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Article

Artificial Intelligence-Driven Corporate Financial Forecasting and Risk Assessment Modeling

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Abstract: With the continuous development of the global economy, the financial risks faced by enterprises have become more and more complex and diverse. In order to achieve more accurate prediction and assessment of enterprise financial risk, this paper constructs financial risk early warning indicators from the perspectives of solvency indicators, operating ability indicators, etc., standardizes the data using Max-Min standardization method, and reduces the dimensionality of the financial risk early warning indicators with the help of Principal Component Analysis (PCA), which reduces the problem of multiple covariance in the process of model construction. Based on the deep learning method, the combination of self-encoder and convolutional neural network is used to construct the enterprise financial prediction and risk assessment model based on AE-ResNet. Comparing this paper's model with traditional models such as ANN, 1DCNN, 2DCNN, etc., this paper's model performs optimally in evaluation indexes such as accuracy (0.9637), TPR (0.9415), $G-Mean$ (0.9533) and AUC (0.9895), and the model has excellent performance.

Keywords: principal component analysis; self-encoder; convolutional neural network; ResNet; financial risk early warning

1. Introduction

In recent years, the frequent occurrence of "black swan" events and the intensification of "gray rhino" risks have brought considerable impact on the global business environment [1-2]. And the continuous development of the market and the economy, enterprises face a variety of financial risk issues, enterprise financial management is particularly important [3]. Therefore, in the increasingly fierce market competition, the demand for accurate financial forecasting and risk assessment is extremely urgent, which is related to the sustainable development of enterprises. However, traditional financial forecasting methods, such as the discounted cash flow method and regression analysis, although they have performed well in past business operations, the limitations of these methods are becoming increasingly apparent in the modern, fast-changing business environment, where they usually rely on historical financial data, assuming that future market behaviors will be consistent with the past [4-5]. External factors such as fluctuations in the global economy, policy changes, and increased market competition have led to a high degree of uncertainty in firms' financial positions, and traditional models have difficulty coping with these changes [6-7]. In addition, as the variety and size of data increases dramatically, firms must deal with a large amount of complex data, including unstructured data (e.g., social media, market dynamics, etc.), which traditional models lack the ability to handle, and these unstructured data may contain information that is critical to financial decision making, and traditional forecasting models usually fail to capture these potential signals [8-10]. In addition, these methods rely on the subjective judgment of analysts, which may result in forecasting accuracy being affected by personal bias, especially in highly complex and rapidly changing market environments [11].

Driven by the wave of digitization, companies encounter increasingly complex and highly dynamic financial environments. In the context of financial risk assessment, classical approaches include financial ratio analysis, cash flow analysis, and statistically based risk quantification models, which have historically played an important role [12-14]. However, in an environment of increasing data, their limitations are becoming increasingly apparent, such as the challenges of dealing with the real-time, integrity, and complexity of data, as well as how to adjust for data bias due to the onslaught of high-dimensional data, and the challenges of grasping the full picture of risk and responding to changes in risk in a timely manner, which makes the traditional methods ineffective in responding to the complex and ever-changing risk environments of modern enterprises [15-17].

With the rapid progress of science and technology, Artificial Intelligence (AI) technology has been widely used in the field of enterprise management and finance. And AI can quickly absorb a full range of data such as financial statements, cost details, revenue streams, etc. of enterprises for several years or even decades, and excavate the deep-seated laws of the data [18]. With the help of network crawler technology, big data docking and other means, AI tracks the price trend of raw materials, interest rate and exchange rate fluctuations, competitors' new product releases and other information in real time, and integrates these external variables into the financial prediction model, which helps enterprises plan response strategies in advance and greatly improves cost Planning response strategies, greatly improving the accuracy of cost prediction, making the overall financial forecast of the enterprise closer to the actual development trajectory [19-22]. In addition, AI provides an effective means of risk prevention and control for enterprises. After identifying risks, it is more important to accurately measure the severity of the risk and find an effective way to resolve it, while AI realizes quantitative assessment of various types of risks and improves enterprise financial risk management by evaluating the financial situation of the enterprise and combining internal financial data with external market intelligence [23-25]. Therefore, the research of AI-driven financial prediction and risk assessment model has important theoretical and practical value for improving the ability of enterprise financial risk assessment.

