IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 21 April 2023, accepted 25 May 2023, date of publication 29 May 2023, date of current version 1 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3280934

RESEARCH ARTICLE

Design and Implementation of China Financial Risk Monitoring and Early Warning System Based on Deep Learning

PENG DU[1] AND HONG SHU[2]
[1]School of Economics and Management, Shaanxi University of Science and Technology, Xi'an, Shaanxi 710021, China
[2]Department of Public Courses, Shaanxi Polytechnic Institute, Xianyang, Shaanxi 712000, China

Corresponding author: Peng Du (24451038@qq.com)

ABSTRACT Affected by the COVID-19 epidemic, financial regulators urgently need to establish a sensitive and scientific financial risk pre-alarm system that is suitable for the economic environment under the COVID-19 epidemic. The perfect pre-alarm system is based on in-depth scientific theoretical research, so it is of great practical significance to study the financial security assessment and systemic financial risk pre-alarm. The accumulation of massive data puts forward higher requirements for the effective organization and management of financial information. How to quickly extract effective information and analyze and predict it effectively on the basis of data has become an important issue in academic and industrial research. Exploring the nature of financial markets, analyzing and mastering the potential development rules between data not only provide effective technical support for financial management and investment business, but also play a pivotal role in promoting the steady growth of financial markets. This article proposes a financial risk pre-alarm model based on deep learning (DL). This model can detect the financial risk behaviors brought by a few people, and provides a new theory and method for the financial risk management (FRM) system. This algorithm solves the difficulties that traditional models are difficult to deal with highly nonlinear models and lack of adaptive ability.

INDEX TERMS Financial risks, deep learning, financial information, risk warning.

I. INTRODUCTION

Due to the progress of social economy, the financial market has become an important part of the national economy and an important embodiment of the country's competitive strength [1]. The accumulation of massive data puts forward higher requirements for the effective organization and management of financial information. How to quickly extract effective information and analyze and predict it effectively on the basis of data has become an important issue in academic and industrial research [2]. Exploring the nature of financial markets, analyzing and mastering the potential development rules between data not only provide effective technical support for financial management and investment business, but also play a pivotal role in promoting the steady growth of financial markets [3]. Economic development cannot be separated from financial support, which needs a good financial ecosystem. Improving the financial ecosystem is an important guarantee for the sustainable and healthy expand of the financial industry, and it can also effectively prevent and resolve financial risks [4].

Financial institutions should lay stress on the construction of financial ecosystem, and solve the shortcomings in the construction of financial ecosystem through effective strategies, so as to make the financial industry develop more scientifically and reasonably, and thus make the Internet financial economy achieve stable, regular and harmonious development [5]. Finance is the core of modern market economy. It permeates all fields, all levels, all kinds of economic subjects and all kinds of economic processes of the national economy, and at the same time, it is strongly influenced by all fields, all levels, all kinds of economic subjects and all

The associate editor coordinating the review of this manuscript and approving it for publication was Guillaume Parent.

kinds of economic processes of the national economy [6]. Financial information is the most intuitive form of market performance, and it is often used to mine the laws behind the market. In practice, a large number of financial information are arranged in chronological order, so the analysis of financial market is actually the analysis of time series data [7]. Deep neural network (DNN) has strong learning ability, and its technology development has deeply influenced many fields, and it has achieved success in more and more fields.

Although the traditional data analysis method has obvious effect in small data volume, it has poor analysis effect for a large number of non-stationary data, and it is difficult to find the hidden rules between data. DL technology can learn the rules between data from a large number of data, and at the same time can classify and predict the data [8]. It is the core of modern financial economy, and the financial ecosystem is an important factor to promote financial development. Constructing a good financial ecosystem is of great practical significance to promote the expand of modern economy. The Internet not only has the corresponding technical platform, but also has the characteristics of the connection function given by the complete architecture, so that it can be free from the constraints of time, space and region. Compared with the traditional industry, its coverage range and transmission speed have increased. Statistically speaking, any estimation and forecast can't be 100% accurate, so it is necessary to describe the uncertainty of estimation and forecast [9].

