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Research on the Design of Financial Management Model Based on SOM-PNN Driven by Digital Economy

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In the contemporary financial landscape, institutions rely on big data to conduct comprehensive background analyses and continuous optimizations. Their primary goal is to seamlessly integrate quantitative analysis methods throughout every facet of risk management. This approach enables financial institutions to swiftly attain equilibrium in the intricate interplay between risk and income, ultimately striving for profit maximization within local and even broader domains. This study proposes a novel financial risk prediction methodology by harnessing the power of two types of artificial neural networks: self-organizing maps (SOM) and probabilistic neural networks (PNN). The amalgamation of SOM and PNN leverages their respective strengths, seamlessly integrating them into the algorithm presented in this paper. To compile and predict data, the SOM network employs a two-dimensional topological framework comprising two layers of neurons. Subsequently, the PNN model efficiently yields the final classification results by processing the output generated by the SOM model. This advanced composite model offers accelerated computation, effectively mitigates the influence of noisy data points, and significantly bolsters predictive accuracy. The effectiveness of the proposed method was demonstrated through a comprehensive financial risk analysis conducted on publicly listed companies spanning the years 2016 to 2020. The experimental results show that the SOM-PNN approach has achieved high accuracy in predicting financial difficulties within the selected company samples, surpassing an 85% accuracy rate. Even for the limited sample data, its predictive accuracy reaches 80%, outperforming alternative algorithms.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning approaches → Neural networks

Keywords: financial risk prediction, self-organizing mapping neural network, probabilistic neural network

1. Introduction

1.1. Background

At present, the global economy continues to languish, impeding the ability of many businesses to recover from the repercussions of the financial crisis. To swiftly ameliorate the situation faced by firms and curtail losses, numerous companies and research organizations have embarked upon an examination of corporate financial risks with the intention of rectifying them. Since 1986, neural network algorithms have been employed in the domain of predicting financial risks for businesses [1].

1.2. Research Motivation

With the rapid advancement of internet technology, the world has entered the era of the digital economy. The integration of information technology and big data technology with enterprise financial management has become an inevitable trend of the times. The transformation of financial management models plays a pivotal role in determining whether enterprises can improve economic efficiency, foster development and growth, and effectively navigate the ever-changing market landscape [2, 3]. In the realm of information networks, commercial banks have introduced information network technology, which has made it more convenient to access relevant information through the Internet. Nonetheless, the emergence of network credit risks has accompanied this development [4, 5]. Unprecedented opportunities as well as unpredictable environmental factors, including economic market factors, laws and regulations, social and cultural factors, policies, *etc.*, are presenting challenges to the business development of organizations. The financial status of businesses is unpredictable as a result of all of this, and the financial risks they confront are growing.

Commercial banks have built relatively complete information systems through the use of digital technology, network information technology, and other technologies. However it is difficult to control new digital technologies, and the maturity of different digital technologies varies. Differences in technological maturity may lead to risk accumulation and contagion. Moreover, with the support of financial digital technology, there may be risks such as virus attacks, incomplete encryption technology, and insufficient compatibility between digital technology and platform clients, resulting in the loss of customer information and business data information, or problems such as service interruption, transaction delay, and accounting errors caused by system failures or vulnerabilities.

Through continuous integration with digital technology, a powerful data security system can be established to prevent unauthorized disclosure of customer information. Such a system should employ multi-layer prevention and control mechanisms, resource consolidation, and enhanced risk management measures to ensure data security. At the same time, the system must continuously evaluate the system infrastructure, operational management procedures, and various other aspects to establish a resilient security framework during the transaction process, promptly identify vulnerabilities in the information data system, and maintain the stable operation of the platform.

1.3. Research Methods and Contributions

Financial risk levels may surpass the alert level in order to prevent financial disasters brought on by poor management or poor decision-making. The currently commonly used financial management early warning models are mainly based on nonlinear combination models and improved particle swarm optimization algorithms. The former combines support vector machines and logistic regression models, while the latter uses particle swarm optimization algorithms to improve neural network parameters to achieve financial management early warning. However, the two warning models have poor anti-interference and convergence efficiency issues, leading to low warning accuracy and efficiency in the final warning results. Neural networks are an effective tool for financial analysis. The advantages of applying neural network analysis methods to credit risk assessment are that they do not have strict assumptions and have the ability to handle nonlinear problems. They can effectively solve the problem of nonnormal distribution and nonlinear credit evaluation. The result is between 0 and 1. Under the measurement of credit risk, it is the probability of default. In [6], the author used a neural network trained with backpropagation to analyze the impact of cost-benefit analysis on the financial benefit evaluation of investment projects. Artificial neural networks (ANN) are a parallel decentralized processing model. Their construction concept is based on the simulation of neural operations of the human brain. ANN not only has good pattern recognition ability, but can also overcome the limitations of statistical methods. Due to its fault-tolerant ability, it does not have strict requirements for data distribution and has the ability to handle data omissions or errors. The most valuable feature of ANN is its learning ability, which allows it to self-learn and train based on newly prepared data at any time and adjust its internal storage weight parameters to cope with the changing operational environment of the enterprise. Traditional statistical methods do not possess this learning ability. Self-organizing mapping (SOM) and probabilistic neural networks (PNN) are commonly used models in ANN algorithms.

The SOM network training is relatively simple and can automatically classify input data without requiring a large number of data samples [7]. PNN has a powerful pattern classification function, simple structure, and can use linear algorithms to complete the work of nonlinear algorithms [8]. This paper is based on the respective characteristics of SOM and PNN, and combines them in series to form an SOM-PNN integrated neural network model. This paper considers combining SOM with PNN to classify variables, which is capable of processing data efficiently, even highly connected corporate financial indicators. The financial risk status of publicly traded corporations can be predicted more accurately and scientifically by identifying variables. The most accurate indicator of a company's operating circumstances is its financial data. When the organization is experiencing financial challenges, it can be determined by examining pertinent financial indicators. The financial data of a company serves as the most direct manifestation of its operational state. This paper makes several notable contributions, outlined as follows:

In order to examine the significance of financial risk prediction technology for a company's production and operation, this paper combines research on risk warning systems and theories connected to financial risk.

