation score is.

Table 1. Division of samples.

Test Set Data	36495
Training Set Data	9124
Total	45619

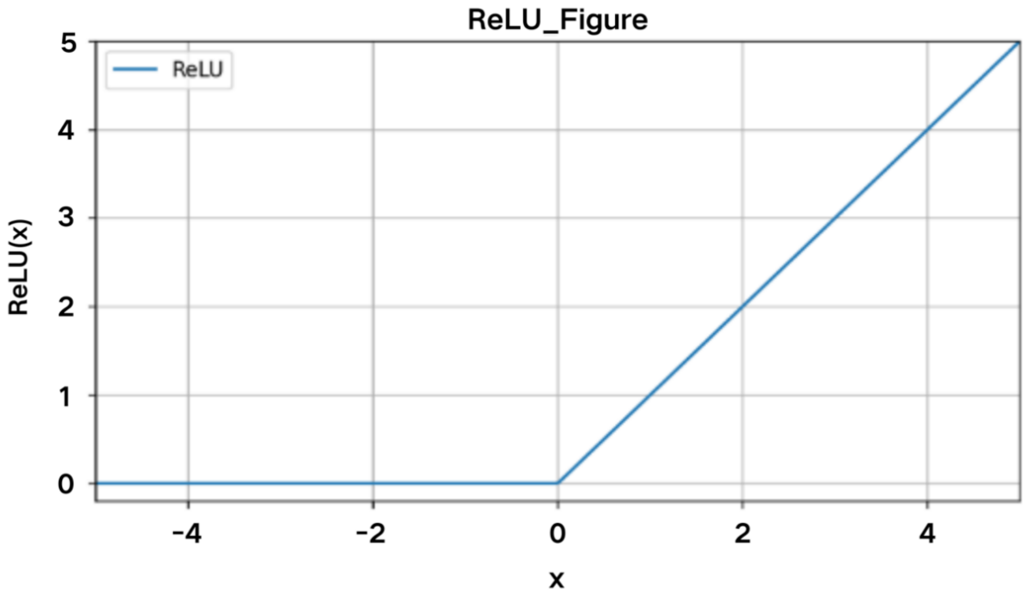

Fig. 2 ReLu function image

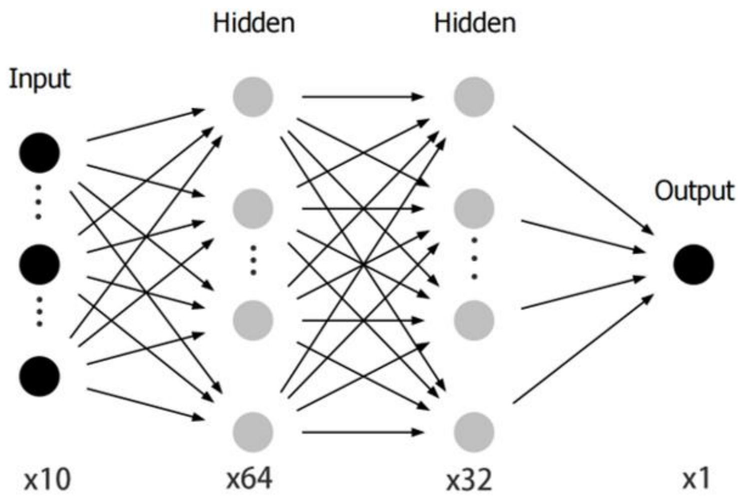

Fig. 3 Network topology architecture

4. Results & Analysis

In this paper, the mean absolute error (MAE) is applied to assess the prediction performance of the model. MAE is a statistical index to measure the average discrepancy between the predicted value and the actual value, ranging from (0, +∞). A model is considered perfect when the predicted value fully coincides with the true value. Therefore, the smaller the value of MAE, the better the accuracy of the prediction model. The model used 50 rounds of training, the training time was 31.8649 seconds, and the final MAE on the test set was 0.3146. Fig. 4 shows the changes in the model's average absolute error on the training set and validation set with the number of training rounds. The training MAE curve reflects the fitting situation of the model on the training set. The validation MAE curve is used to evaluate the model's generalization capability. As the training progresses, the model gradually learns the features of the data, and both the training MAE and validation MAE gradually decrease, indicating that the model has good generalization ability. Fig. 5 illustrates how the loss of the model on both the training set and validation set evolves with the number of training rounds. The training loss curve reflects the fitting degree of the model on the training set. The validation loss curve is used to evaluate the generalization ability of the model. Since the model parameters are randomly initialized, there is a large difference between the predicted results and the true values, so the training loss is relatively high. However, as the training advances, the model steadily acquires an understanding of the data's characteristics, and both the training loss and validation loss gradually decrease, indicating that the model has good predictive ability on unseen data. In summary, as the number of training rounds increases, the model's mean absolute error (MAE) on both the training set and the test set gradually decreases, and no overfitting occurs. Additionally, the MAE on the test set is approximately 0.3, which is within a relatively small error range. This indicates that the model is reasonable and feasible for predicting enterprise credit scores.