II. RELATED WORK

At present, we design and adjust a variety of DL models, and forecast the market of products including stocks, futures and securities. Huang J et al., by constructing a comprehensive index system and applying certain empirical means, synthesized all the indexes that can fully reflect the financial risks into a single index, and analyzed and evaluated the dynamic financial security situation in China by observing the changes of the index [10]. Liang et al. described the position of financial technology in the field, and summarized the latest technologies in wealth management, risk management, financial security, financial consulting and so on [11]. However, in the actual use process, investors need to study some basic attributes of the company, such as company size, asset accumulation and profitability. Dai et al. used financial information and macroeconomic data as forecasting indicators, and combined quantitative analysis with traditional fundamental analysis to forecast the short-term financial performance [12]. Only developed a nonlinear transformation method, which greatly improved the speed of learning algorithm, and thus helped to find a better generalized classifier [13]. Yoshikawa and Goda developed a fast and extensible discriminant algorithm, which can be used in natural language analysis. It can get performance only by using a few basic text features, and it is not much different from the existing performance, and greatly improves the speed [14]. Anton made an empirical comparison between ARIMA, a traditional time series model, and mainstream ML models including logistic regression, multi-layer perceptron, support vector machine and self-encoder. The results show that ML has better prediction accuracy than traditional models [15]. Bento et al. used recursive RNN and long-short memory network LSTM to predict the correlation coefficient of stock price. Recursive DNN has a strong dependence on time, and when the time interval is long, the RNN network is prone to gradient disappearance. LSTM network can connect large time intervals without losing information, and its long-term time-dependent prediction property is enhanced [16]. Adosoglou et al. discussed the feasibility of short-term stock price prediction by DNN, RNN and LSTM in stock price prediction, and proved that the prediction effect of LSTM network is better than the first two [17]. Sun et al. put forward an improved Deep Belief Network (DBN) to model and analyze the data, and use its ascending, descending and irregular curves for training, and then predict and screen the financial information with the trained data [18]. Ribeiro et al. predicted the stock index and futures price with high frequency, and designed a specific trading strategy based on this forecasting method. The experiment achieved remarkable results [19].

Traditional econometric models or models with parameters have no ability to analyze and model complex, high-dimensional and noisy financial market data series, and traditional DNN methods can't accurately analyze and model such complex data series. At the same time, traditional ML methods rely heavily on the subjective design of modelers, which easily leads to model risks. Combining with the characteristics of traditional financial risk pre-alarm system, in order to better assist investors in evaluating and making financial information decisions, this article puts forward the need to build a reliable and effective financial information forecasting model. On the basis of financial risk pre-alarm, it integrates DL algorithm to analyze financial information, and completes the financial risk pre-alarm system based on DL.

III. METHODOLOGY

A. APPLICATION OF DL IN FRM

Risk is the inherent attribute of financial activities. For example, from the perspective of internal and external causes of risk, there are conventional risks such as credit risk, liquidity risk and operational risk in the financial system. If these risks are not handled properly, they will become endogenous factors of financial systemic risks. The financial industry mainly deals with money and credit. From an economic point of view, credit is the act of transferring goods or funds on the condition of repaying principal and interest. In the later period of market economy, with the gradual prosperity of modern banking and the shrinking of commercial credit business, bank credit emerged and became the most important form of credit in modern economic exchanges, and the credit relationship has the characteristics of fragility. Once the credit chain breaks, the credit risk or liquidity risk increases, which leads to chain

reaction, which may eventually lead to financial crisis. The continuous growth of finance technology brings opportunities to the field of FRM, while DL is also facing many challenges in the field of FRM.

In the stage of continuous accumulation of financial risks, it is likely that financial crisis will eventually form, which will have a very serious impact on the expand of social economy. Therefore, the construction of financial ecosystem can not only promote the stable progress of financial industry, but also greatly promote the stable expand of the country and society. The construction of the financial ecosystem can make the Internet financial economy develop more scientifically and reasonably, thus realizing the sustainable expand of the financial economy, promoting the more regular expand of the financial economy and making the financial industry develop steadily. The application of DL not only promotes the improvement of forecasting methods in this field. Systemic financial risk refers to the crisis situation of one or several important financial institutions, which causes violent shocks of other financial institutions through the interconnection between financial institutions, and then produces substantial negative effects on the wider economic operation [20]. Therefore, the theory of financial systemic risk not only studies the causes of risks, but also studies the contagion mechanism of financial risks. The network architecture and algorithm training stage of financial prediction system are shown in Figure 1.