In this paper, 20 indicators are selected from five perspectives, namely, solvency index, operating capacity index, profitability index, development capacity index, and cash flow capacity index, to quantify the enterprise financial risk. In the pre-processing work of the research data, the Max-Min standardization method is used to map the maximum and minimum values of the data to 0 and 1, and the other values are mapped to real numbers between 0 and 1 through linear transformation, eliminating the difference in the scale between the data and improving the stability and interpretability of the data. Using the principal component analysis method, the data of the initially selected financial risk early warning indicators are processed, and specific feature vectors are selected as principal components to realize the dimensionality reduction of the indicators. After completing the dimensionality reduction to avoid the problem of multicollinearity, the self-encoder is combined with the convolutional neural network, and the data are input into the self-encoder for training, and then the dimensionality reduction data are extracted and input into the convolutional neural network for training to build the enterprise financial prediction and risk assessment model based on AE-ResNet. Simulation experiments of corporate financial forecasting and risk assessment are carried out, and the performance of the model is compared with RF, LR, SVM, KNN and other models to test the model performance and explore the prospect of its use in reality.

2. Sample Data Selection and Financial Risk Early Warning Indicator Construction

Enterprises carry out financial risk prediction, which can analyze the financial health of the enterprise in depth in an all-round and multi-angle way, and promote the benign and healthy development of the enterprise. To contribute a more accurate analysis means for enterprise financial risk prediction, this chapter will build up the financial risk early warning indicators, determine the principal component factors through principal component analysis, and provide the basis for the construction of enterprise financial prediction and risk assessment model later.

2.1. Research Data Sources

Listed companies with special treatment due to “abnormal financial status” are defined as financial crisis companies, i.e., ST companies, while listed companies without special treatment are regarded as normal financial status companies, i.e., non-ST companies.

The data of this paper is obtained from the listed companies in the A-share market of Shanghai and Shenzhen in China, and the sample of this study is the A-share listed companies in Shanghai and Shenzhen stock exchanges that are ST and *ST in 2024 and not ST in 2022 and 2023, excluding the companies that have been dealt with by special treatment due to non-financial abnormalities and those with serious missing data. Since the companies labeled as ST rely on the financial statement data of the previous year, if we use the financial data of the year before ST to predict the financial risk of the enterprise, we tend to overestimate the predictive effect of the model, so we choose the financial data of two years before ST, i.e., 2020, to conduct the relevant research.

2.2. Construction of Early Warning Indicators for Financial Risk

There are many kinds of indicator factors affecting the financial risk of enterprises, but there are many non-financial indicator factors which are influenced by the environment and difficult to quantitatively judge their impact on financial risk. Drawing on existing research experience, at the same time, according to the principle of selecting financial early warning indicators, selecting the financial indicators with high frequency of use and high practicality, initially screened 20 alternative early warning indicators, the specific indicators are shown in Table 1. As can be seen from the table, this paper selects appropriate indicators from five perspectives: solvency indicators, operating ability indicators, profitability indicators, development ability indicators and cash flow ability indicators to quantitatively reflect the main sources of risk.

Table 1. Financial risk early warning index system.

Indicator category	Name of indicator	Indicator code
Debt paying ability index	Flow ratio	A1
	Fast ratio	A2
	Cash ratio	A3
	Asset-liability ratio	A4
	Property rights ratio	A5
Operating Capability Indicators	Accounts receivable turnover rate	A6
	Inventory turnover rate	A7
	Current asset turnover rate	A8
	Fixed assets turnover rate	A9
	Total asset turnover rate	A10
	Business cycle	A11
Profitability index	Net profit margin of total assets	A12
	Return on net assets	A13
	Return on assets ratio	A14
	Gross operating margin	A15
Development ability index	Growth rate of operating income	A16
	Growth rate of total assets	A17
	Capital preservation and appreciation rate	A18
	Capital accumulation rate	A19
Cash flow ability index	Total cash recovery rate	A20

2.3. Pre-Processing of Research Data

2.3.1. Data Standardization

The purpose of data standardization is to adjust data of different nature as well as of different magnitudes to an analogous range by indexing them for better comparison and analysis. Standardization can help to eliminate differences in magnitude between data and avoid situations where the effect of the dependent variable on the independent variable in regression analysis is masked by differences in magnitude. In addition to this, it can improve the stability and interpretability of the data, making it easier to understand and apply.

The method used in this paper is the Max-Min standardization method, as shown in equation (1). This method maps the maximum and minimum values of the data to 0 and 1, and maps the other values to real numbers between 0 and 1 through linear transformation, which makes the data with different magnitudes comparable and more conducive to data analysis and model construction:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X denotes the initial raw data; X' denotes the normalized data; $X_{\max}$ denotes the maximum value in the initial data set; and $X_{\min}$ denotes the minimum value in the initial data set.

2.3.2. Data Downscaling

In this paper, we use principal component analysis (PCA) to process the data of the primary selection indexes in this paper, and the PCA algorithm is based on linear transformation, which is able to map the original high-dimensional data into a low-dimensional space while maximizing the retention of the main information of the original data of the primary selection [26]. This can reduce the dimensionality of the original data features without losing too much information, improve the running efficiency of the model, and reduce the risk of overfitting. The algorithm flow is as follows:

1) Centering the data: for a given n samples, each sample has m features, each feature needs to be centered, i.e., each feature is subtracted from its mean value, making the mean value of each feature 0.