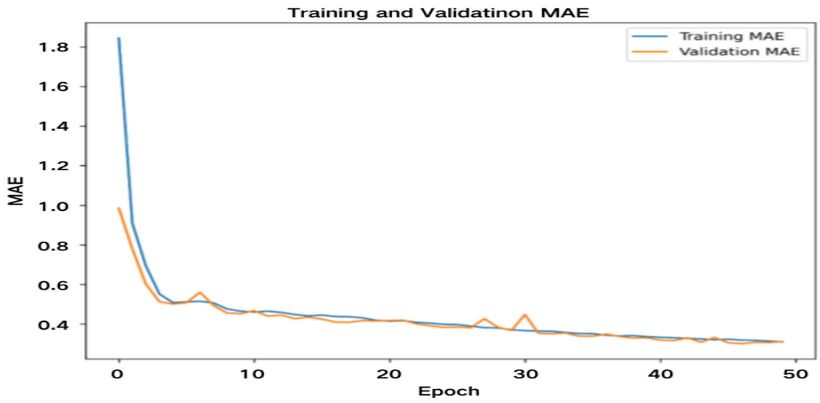

Fig. 4 Training and Validation MAE

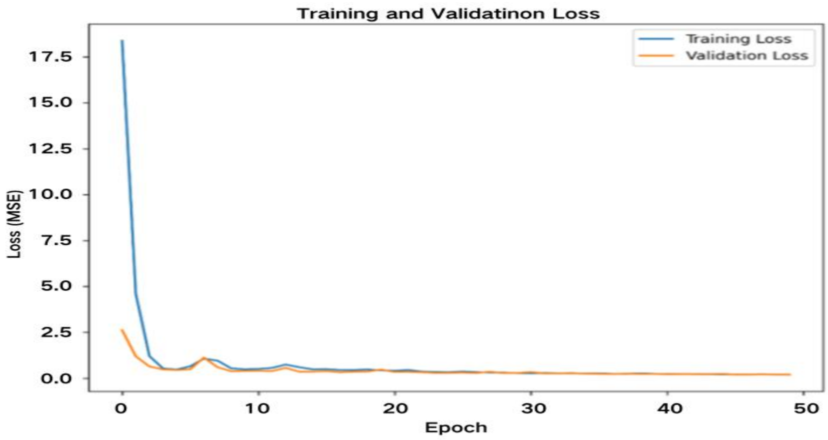

Fig. 5 Training and Validation Loss

5. Conclusion

In summary, the model for financial analysis and evaluation of listed companies in this study has an evaluation difference of only 0.3 (on a 10-point scale) and an accuracy rate of about 97%. This indicates that the neural network model based on deep learning has shown high accuracy and efficiency in evaluating financial risks and has good generalization, which is conducive to providing a risk assessment solution for listed companies that combines predictive performance and risk management adaptability. It has significant reference value for helping financial risk prevention and control transition from "passive response" to "active governance."

References

[1] Xingli W, Liao H. Utility-based hybrid fuzzy axiomatic design and its application in supply chain finance decision making with credit risk assessments. Computers in Industry, 2020, 114: 103144-103144.

[2] Jabeur B, Sami, Stef, et al. Bankruptcy Prediction using the XGBoost Algorithm and Variable Importance Feature Engineering. Computational Economics, 2022, 61(2): 1-27.

[3] Huang X, Liu X, Ren Y. Enterprise credit risk evaluation based on neural network algorithm. Cognitive Systems Research, 2018, 52: 317-324.

[4] Gu Z, Lv J, Wu B, et al. Credit risk assessment of small and micro enterprise based on machine learning. Heliyon, 2024, 10(5): e27096-.

[5] Xindong P, Haihui H. Fuzzy decision-making method based on cocoso with critic for financial risk evaluation. Technological and Economic Development of Economy, 2020: 1-30.

[6] Wang F, Ding L, Yu H, et al. Big data analytics on enterprise credit risk evaluation of e-Business platform. Information Systems and e-Business Management, 2019,18(3):1-40.

[7] K A L, Kyle P, Alice H, et al. A Comparison of Machine Learning Methods and Conventional Logistic Regression for the Prediction of In-Hospital Mortality in Acute Biliary Pancreatitis. Pancreas, 2022, 51(10): 1292-1299.

[8] Kumar A T, Mangalpady A, Perumal E V, et al. Quantitative Analysis of Solar Photovoltaic Panel Performance with Size-Varied Dust Pollutants Deposition Using Different Machine Learning Approaches. Molecules, 2022, 27(22): 7853-7853.

[9] Song Ge, Ma Tao. Research on financial risk early warning model of listed companies based on deep learning. Value engineering, 2019, 38(01): 53-56.

[10] Liu Xuelin. Research on financial early warning model of listed companies in China based on deep learning. Tianjin University, 2018.

[11] Zhang J. Investment risk model based on intelligent fuzzy neural network and VaR. Journal of Computational and Applied Mathematics, 2020, 371: 112707.

[12] Qin Yanjing. Research on Financial Risk Early Warning of Listed Companies in China Based on Deep Learning: A Case Study of La Chapelle. University of International Business and Economics, 2022.

[13] J. T F. The Pearson Bayes factor: An analytic formula for computing evidential value from minimal summary statistics. Biometrical Letters, 2021, 58(1): 1-26.

[14] S. M U, Guotai C, M. A M J A, et al. Leveraging random forest in micro-enterprises credit risk modelling for accuracy and interpretability. International Journal of Finance & Economics, 2020, 27(3): 3713-3729.