By integrating the PNN model with SOM, the paper achieves a reduction in the number of training samples, thereby enhancing computational speed.

The utilization of the SOM reference vector mitigates the impact of noisy samples, leading to an improvement in the accuracy of the PNN model.

The SOM-PNN model culminates in a final output that comprises probability-based classification results, effectively addressing the limitations of the SOM model.

This paper performs an in-depth analysis of various datasets through simulation experiments using Chinese listed firms as samples. The results show that the accuracy of traditional company financial risk prediction in the data sample is quite high in the SOM-PNN network prediction risk test.

The main organizational structure of this paper is as follows: Section 2 introduces a literature review of related work. Section 3 provides the basic principles and process of financial risk prediction research based on the SOM-PNN model. Section 4 outlines the experimental results, analysis, and conclusions are provided in Section 5.

2. Related Work

Neural networks have a wide range of applications in the business field, especially in financial management. For example, neural networks use financial ratio indicators as input data to predict the risk of operational failure of listed companies. On the basis of establishing a warning model for company business failure using traditional discriminant analysis and logistic regression analysis methods, a comparative study was conducted using artificial neural network methods to address this issue. The results indicate that the prediction accuracy of the artificial neural network method is much higher than the two traditional statistical methods. In addition, neural networks have also been applied to financial management fields such as credit rating, mortgage risk assessment, stock market prediction, and financial distress prediction.

To avoid financial risks and economic losses for enterprises in the digital economy, many scholars have conducted extensive research work. In [9], the authors analyzed the Shanghai financial database by using the short-term memory network method. The outcomes of the experiments demonstrate the high recognition accuracy of the suggested approach. However, in many applications, all aspects of this method are difficult to implement. In terms of risk prediction, BP neural networks have already had many applications. A quadrant detector response approximation model based on the BP neural network using different training algorithms is proposed in [10]. As a result, this method is expected to become a useful technology for determining the position of light beams; nevertheless, the technology is still in its infancy. In [11], a genetic algorithm-based BP neural network model was proposed. The genetic algorithm is a way to get the best answer by modeling the natural evolution process. It is a computation model of natural selection and genetic mechanisms replicating Darwin's biological evolution process. This algorithm fully utilizes the overall grasp of the genetic algorithm in the search process. However, compared to the above methods, this method is more complex and difficult to implement. The paper mentioned above offers a thorough analysis of the BP neural network method and its use in predicting corporate financial risk.

There is no denying that this research has significantly influenced the growth of related professions [12–13]. How entrepreneurs innovate the enterprise ecosystem during the entrepreneurial process is proposed in [14]. This work discusses various platform-based enterprise innovations, as well as the concerns and issues that the innovation platform ecosystem may bring to enterprises. To further explore the factors influencing corporate performance, authors in [15] present relevant results which indicate that market orientation has a direct impact on organizational performance.

In order to accomplish distributed storage and parallel processing, ANN replicates the structure and operations of biological neural networks [16]. The ANN prediction model is widely used in practical applications [17, 18], such as medical diagnosis [19], agricultural product price prediction [20], *etc.*, and has the advantages of nonlinear mapping and high fault tolerance. The SOM neural network model is a commonly used model in ANN algorithms. The authors used a SOM neural network model to classify the danger of waterlogging in 56 low-lying locations in Beijing [21]. The findings show that the SOM model is suitable for automatically quantifying waterlogging risk. It can produce more objective and accurate classification results by successfully overcoming the interference of subjective elements. GAN-SOM is a new deep learning-based clustering architecture that is suggested in order to accomplish the goal of concurrently encoding and clustering data samples. The newly defined clustering loss can be optimized by jointly training this network and the GAN. The SOM neural network is mostly used in reference to segment blood arteries in order to enhance the testing performance of medical equipment and increase the success rate of surgery [22]. The entrepreneurial process is examined in [23] for how entrepreneurs innovate the firm ecosystem. The worries and problems that the innovation platform ecosystem may present to businesses were also explored and discussed. The authors also looked at various platform-based enterprise innovations. Some novel ideas have been put out in [24] to further study the aspects that affect corporate performance, and research findings show that market orientation directly affects organizational performance.

This paper proposes a method based on SOM-PNN to analyze the financial model of enterprises. The method proposed in this paper combines the advantages of SOM and PNN. Firstly, preprocess the sample data. Then use SOM to obtain various financial ratio indicators, after which use PNN for weight analysis. Finally, the predicted results are obtained.

3. Research on Financial Risk Prediction via SOM-PNN Model

In this section, we first introduce the principles and learning steps of the SOM model. Secondly, the principle of the PNN model is introduced. Then, we combine the two to form a SOM-PNN integrated neural network model. Finally, the risk prediction process based on SOM-PNN is presented.

3.1. Principle of SOM Model

The clustering of SOM neural networks is based on the distribution characteristics of input vectors and the function of neurons. Throughout the entire learning process, the neural network only needs to provide some unlabeled sample data, which can automatically find patterns between samples, adaptively adjust weights, and complete data classification. The model trains neural networks by extracting important features or inherent laws from the data and dividing the data into different regions to achieve clustering of the data. Compared with other neural network models, SOM can not only classify input vectors during the training process, but also display the distribution of input vectors in the network.

The SOM network structure described in this paper is a two-layer structure consisting of an input layer and an output layer. The input layer consists of n nodes, corresponding to n input vectors. The weight connects each neuron of the two layers. The full interconnection of the input and output layers ensures that all collected information is transmitted to the output neurons. The structure of the SOM neural network is shown in Figure 1.