2) Calculate the covariance matrix: for the centered data, it is necessary to calculate its covariance matrix C, which is a matrix of $m \times m$, where C_{ij} denotes the covariance between the i-feature and the j-feature [27]. The covariance matrix can be calculated by the following equation:

$$C = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})(x_i - \overline{x})^T \tag{2}$$

where x_i is an m-dimensional vector, denoting the i th sample; $\overline{x}$ is an m-dimensional vector, denoting the mean of all samples. When the number of samples is large, the denominator in this paper is taken as n in order to facilitate the calculation.

3) Calculate eigenvalues and eigenvectors: for the covariance matrix C, we can calculate its eigenvalues and eigenvectors. The eigenvalue represents the variance in the direction corresponding to the eigenvector, and the eigenvector represents the projection of the data in that direction. We can realize dimensionality reduction by calculating the eigenvalues and eigenvectors of C.

4) Selecting principal components: sort the data in descending order according to the size of the eigenvalues and select the first K eigenvectors as principal components. These principal components represent the K most important directions of the data, where K is the number of dimensions to which the data is desired to be reduced.

5) Mapping the data to a new space: the original data x is mapped to a new k-dimensional space y, where the i th component of y can be calculated by the following equation:

$$y_i = x^T v_i \tag{3}$$

where v_i denotes the feature vector of the i th principal component.

2.4. Correlation Analysis of Early Warning Indicators of Financial Risk

The Max-Min standardization method was used to standardize the data. Because the preliminary financial risk early warning indicators contain too many indicators, there may be a high degree of correlation between them. In order to avoid the occurrence of multicollinearity in the modeling, it is necessary to analyze the correlation between the selected financial indicators before the construction of the enterprise financial forecasting and risk assessment model. The correlation heat map between the early warning indicators is shown in Figure 1. The horizontal and vertical coordinates represent the preliminary financial risk warning indicators, and the value at the intersection of the horizontal and vertical coordinates represents the correlation coefficient between the two indicators. If the absolute value of the correlation coefficient is greater than 0.7, it usually indicates that the correlation between the indicators is strong, and there is a greater possibility of multicollinearity in the construction of the model; the correlation coefficient between 0.4 and 0.7 indicates that the correlation between the indicators is at a medium level, and the correlation coefficient of 0.4 or less indicates that there is a weaker correlation between the indicators. From the figure, it can be seen that there are high correlations between indicators such as gearing ratio and leverage ratio, non-performing loan ratio and loan provision coverage ratio. Therefore, before the construction of the enterprise financial forecasting and risk assessment model, it is necessary to reduce the dimensionality of the indicators with the help of a reasonable principal component extraction method.