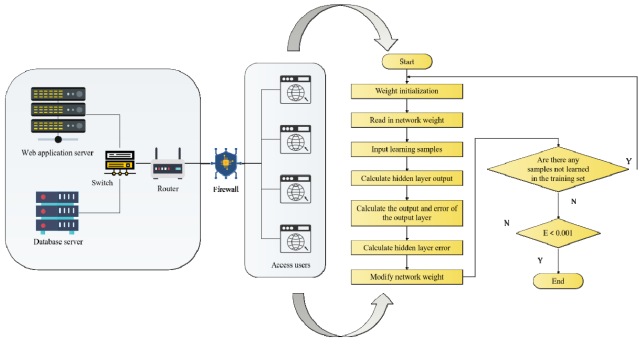

FIGURE 1. Network architecture and algorithm training stage of financial risk prediction system.

In the financial industry, due to the information asymmetry between borrowers and lenders, the fluctuation of the real economy will be amplified by financial instruments and financial products, resulting in overreaction. The mechanism of financial systemic risk is complex, and financial micro-subjects' business activities and macro-policies may directly or indirectly cause financial systemic risk from different aspects [21].

B. FINANCIAL RISK PRE-ALARM MODEL BASED ON DL

In the modern economic system, the financial system has gradually become a system that operates independently of the real economy, and the changing trend of capital and asset prices has gradually deviated from the basic aspects of macro-economy. The change of asset price is becoming more and more independent, and it has become an independent source of fluctuation and formed its unique law of movement. If the profit margin of the project invested by the borrower with the borrowed funds increases, it will further stimulate the scale of the borrower's loan demand, and as a result, the proportion of bank assets exposed to risks will further increase, and at the same time, there will be hidden financial systemic risks. When the market price drops, the price of collateral decreases, the available loan scale decreases, and the borrower can only reduce the investment scale and social financing scale. DL aims to learn multi-level representations from data, and higher levels can represent more abstract concepts [22].

This process will make the final output value consistent with the expected value through the alternation of two transmission modes, thus ensuring the correctness of the network output. The input variable, hidden layer variable and output variable are x, y, z, respectively. When the input layer is connected to the hidden layer, the weight value is w_{ji}, and the transfer function is:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

When the hidden layer is connected to the output layer, the weight is w_{tj}, and the transfer function is linear. The variable output value calculation formula of the hidden layer node in DNN is:

$$y_j = f\left(\sum_i w_{ji} x_i - \theta_j\right) \tag{2}$$

Type, θ_j is the threshold of the j unit of the hidden layer, set:

$$net_j = w_{ji} x_i - \theta_j \tag{3}$$

The calculation formula of the variable output value of the node is:

$$y_t = f\left(\sum_i w_{tj} y_j - \theta_t\right) \tag{4}$$

where θ_t is the threshold of t unit in the output layer. Set:

$$net_l = w_{tj} y_j - \theta_t \tag{5}$$

The DNN calculation rule is that the network weights and thresholds should be calculated along the negative gradient direction, which is the fastest decreasing direction of the transfer function:

$$x_{k+1} = x_k + (-g_k) \times \alpha_k \tag{6}$$

where x_k represents the matrix of weights and thresholds, $-g_k$ represents the negative gradient of the function, and α_k represents the learning rate of the model.

The assessment of investment project risk by DNNrequires a certain quantity of known samples as training sets to train the neural network, and then the project to be evaluated can be evaluated. The training sample set is generally authoritative assessment results with high credibility, which can

be obtained by experts' assessment of the actual operation results of a few typical Internet financial investment projects. For the project to be evaluated, as long as the experts give the value of each risk index, the DNN assessment system can be used for comprehensive risk assessment, and the assessment score is given by the output layer. DNN has strong recognition and classification ability, so DNN plays its great superiority and vitality in function approximation, pattern recognition, classification and data compression. Then, the sample data to be predicted or tested is input into the model, and the data judgment result is obtained. The principle of DNN is shown in Figure 1.