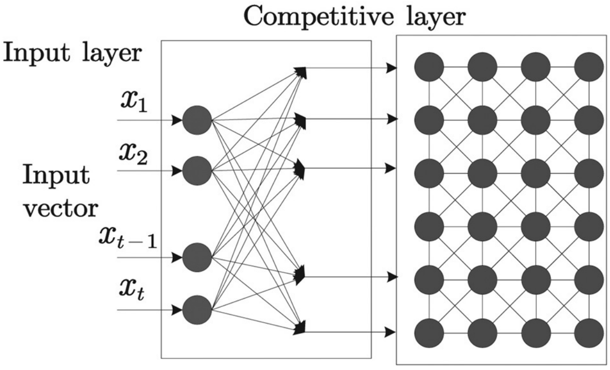


Figure 1. SOM model structure diagram.

3.2. Learning Steps of SOM Model

The training process of SOM neural networks generally includes three stages: competition, cooperation, and adaptation. The learning steps of the SOM model as as follows:

Step 1. Initialize the weights. Set the initial weights of each node in the output layer. Predefine a training length or set the error threshold for program termination as the termination condition for training.

Step 2. Input the vector $x = [x_1, x_2, ..., x_n]$ into the input layer.

Step 3. Find the winning neuron. Calculate the distance between the j-th neuron w_j of the output layer and the input vector X, using the following formula:

$$d_j = \|X - w_j\| = \sqrt{\sum_{i=1}^{n}\left(x_i - w_{ij}\right)^2}, \quad \|X - w_c\| = \min\{d_j\}, \tag{1}$$

where w_{ij} is the weight value between the i-th input layer neuron and the j-th output layer neuron, and w_c is the best matching node.

Step 4. Weight learning. The correction formula is as follows:

$$w_{ij}(t+1) = w_{ij}(t) + \phi(t)\beta(t)(x_i - w_{ij}(t)), \tag{2}$$

where $\phi(t) \in (0, 1)$ is the learning rate of step t, and $\beta(t)$ is a neighborhood function. Generally speaking, $\phi(t)$ changes linearly or exponentially as the training progresses, and $\beta(t)$ is a Gaussian function or bubble function. The learning rules are as follows:

$$\phi(t+1) = \phi(t) - \frac{\phi(0)}{T}$$
$$\beta(t) = \exp\left(-\frac{d_{cj}^2}{2r^2(t)}\right) \tag{3}$$
$$r(t+1) = INT\left(\left(r(t)-1\right)\cdot\left(1-\frac{t}{T}\right)\right)+1,$$

where d_{cj} is the distance between neurons C and j, $r(t)$ is the domain radius, INT is the rounding function, and T represents the number of learning times.

Step 5. Return to step 2, set $t = t + 1$, and go on with the subsequent learning cycle until the cycle's maximum number of iterations or the learning rate is reached, at which point the cycle is complete.

3.3. Principles of PNN

Similar to SOM neural networks, PNN is also a feedforward neural network. The PNN judgment criterion is the Bayes minimum risk criterion mentioned earlier. The PNN model is a variation of the radial basis function, which combines Bayes classification rules and probability statistics ideas to process samples of different types or patterns as output in the form of judgment decisions. Its principle and function can be explained through the theory of probability statistics. This model has a simple structure and fast convergence speed and is commonly used to solve nonlinear problems in pattern recognition.

Assuming the input sample vector is $X = [x_1, x_2, ..., x_n]^T$, and each classification alias is m_i (i = 1, 2, ... N), according to Bayes classification theorem, the conditional probability $P(m_i | X)$ of each category can be calculated according to the formula:

$$P(m_i | X) = \frac{P(X | m_i)P(m_i)}{P(X)} = \frac{P(X | m_i)P(m_i)}{\sum_{i=1}^{N} p(X | m_i)p(m_i)} \tag{4}$$

where $P(m_i | X)$ is the likelihood function of category m_i to X, also is the conditional probability function of each category. $P(m_i)$ is the prior probability of the category m_i. $P(X)$ is the evidence factor to ensure that the sum of probabilities for all input samples is 1.

The value of posterior probability is the judgment basis of unknown category. When the following criteria are met, X belongs to category m_i. Given $i, j \in [1, ..., N]$, $i \neq j$, we have

$$P(m_i \mid X) > P(m_j \mid X) \tag{5}$$

This equation (5) can be written as

$$P(X \mid m_i)\, P(m_i) > P(X \mid m_j)\, P(m_j) \tag{6}$$

and further as:

$$P(X \mid m_i) = \frac{1}{P(m_i)} \max_{j=1}^{N} \left\{ P\left(X \mid m_j\right) P\left(m_j\right) \right\}. \tag{7}$$

When $P(m_i) = P(m_j)$ we have

$$P(X \mid m_i) = \max_{j=1}^{N} \left\{ P\left(X \mid m_j\right) \right\}. \tag{8}$$

Combining the Bayes minimum risk criterion, assuming that there are two known faults in the input sample, namely mode a and mode b, we have

$$\begin{aligned} &d_a q_a f_a(X) > d_a q_a f_b(X) \\ &d_a q_a f_a(X) < d_a q_a f_b(X) \\ &d_a = N_a / N, \;\; d_b = N_b / N, \end{aligned} \tag{9}$$

where d_a and d_b are the conditional probability of modes a and b, respectively. N is the number of input samples. N_a and N_b are the number of samples of failure modes a and b, respectively. q_a and q_b are cost factors. $f_a(X) = P(X \mid a)$ and $f_b(X) = P(X \mid b)$ are conditional probability density functions of a and b.

Parzen proposed the method of probability density function (PDF): input enough samples, and the approximate conditional probability can be obtained through the PDF method. The formula is as follows:

$$\begin{aligned} &f_a(X) = \\ &\frac{1}{(2\pi)^{n/2}} \cdot \frac{1}{N_a} \cdot \sum_{i=1}^{N_a} \exp\left[-\frac{(X - X_{ai})^T (X - X_{ai})}{2\sigma^2} \right] \\ &f_b(X) = \\ &\frac{1}{(2\pi)^{n/2}} \cdot \frac{1}{N_b} \cdot \sum_{i=1}^{N_b} \exp\left[-\frac{(X - X_{bi})^T (X - X_{bi})}{2\sigma^2} \right] \end{aligned} \tag{10}$$

where X_{ai} and X_{bi} represent the i-th input samples of fault modes a and b. σ is a smoothing parameter that determines the width of the above function curve.