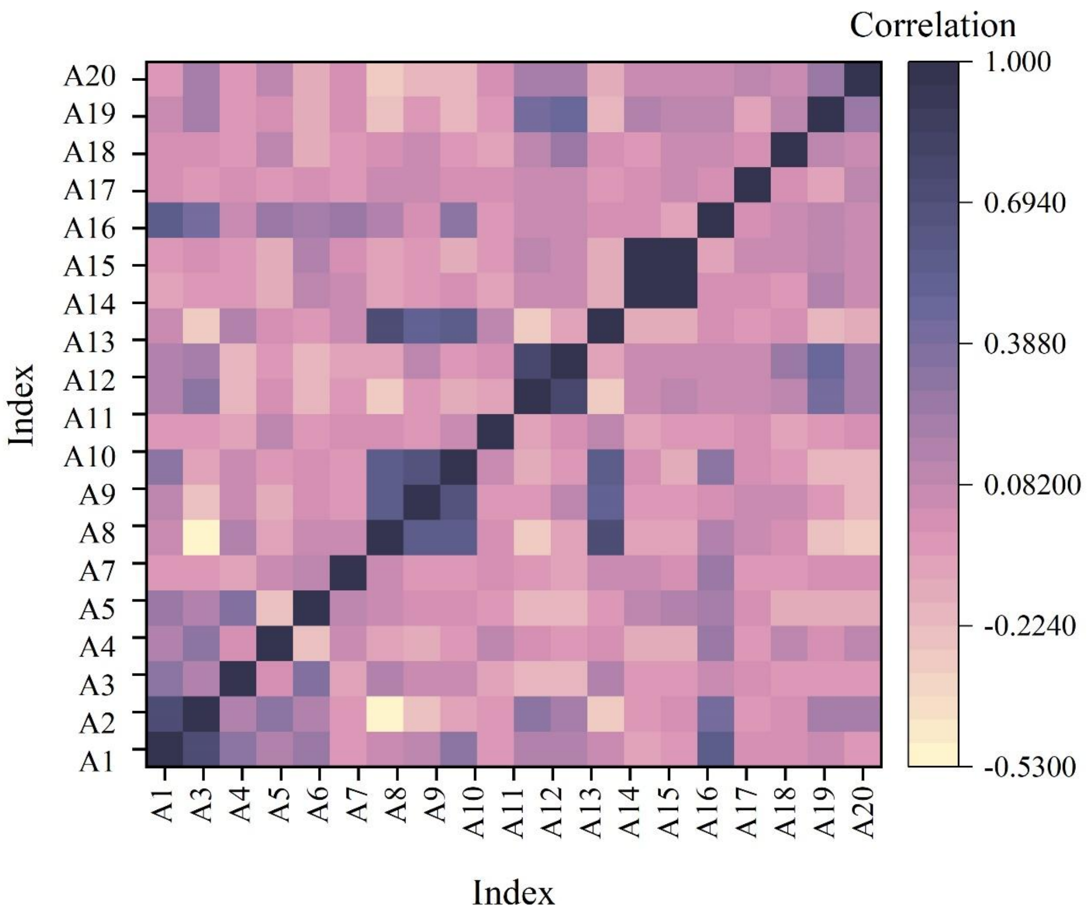

Figure 1. Index correlation heat map.

2.5. Principal Component Analysis of Early Warning Indicators of Financial Risk

2.5.1. Principal Component Suitability Tests

The suitability of principal component analysis presupposes that the selected independent variables are tested accordingly. After standardizing the raw data of financial indicators, KMO and Bartlett's sphericity methods were applied to test the standardized variables. In general, when the coefficient of KMO test is >0.5 and the probability of significance of Bartlett's test of sphericity is <0.05, it is suitable for principal component analysis.The test of KMO and Bartlett is specifically shown in Table 2. As can be seen from the table, the KMO value is 0.638, and the significance probability corresponding to Bartlett's test is 0.001, which indicates that it is suitable for principal component analysis.

Table 2. KMO and Bartlett 's test.

Test	Result
KMO sampling appropriateness quantity	0.638

Bartlett 's sphericity test	Approximate chi-square	5416.663
	Degree of freedom	200
	Prominence	0.001

2.5.2. Principal Component Extraction

The number of principal components is determined by the cumulative contribution rate and the eigenvalue, usually the eigenvalue of each principal component should meet the standard of greater than 1, and the cumulative contribution rate is required to reach 80%. Using Python software to carry out principal component analysis on the standardized financial index data, the eigenvalues and cumulative contribution rate of each principal component are calculated, as shown in Table 3. As can be seen from the table, the first seven principal components have reached the requirement of eigenvalue greater than 1, and the cumulative contribution rate of these seven principal components is 87.505%, which is more than 80%, indicating that these seven principal components can adequately replace the original data of the 20 financial risk early warning indicators, which provide sufficient information for the original data and play a role in the generalization of the overall generalization, and the results of the factor analysis have achieved the expected effect, which is relatively Ideal. Therefore, the first seven principal components are extracted here for subsequent related research.

Table 3. Principal component eigenvalue and contribution rate.

Principal component name	Eigenvalue	Explain variance (%)	Cumulative variance contribution rate (%)
F1	5.07	25.35	30.35
F2	3.161	15.805	46.155
F3	3.063	15.315	61.47
F4	1.536	7.68	69.15
F5	1.284	6.42	75.57
F6	1.196	5.98	81.55
F7	1.191	5.955	87.505

The drawing of the fragmentation diagram is specifically shown in Figure 2. The fragmentation diagram can also be visualized to determine the number of public factors is 7, which can be represented by these 7 principal component factors of the original 20 financial indicators.