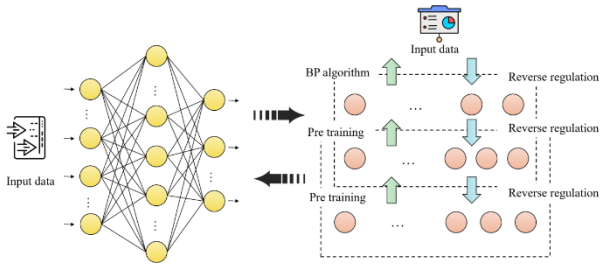

FIGURE 2. DNN principle.

The traditional mathematical statistics method can well calculate the error and correlation between data with a small amount of data. With the rapid growth of financial market, more and more data need to be processed, and a large number of data contain invalid redundant data. The low investment of enterprises leads to low income, low capital and further low investment, and the vicious circle will eventually lead to economic depression. If banks try to sell their risky assets in order to meet the liquidity needs of depositors, which leads to the reduction of loan scale, the bank's selling of assets will also lead to the decline of asset prices, which in turn will lead to the spread of financial risks.

In this DNN, an automatic stack de-noising encoder is used for unsupervised pre-training, the weights are adjusted layer by layer, and then the DNN is fine-tuned in a supervised way, and a dropout layer is connected after each hidden layer. The parameters to be determined in the pre-training stage are the weight matrix and the deviation in each denoising automatic encoder. The purpose of pre-training is to find the distributed representation of data, which can explain the changes in the data and amplify those changes that play a key role in classification. Through a series of nonlinear transformations, the pre-training process can create a feature detection layer, avoid the error information from spreading in multilayer networks, and help to overcome the problem of gradient disappearance. Two classical implementations of pre-training are deep confidence network and stack denoising automatic encoder [23]. Both strategies minimize the log likelihood of the generated model, so they usually show similar performance.

After training with training data sets, ML can perform classification tasks. However, the training data may lack representativeness, which will affect the classification performance of ML. Distributed representation can adapt to the lack of representativeness of training data [24]. Taking the classification of traders as an example, traders show different trading styles, that is, using different strategies and following different stop-loss rules. Let the time series be $x_1, x_2, \ldots$, and the moving average method can be expressed as:

$$F_{t+1} = (x_t + x_{t-1} + \ldots x_{t-N+1}) / N \tag{7}$$

Further deduced as:

$$F_{t+1} = \frac{1}{N} \sum_{t-N+1}^{t} x_i \tag{8}$$

where: x_t is the latest observed value and F_{t+1} is the predicted value of the next period. In order to calculate the moving average, there must be N past values. After finishing, the calculation formula of moving average method can be simplified as follows:

$$F_{t+1} = \frac{x_t}{N} - \frac{x_{t-N}}{N} + F_t \tag{9}$$

Assuming that there is no x_{t-N} value, the $(t - N)$ period value in the formula can be replaced by an approximate value. Using the predicted value F_t of the previous period instead of if the data is stable, this is an acceptable approximation:

$$F_{t+1} = \frac{x_t}{N} - \frac{x_{t-N}}{N} + F_t \tag{10}$$

Become:

$$F_{t+1} = \frac{x_t}{N} - \frac{F_t}{N} + F_t \tag{11}$$

Namely:

$$F_{t+1} = \left(\frac{1}{N}\right) x_t + \left(1 - \frac{1}{N}\right) F_t \tag{12}$$

Because N is a positive number greater than zero, $\frac{1}{N}$ is between 0 and 1. If a is used instead of $\frac{1}{N}$, then:

$$F_{t+1} = a x_t + (1 - a) F_t \tag{13}$$

This method does not need to store all historical data, so it can greatly reduce the problem of data storage. Sometimes, only one latest observed value, the latest predicted value and the value can be used to predict the financial risk.

Traditional financial analysis methods are difficult to get the key features among all data, but all the data have strong local features, which often make it difficult for users to judge the market and make decisions, thus affecting users to analyze the current industry features from a large amount of data [25]. When the asset price rises, the issue price of direct financing will rise, the market liquidity will be quite sufficient, and borrowers can also get larger-scale financing. When the asset price falls, the market liquidity will decrease, the difficulty of direct financing of market participants will increase, and the decrease of investment will be accompanied by a large number of default events, and the risk will further spread.