Now, we normalize equation (10) and combine it with equation (9). We have

$$\begin{aligned} (X - X_{ai})^T (X - X_{ai}) = -2(X^T X_{ai} - 1) \\ (X - X_{bi})^T (X - X_{bi}) = -2(X^T X_{bi} - 1) \end{aligned} \tag{11}$$

$$q_a \sum_{i=1}^{N_a} \exp\left[\frac{X^T X_{ai} - 1}{\sigma^2} \right] \geq q_b \sum_{i=1}^{N_b} \exp\left[\frac{X^T X_{bi} - 1}{\sigma^2} \right] \tag{12}$$

$$q_b \sum_{i=1}^{N_b} \exp\left[\frac{X^T X_{bi} - 1}{\sigma^2} \right] \geq q_a \sum_{i=1}^{N_a} \exp\left[\frac{X^T X_{ai} - 1}{\sigma^2} \right] \tag{13}$$

When equation (12) is satisfied, sample X belongs to fault mode a. Similarly, when equation (13) is satisfied, sample X belongs to fault mode b.

After standardizing the input samples, enter the pattern layer. The number of nodes in the pattern layer is determined by the product of the input samples and the cost factor. The mode layer performs a weighted sum of the incoming input samples and passes them to the sum layer through the activation function (usually a Gaussian function). The output of the decision-making layer is:

$$\begin{aligned} R_{ai} = \exp\left[\frac{X^T X_{ai} - 1}{\sigma^2} \right] \\ R_{bi} = \exp\left[\frac{X^T X_{bi} - 1}{\sigma^2} \right] \end{aligned} \tag{14}$$

After the sum of R_{ai} or R_{bi} in the same fault mode is multiplied by the cost factor q, the result is transmitted to the decision-making layer for judgment, and the maximum value is taken as the output.

3.4. The SOM-PNN Model

Both SOM and PNN models are used for data classification, but both have certain shortcomings. SOM has a more accurate recognition rate but cannot output the final classification category. PNN avoids this limitation, but when estimating the probability density function, its memory and the amount of computation required for classification are related to the number of samples. When the number of samples is large, it is easy to cause a large memory demand and a significant decrease in computational speed. A model that combines the two can precisely address the shortcomings of each model. Therefore, this paper proposes to use the SOM-PNN neural network model to solve the problem of data classification and prediction.

In this paper, the SOM-PNN model consists of two parts connected in series, namely, the d-dimensional prototype vector of the SOM output layer is the PNN input layer vector. The learning process is as follows:

Assuming the original training set is $X = X_1 \cup X_2 \cup ... \cup X_m \cup ... \cup X_M$ with X_m being the training set for category m. Train one SOM using each X_m in the original training set, denoted as *SOMm*, and the number of prototype vectors in *SOMm* is represented by K_m. $c_{m,k}$ is the prototype vector corresponding to the K-th output node and satisfies $1 \le k \le K_m$. N represents the number of samples mapped to $c_{m,k}$ in X_m.

$$N(c_{m,k}, X_m) = |\{x \mid x \in X_m, BMT(x) = c_{m,k}\}| \tag{15}$$

where BMT is the optimal matching unit. Meanwhile, the importance of the k-th prototype vector in *SOMm* is determined by $\rho(c_{m,k})$ measurement, and satisfying the following equation

$$\rho(c_{m,k}) = N(c_{m,k}, X_m) \tag{16}$$

The SOM-PNN model uses the prototype vector in *SOMm* to construct the probability density function of category m in PNN, instead of using the training samples in X_m.

$$f_m^{SOM}(x) = \frac{1}{(2\pi)^{\frac{2}{d}} \sigma^d K_m = \sum_{k=1}^{K_m} \exp\left(-\frac{(x-c_{m,k})^T (x-c_{m,k})}{2\sigma^2}\right)} \tag{17}$$

Considering the importance of the prototype vector, equation can (17) be expressed as:

$$f_m^{SOM}(x) = \frac{1}{(2\pi)^{\frac{2}{d}} \sigma^d K_m = \sum_{k=1}^{K_m} w_{m,k} \cdot \exp\left(-\frac{(x-c_{m,k})^T (x-c_{m,k})}{2\sigma^2}\right)} \tag{18}$$

where $w_{c,k} = \dfrac{\rho(c_{m,k})}{\sum_{i=1}^{K_m} \rho(c_m, i)}$ is the weight of the k-th prototype vector in *SOMm*.

The final form of PNN can be represented as follows:

$$PNN = \left\{\left(p_m f_m^{SOM}(x)\right)\right\}_{m=1}^{M} \tag{19}$$

where M represents the total number of categories, and p_m is the prior probability of category m

$$m^* = arg \max_m \left\{\left(p_m f_m^{SOM}(x)\right)\right\}_{m=1}^{M} \tag{20}$$

SOM has the function of feature extraction, which means that the mapping map output by SOM not only reflects the characteristics of the original data, but also compresses the data. The method of combining PNN and SOM used in this way is:

1. Firstly, the SOM network is trained using a training sample set, and after training and annotation, the SOM graph is obtained. Then, the reference vectors of the obtained SOM graph nodes are used as training samples for PNN.
2. Next, test the entire network with test samples to obtain the final classification results, as shown in Figure 2.