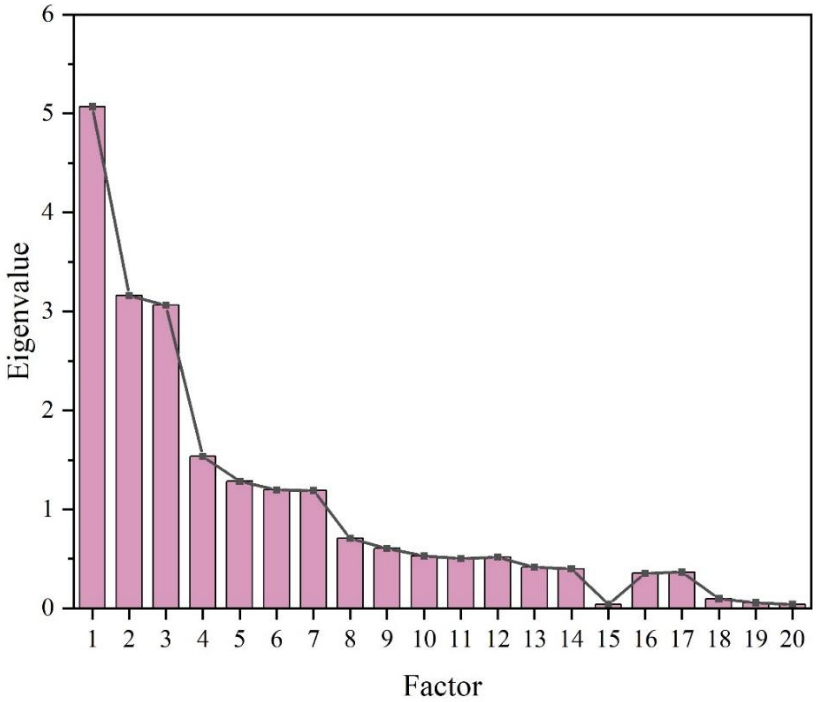

Figure 2. Stone map.

2.5.3. Principal Component Factor Interpretation

In the orthogonal rotation method, the rotation factor load matrix is obtained by using the method of maximum variance, so as to further explain the economic meaning of each principal component factor, the larger the load value in the load table, the stronger the ability of the principal component factor to explain the corresponding original index, so as to represent a certain index category. The factorial loading matrix after rotation is shown in Table 4. According to the table, it can be seen that the load value of F1 on A12, A14 and A18 is larger, and the correlation degree on these three variables is higher, and A12 and A14 are profitability indicators, and A18 is the development ability index, so F1 reflects the profitability development ability of the enterprise; The load value of F2 on A9 and A17 is larger, so F2 is explained by these two variables, and A9 and A17 are the operating capacity index and development capability index respectively, so F2 represents the operating ability and development ability of the enterprise; In F3, the load capacity of A1 and A2 is more obvious, and they belong to the solvency index, so F2 represents the solvency of the enterprise; The load value of F4 on A7, A8 and A10 is larger, and the correlation between these three variables is higher, so F4 is explained by these three quantities, and A7, A8 and A10 are the indicators of operating capacity, so F4 reflects the operating capacity of the enterprise; In F5, A16 has the greatest factor load, is 0.873, which is higher than the factor load of any other index, and A16 is the development capacity index, so F5 is mainly explained by the development ability; in F6, the load value of A6 is the most obvious, which is 0.903, and A6 is the operating capacity index, so F6 reflects the operating capacity of the enterprise; F7 has a larger load value on A20, so F7 is explained by these two variables, and A20 is the cash flow capacity index, so F7 represents the cash flow capacity of the enterprise.

Table 4. Component score coefficient matrix.

Variable	Principal component						
	F1	F2	F3	F4	F5	F6	F7
A1	0.136	-0.006	0.895	-0.025	0.06	-0.082	0.068
A2	0.116	0.005	0.921	-0.021	0.043	-0.069	0.067
A3	0.235	-0.064	0.618	-0.073	-0.172	-0.008	0.09
A4	-0.386	0.304	-0.631	0.245	0.007	0.094	0.145
A5	-0.312	0.894	-0.107	0.236	-0.024	-0.003	0.378
A6	-0.002	-0.024	-0.094	0.113	0.021	0.903	0.207
A7	-0.143	-0.046	0.012	0.93	0.02	-0.113	0.033

A8	0.057	0.167	-0.153	0.883	-0.151	0.233	0.126
A9	-0.093	0.937	-0.044	0.171	0.001	-0.01	-0.344
A10	0.037	0.333	-0.06	0.903	-0.084	0.1	-0.098
A11	-0.228	-0.095	-0.117	-0.234	0.71	-0.214	0.243
A12	0.943	0.118	0.144	0.028	-0.075	0.008	0.219
A13	0.776	-0.349	0.058	-0.15	0.114	-0.021	-0.268
A14	0.935	0.104	0.136	0.025	-0.071	0.003	0.227
A15	0.058	-0.141	0.658	-0.29	0.029	0.246	-0.033
A16	-0.018	-0.016	0.138	-0.039	0.873	0.115	0.222
A17	0.232	0.942	0.019	0.01	-0.065	-0.016	-0.23
A18	0.888	-0.21	0.167	-0.08	-0.082	-0.006	-0.121
A19	-0.342	0.189	-0.155	-0.028	0.055	-0.039	-0.121
A20	0.472	-0.221	0.233	-0.524	-0.159	0.184	0.738

3. Corporate Financial Forecasting and Risk Assessment Model Based on AE-ResNet

In the above paper, this paper constructs financial risk early warning indicators, and with the help of reasonable principal component extraction method to reduce the dimensionality of the financial risk early warning indicators, to avoid the problem of multiple covariance in the process of constructing the enterprise financial prediction and risk assessment model. Based on this, this chapter proposes the AE-ResNet model with the combination of self-encoder and convolutional neural network to assess and warn the financial risk of enterprises.