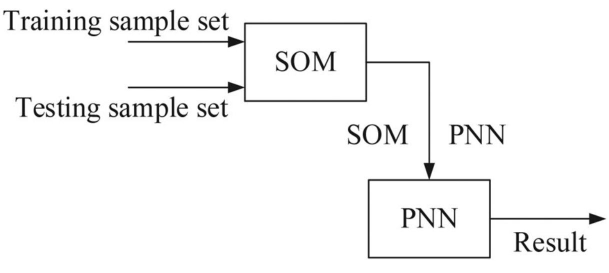


Figure 2. SOM-PNN model.

3.5. Risk Prediction Process Based on SOM-PNN

This paper categorizes the sample data companies into three types: regular companies, first time loss companies, and special treatment (ST) companies, in an effort to better predict financial risks. The circumstance where the return in year $t-1$ is positive and the return in year t is negative is referred to as the first loss. The exchange environment for the current year was used by ST company to determine. Generally speaking, an ST company is defined as a difficult company. This paper gives these three sorts of companies, respectively, the numbers 0, 1, and 2, for the convenience of a subsequent description [25].

The application of SOM-PNN integrated neural network in enterprises is still rare, so its application in this field is a very meaningful exploration and attempt. The model uses a two-dimensional topological structure. The number of neurons in the transport layer composed of two neural layers is consistent with the number of variables it contains. Its function is to obtain data (in our application, it is a variety of financial ratio indicators). Set m as the number of neurons in the input layer. At the same time, set $n_x \times n_y$ as the number of neuron output layers, and form a rectangle with x rows and y columns on this layer.

The model mainly consists of the following three main parts:

1. Data preprocessing. In this application, two preprocessing methods are used, namely ratio analysis and variance analysis. Ratio analysis: convert the data in the financial statements into financial ratio indicators as the input of the network. Variance analysis: analyze the financial ratio indicators and select the indicators that have a great impact overall to simplify training samples and improve the efficiency of model training.
2. SOM neural network. The network consists of an input layer and a competitive output layer, which are fully connected, meaning that each input layer neuron and each output layer neuron have a feedforward connection. Mainly responsible for forecasting, it is the core part of the model.
3. Data post-processing. The task of post-processing is to analyze and process the output results:
    a) Use PNN to transform the output results and directly provide classification results, solving the difficulty of SOM's inability to provide probability classification, making the auxiliary decision-making information clearer, and improving the classification accuracy.
    b) Through weight analysis and other methods, analyze the factors that have the most significant impact on the results, and then analyze the financial characteristics of bankrupt enterprises and enterprises with solvency.

4. Experimental Results

In this section, we provide a numerical evaluation to demonstrate the effectiveness of the algorithm proposed in this paper. Firstly, the nature of the data source is provided. Then, different algorithms are used for comparative experiments on the data, ultimately proving the effectiveness and superiority of the algorithm proposed in this paper.

4.1. Sample Data Selection

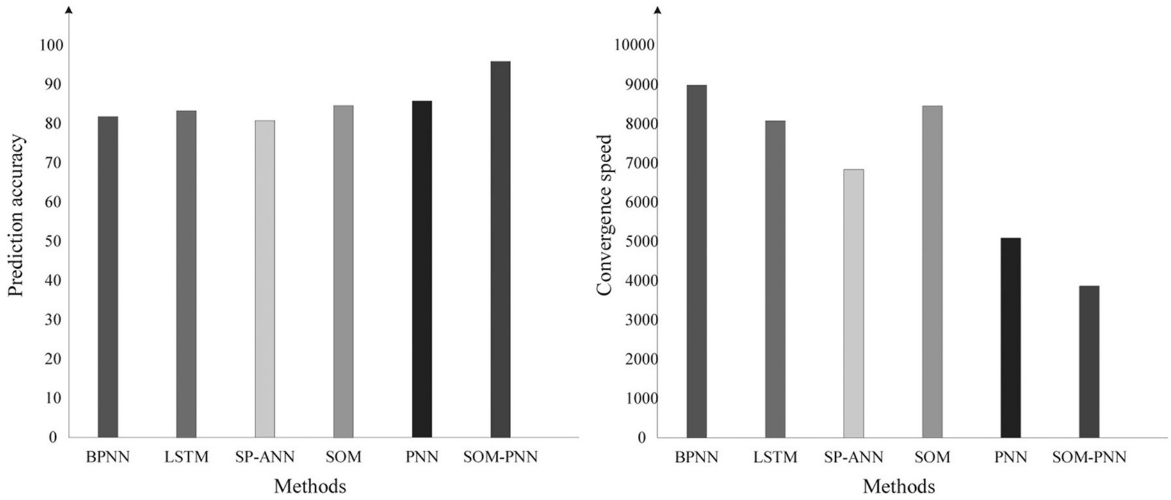
In this research, we examined whether the financial conditions of companies on the Chinese A-share market that were not exposed to financial concerns would deteriorate in the upcoming year. This paper selects the corresponding financial situation from 2016 to 2019 as the modeling sample and selects the financial index and corresponding financial situation from 2020 as the testing sample.

4.2. Research Method

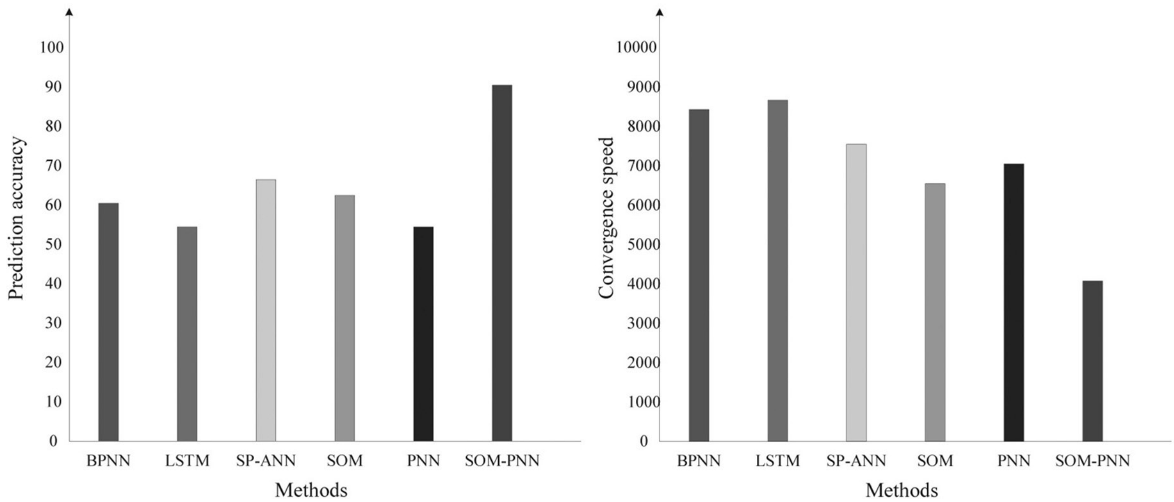
In order to highlight the effectiveness of the method proposed in this paper, we used different number of samples under different interference conditions as the test set. In this paper, different prediction methods are selected to demonstrate the effectiveness of the proposed method, including BPNN method, LSTM method, SP-ANN method.

4.3. Experimental Results

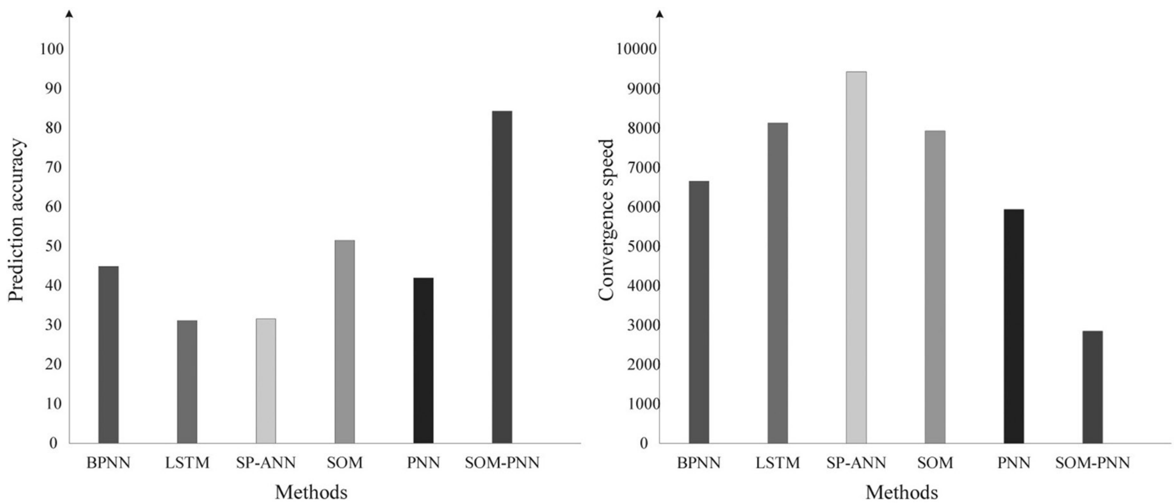
In practical problems, data often contains some unavoidable noise. In order to verify the effectiveness of the algorithm under the interference data, this paper adds interference data to the actual data. Figure 3 shows the comparison of data without interference, while Figure 4 shows the comparison of data with interference.



(a) Sample data: 2016-2019.



(b) Sample data: 2017-2019.



(c) Sample data: 2018-2019.

Figure 3. Comparison of prediction accuracy and convergence speed of different methods in different sample data without interference data.

Figure 3 compares the prediction accuracy and convergence rates of several algorithms in various sample data without interference. The experimental findings demonstrate the excellent prediction accuracy of the method proposed in this paper, with a prediction accuracy that can exceed 85% even when the sample size is insufficient. Compared to other methods, the proposed method not only has a higher prediction accuracy, but also has lower convergence times, meaning it can achieve convergence conditions faster and reduce the computational complexity of the data.

Figure 4 presents a comparative analysis of prediction accuracy and convergence speed across various methods using different sample data, including those with interference data. The experimental results convincingly demonstrate that the method proposed in this paper exhibits superior prediction accuracy. Even when faced with limited sample sizes, the proposed method achieves a prediction accuracy rate exceeding 80%. Notably, in comparison to alternative methods, the proposed approach not only attains higher prediction accuracy but also showcases lower convergence times. This enables faster attainment of convergence conditions and reduces the computational complexity associated with the data.

To examine the influence of the model's structure on the prediction outcomes, experiments with different numbers of hidden layer nodes (h) were conducted, and the results are presented in Figure 5. The findings clearly demonstrate that the method proposed in this study achieves higher prediction accuracy and faster convergence speed across various configurations of hidden layer nodes.

In order to further demonstrate the effectiveness of the algorithm proposed in this paper, a statistical significance test was conducted on the basis of the test dataset. The results indicate that the proposed method is closer to the actual results.

Based on the outcomes of the experimental investigation, the model proposed in this paper has the following advantages:

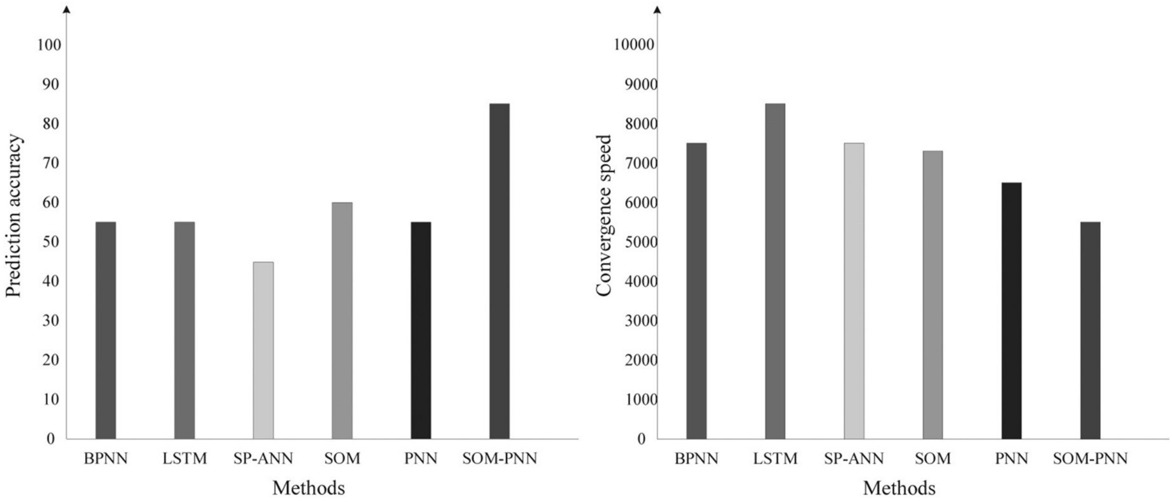
Firstly, by combining the PNN model with SOM, the number of training samples is reduced, and the computational speed is improved. Secondly, the reference vector avoids interference from noisy samples, and the accuracy of PNN is also increased.