3.1. Self-Encoder AE

Self-encoder is one of the unsupervised learning which consists of an input layer, an intermediate hidden layer and an output layer. The input and output layers have the same number of neurons, while the number of neurons in the hidden layer is smaller than the input and output layers, thus realizing the purpose of dimensionality reduction [28].

Self-encoder consists of the following two main steps:

1) Encoding the input data: a^1 is the input layer node and a^2 is the hidden layer node, the mathematical equation can be expressed as:

$$Z^2 = a^1\left(W_B + b^2\right) \tag{4}$$

$$a^2 = f\left(Z^2\right) \tag{5}$$

W_B is the weight matrix, denoting the weight of the i th node of the input layer to the j th node of the hidden layer. b^2 denotes the bias parameter of the hidden layer. f is the activation function, and in this paper, the LeakyReLU activation function is chosen for activating the encoder.

2) Decode the data obtained from the hidden layer:

$$Z^3 = a^2\left(W_B^T + b^3\right) \tag{6}$$

$$a^3 = f_p\left(Z^3\right) \tag{7}$$

a^3 is the output layer node, b^3 denotes the bias parameter of the output layer, and W_B^T is the transpose matrix of W_B. f_p is the activation function, and the Sigmod activation function is chosen for the decoder in this paper.

In this paper, the single hidden layer self encoder model is used, because it has the advantages of easy to understand, low training cost, and has a low loss rate and high accuracy, compared with the stack self encoder, it can avoid the occurrence of gradient explosion and other risky problems.

3.2. Residual Network ResNet

A convolutional neural network consists of a convolutional layer, a pool sampling layer and a fully connected layer. The principle is to achieve layer-by-layer backward conditioning by minimizing the loss function to the weight parameters in the network using gradient descent. It is described in mathematical equation as follows:

$$y = F(x, W_i) + x \tag{8}$$

$$F = W_2\sigma(W_1 x) \tag{9}$$

x is the input, y is the output, $F(x, W_i)$ is the residual, and the residual part is shown in Eq. (9), with a ReLu-activated bi-layer weight in the middle, σ is ReLu, and W_1, W_2 are the weights. The summation of $F(x, W_i)$ and x is obtained by summing element by element, if the two dimensions do not match, a linear mapping needs to be executed for x to achieve the matching dimension. The final output is shown in equation (10):

$$y = F(x, W_i) + W_3^T x \tag{10}$$

The model ResNet18 is chosen for this experiment, which consists of 17 convolutional layers and 1 fully connected layer, and has a smaller computational amount and higher accuracy compared to other ResNet models. Since the dataset of this paper is small, choosing ResNet18 can avoid the overfitting phenomenon caused by too many layers of residual networks.

3.3. Construction of the AE-ResNet Model

The experimental model combines the self-encoder with the convolutional neural network, and the structure is shown in Figure 3. Firstly, the data are input into the self-encoder for training, and the loss rate can be obtained during the training process of the self-encoder, and the smaller the loss rate is, the more representative the extracted features are. After the training is completed, the dimensionality reduced data in the hidden layer is extracted, and then it is used as the input data and substituted into the convolutional neural network for training, successively processed by the convolutional layer and the pooling layer, and finally classified by the fully connected layer, and output the classification results and the accuracy, and the higher accuracy is obtained through debugging to ensure the reliability of the model.

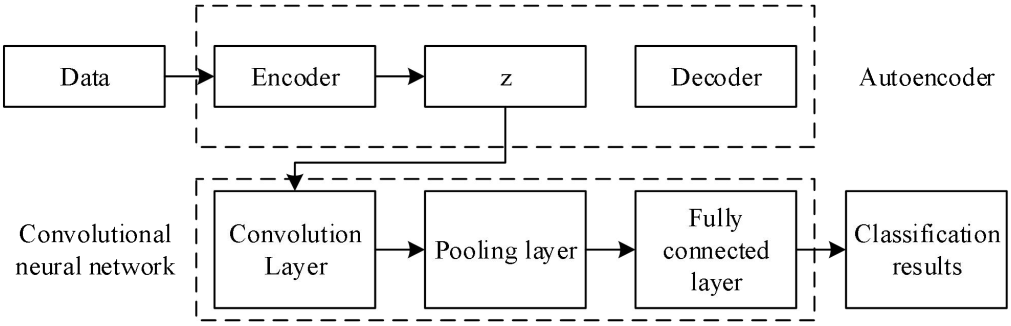

Figure 3. Model structure.

4. Simulation Experiment on Enterprise Financial Forecasting and Risk Assessment

In this chapter, the effectiveness of the AE-ResNet-based enterprise financial forecasting and risk assessment model (hereinafter referred to as “AE-ResNet model”) proposed in this paper will be tested by conducting simulation experiments on enterprise financial forecasting and risk assessment.

4.1. Experimental Data Sources

The dataset used in this experiment, the Polish business bust dataset, was obtained from the UCI database, which was collected from the Emerging Markets Information Service (EMIS).

4.2. Experimental Parameterization

In this section, the experimental parameters of ISE-ResNet are set. In order to choose the most suitable batch size and initial learning rate, the minimum batch size is set to 8, 16 and 32, and the initial learning rate is set to 0.1, 0.01 and 0.001, and each Epoch is trained.

4.3. Comparative Analysis of Model Prediction Results

The AE-ResNet model of this paper is compared and analyzed with the traditional enterprise financial prediction and risk assessment model. The selected comparison models are RF, LR, SVM, KNN, ANN, 1DCNN, 2DCNN, and AdaBoost.The specific ratios of misclassified financially risky enterprises and misclassified healthy enterprises for different models are shown in Figure 4. It can be seen that the AE-ResNet model in this paper has the lowest ratio of misclassified financial risk enterprises among all models, and in terms of the identification ability of healthy enterprises, the AE-ResNet model in this paper also has higher identification ability of healthy enterprises compared to other models, and has high competitiveness, and its performance is only lower than that of 2DCNN.

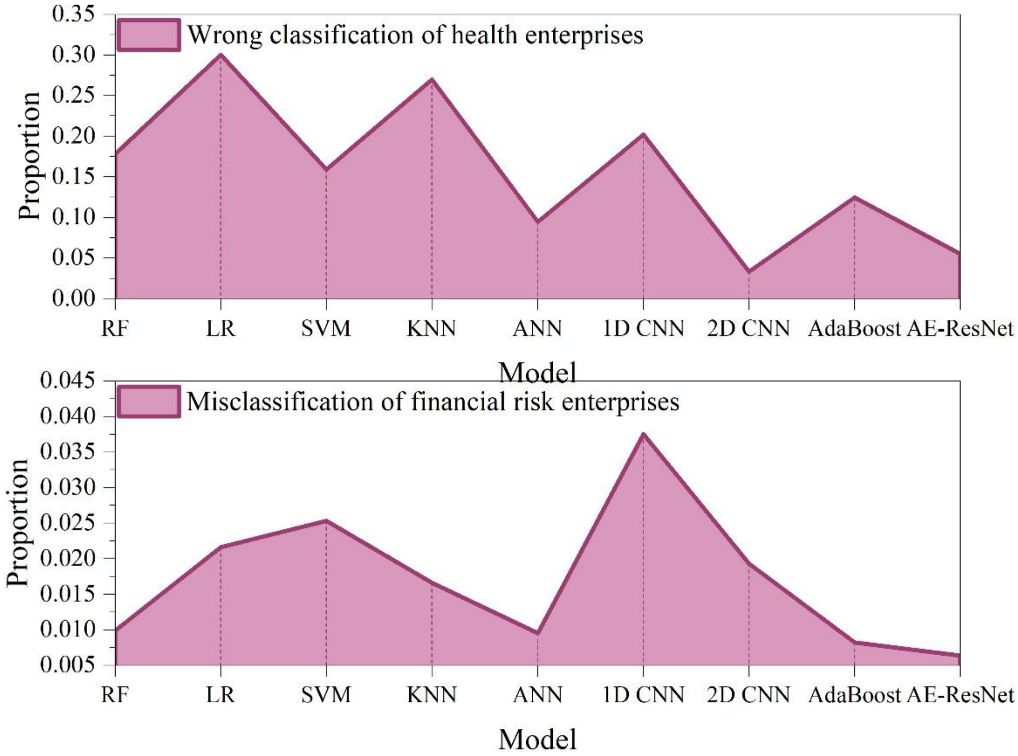

Figure 4. Comparison of prediction results.

The first type of error rate ($Type\ I\ error$), the second type of error rate ($Type\ II\ error$), true rate (TPR), true negative rate (TNR), $G-Mean$. Accuracy (AUC) and Accuracy (ACC), and other 7 assessment indicators to further compare and analyze the prediction results of different models. Among them, TPR represents the proportion of positive categories being correctly predicted as positive categories, and TNR represents the proportion of negative categories being correctly predicted as negative categories. $Type\ I\ error$ represents the proportion of healthy firms that are incorrectly categorized as financially risky. Conversely, $Type\ II\ error$ refers to the proportion of firms with financial risk that are misclassified as firms without financial risk. AUC denotes the proportion of the whole that is accounted for by all correctly categorized samples.