The research in this paper still has the following limitations.

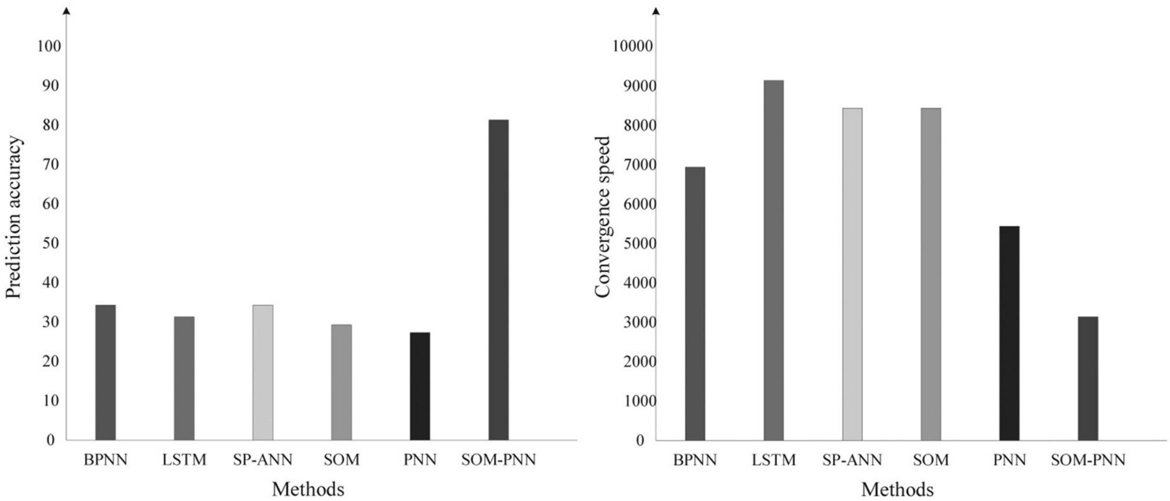
Firstly, the criteria for defining the level of financial distress are limited. This study defines ST company as a financially distressed company, but among randomly selected non ST companies, research on the deterioration of financial conditions is not limited to ST companies. Although some companies have not yet joined ST companies, their production and operation already face serious difficulties.

Secondly, there are the limitations of neural networks. Neural networks lack the explanatory power of models, and people are unable to obtain the relevant importance of input variables based on the weights of the network. There is no model for constructing a network structure for financial distress warning problems, and repeated experiments are necessary. The establishment of hidden layers also needs further exploration. Increasing the number of hidden layer units is beneficial for fitting training samples, but it also weakens the model's generalization ability, which can lead to overtraining problems. Moreover, determining the number of hidden layer nodes is a huge workload.

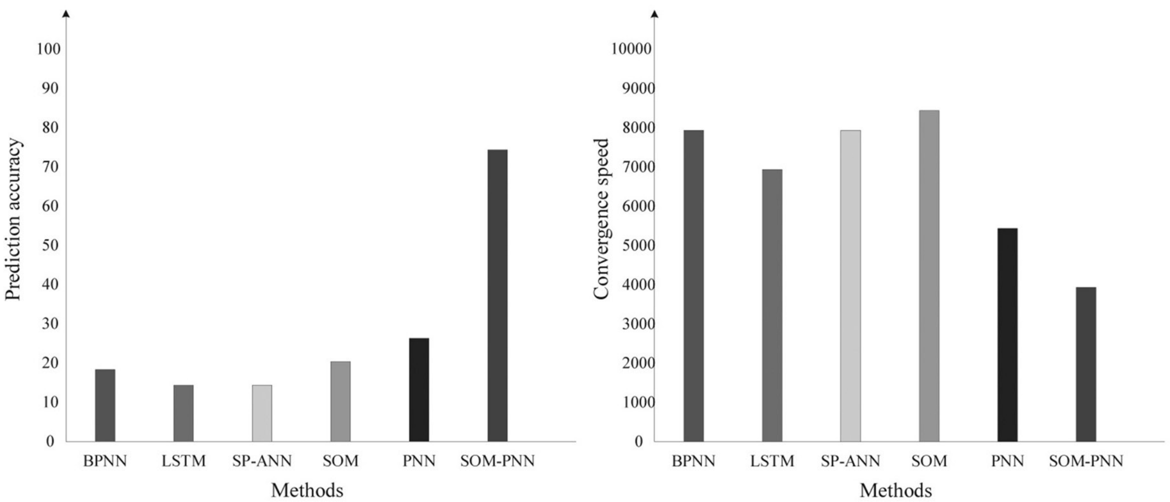
Finally, no matter how complex an artificial neural network is, it can be seen as three parts: input layer, output layer, and hidden layer. We use learning to perform layer by layer overlay training on neural networks, in order to effectively adjust the weights of neurons at all levels of the network. However, there is a problem here, apart from inputs and outputs, we have no knowledge of what happens in the hidden layer, that is, we have no understanding of the logical behavior within the neural network. Therefore, in subsequent research, emphasis will be placed on the internal models of neural networks.