The results of enterprise financial prediction and risk assessment of different models are specifically shown in Table 5. It can be seen that the AE-ResNet model in this paper not only obtains the highest accuracy (0.9637), TPR (0.9415), $G-Mean$ (0.9533) and AUC (0.9895), but also obtains the smallest $Type\ II\ error$ (0.0593). For TNR and $Type\ I\ error$, 2DCNN is more inclined to correctly categorize healthy firms, but less capable of correctly distinguishing financially risky firms. In contrast, the AE-ResNet model in this paper has the optimal ability to differentiate financial risky firms, although its performance in TNR and $Type\ I\ error$ is only second to that of 2DCNN and better than the other comparative models. Obviously, the enterprise financial prediction and risk assessment model based on AE-ResNet constructed in this paper has a better prospect of use in the real enterprise financial prediction and risk assessment work.

Table 5. Empirical comparison of each model.

Model	ACC	$Type\ I\ error$	$Type\ II\ error$	TPR	TNR	$G-Mean$	AUC
RF	0.9177	0.0742	0.2396	0.7597	0.9253	0.8384	0.9307
LR	0.6585	0.3475	0.2457	0.7536	0.6526	0.7014	0.7607
SVM	0.7479	0.2493	0.2742	0.7252	0.7507	0.737	0.7799
KNN	0.7779	0.2148	0.3563	0.6424	0.7871	0.7108	0.8026
ANN	0.9098	0.0844	0.217	0.7832	0.916	0.8474	0.879
1D CNN	0.8113	0.177	0.3917	0.6077	0.8215	0.707	0.7919
2D CNN	0.9552	0.032	0.2697	0.7307	0.9691	0.8406	0.946
AdaBoost	0.9176	0.0743	0.222	0.7781	0.9247	0.8473	0.8355
AE-ResNet	0.9637	0.0338	0.0593	0.9415	0.9648	0.9533	0.9895

5. Conclusion

In order to realize accurate prediction and risk assessment of corporate finance, this paper screens 20 financial risk early warning indicators from five perspectives: solvency indicators, operating ability indicators, profitability indicators, development ability indicators, and cash flow ability indicators. For the correlation analysis of financial risk early warning indicators, there is a high correlation between the balance sheet ratio and leverage ratio, non-performing loan ratio and loan provision coverage ratio, etc. With the help of principal component analysis method, the indicators are downgraded. The applicability test of principal components is carried out, and the KMO value is 0.638, and the significance probability corresponding to Bartlett's test is 0.001, which proves the feasibility of principal component analysis. In the principal component extraction, the eigenvalues of the first seven principal components (F1~F7) are greater than 1 and the cumulative cumulative contribution rate reaches 88.012%, which can adequately replace the 20 financial risk warning indicators of the original data. The rotated factor loading matrix was obtained using the variance maximization method therein, and the principal components were named.F1~F7 were named as profitability development ability, solvency ability, operating ability, development ability, operating ability, and cash flow ability, respectively.

After completing the dimensionality reduction of financial risk warning indicators and avoiding the problem of multicollinearity, the enterprise financial prediction and risk assessment model based on AE-ResNet is constructed, and simulation experiments of enterprise financial prediction and risk assessment are carried out to test the model performance and the prospect of practical use. Traditional models such as RF, LR, SVM, KNN, ANNN, 1DCNN, 2DCNN, AdaBoost, etc. are selected as comparison objects, and in the classification work of financial risky enterprises and healthy enterprises, the lowest bankruptcy enterprises with the lowest misclassification rate of this paper's AE-ResNet model have a higher ability to recognize healthy enterprises. Selecting the first type of error rate ($Type\ I\ error$), the second type of error rate ($Type\ II\ error$), true rate (TPR), true-negative rate (TNR), $G-Mean$. Accuracy (AUC) and Accuracy (ACC) and other 7 evaluation metrics for further comparative assessment of model performance. The AE-ResNet model in this paper achieves the highest value in the accuracy, TPR, $G-Mean$, and AUC evaluation metrics, reaching 0.9637, 0.9415, 0.9533, and 0.9895, respectively, and the highest value in the $Type\ II\ error$ evaluation The minimum value of 0.0593 is achieved on the indicator of the remaining TNR and $Type\ II\ error$ evaluation indicators, this paper's AE-ResNet model performs second only to the optimal 2DCNN, but the 2DCNN's ability to correctly distinguish the financial risky enterprises is weaker. Overall, the AE-ResNet-based enterprise financial prediction and risk assessment model constructed in this paper has stronger comprehensive performance, and can have better performance in the real enterprise financial prediction and risk assessment work, with better prospects for use.

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