(a) Sample data: 2016-2019.

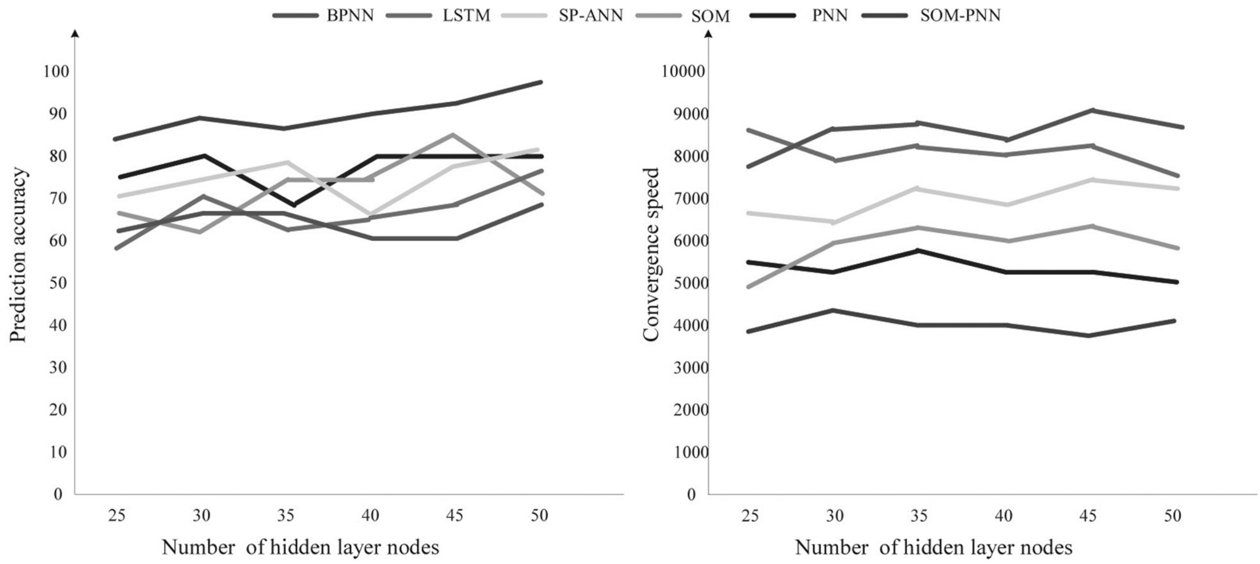


(b) Sample data: 2017-2019.

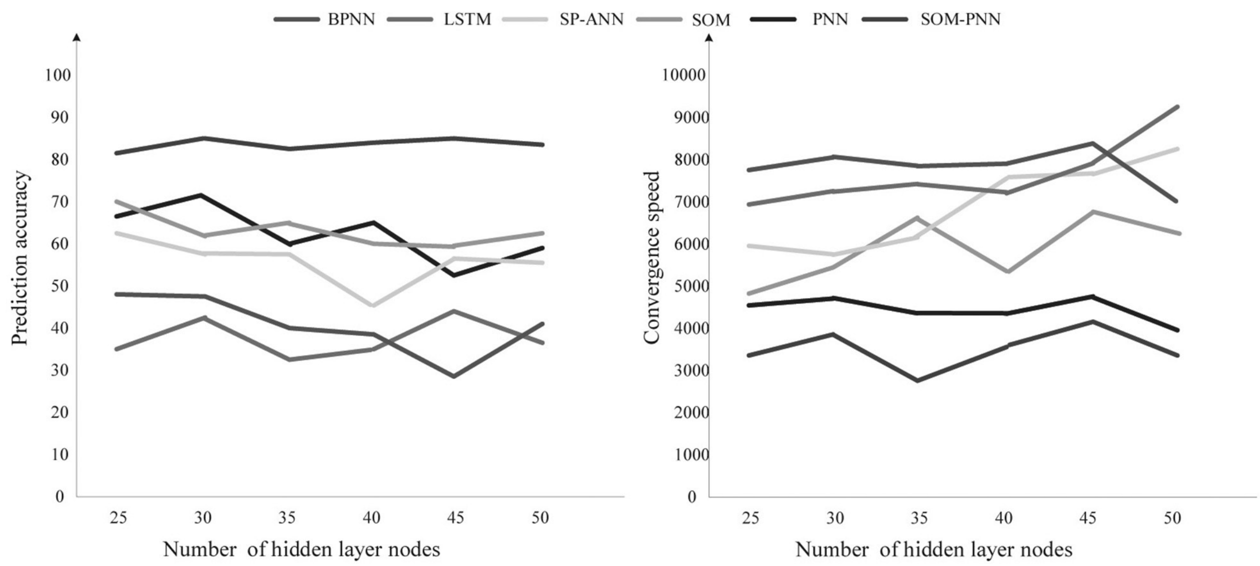


(c) Sample data: 2018-2019.

Figure 4. Comparison of prediction accuracy and convergence speed of different methods in different sample spaces with interference data.



(a) Without interference data.



(b) With interference data.

Figure 5. Comparison of prediction accuracy and convergence speed of different methods in different number of hidden layer nodes.

5. Conclusion

The study of financial management models is the most important part of enterprise risk avoidance, which not only has a technical aspect but also reflects strong policy implications. The SOM-PNN prediction model proposed in this paper combines the advantages of SOM and PNN, improving the efficiency and accuracy of enterprise risk prediction and monitoring. Although the proposed model has good financial management warning efficiency, there are still certain problems due to the failure to consider the different financial influencing factors of different companies. In the future research process, more in-depth research is needed to further improve the efficiency of financial management early warning.

In addition, this model will be used for credit risk early warning, but the work that the model can accomplish is diverse and can be extended to more extensive application fields such as credit assessment, tax rating assessment, customs clearance rating assessment, insurance and venture capital.

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