IV. RESULT ANALYSIS AND DISCUSSION

According to the theory of financial instability, the fragility of financial market and speculative investment bubble are caused by the inherent attributes of financial market. When the economy is in the boom stage, it is relatively easy for investors to take certain risks to make profits, and at the same time, they will neglect or underestimate the financial risks. If the profits exceed the capital scale required to repay the principal, it will stimulate investment to generate speculative psychology. Once the debt scale exceeds the amount that the debtor's income can repay, the financial crisis will follow.

The form of financial development is constantly innovating, among which Internet finance has become the darling of the new generation, and more and more people are beginning to invest in the Internet, mainly because the Internet has brought a series of conveniences to everyone's work. However, the Internet financial platform also has certain financial risks. As a new form of financial platform, it develops rapidly, so that the regulatory authorities have not worked out effective management measures and supervision mechanisms. In this paper, 30 sample platforms are selected for verification and analysis. Compared with the traditional systemic risk pre-alarm model, DL model, based on the theory of artificial intelligence, has the advantage of strong ability to deal with nonlinear problems, and the application scope of pre-alarm model can be expanded. DL technology has strong data nonlinear approximation ability and self-learning ability, which can retain the original data characteristics as much as possible and simulate and predict complex nonlinear phenomena well. The data set used in the experiment contains 10 years of real trading data, which includes more than 30 million transactions of 30,000 traders. Data outlier removal processing is shown in Figure 3.

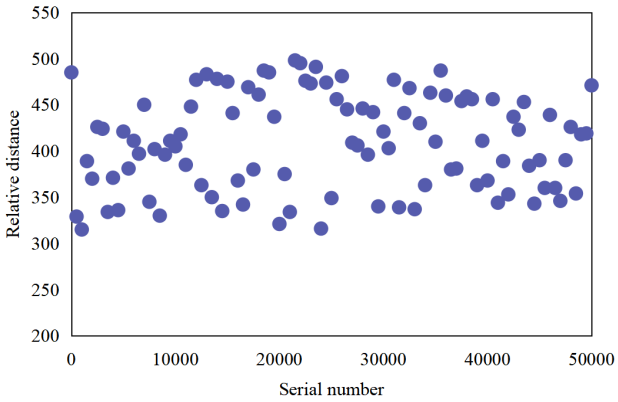

FIGURE 3. Data outlier removal processing.

In DNN, information needs to be adjusted, instead of neurons changing, the connections between neurons will change, that is, the weights will change, and information is widely distributed in these connections. Because DNN has a high degree of fault tolerance and the ability to perform complex calculations, this makes the DNN model adapt to more complex environments, and at the same time, it can produce infinite changes.

Financial risks mainly come from information asymmetry. The main task of financial institutions or information intermediaries is to help customers reduce information asymmetry. If it doesn't reduce the information asymmetry, it won't actually create value for customers, its business can't be sustained, and the organization can't develop healthily. DL searches for nonlinear factors through the combination of factors based on characteristics to realize prediction, and its essence is to find the computational mathematical method of mapping function among them through observed data. Compare the DNN output data with the real financial risk data, as shown in Figure 4.

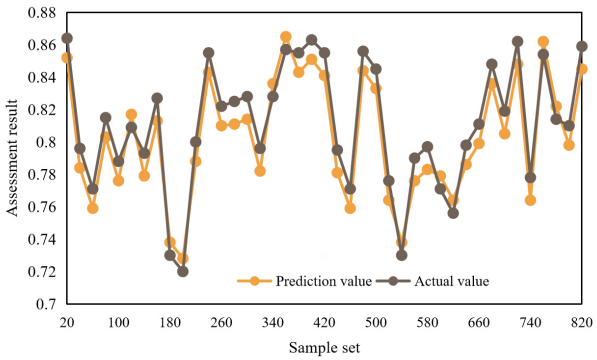

FIGURE 4. DNN learning results.

It is not difficult to see that the result of DNN learning is convergent, and it can approximate the original data well, so it has the basis for forecasting financial information. Every operation, that is, the digital signal is conducted through the input layer and guided to the hidden layer. The biggest function of the hidden layer is the operation, and the most complicated operation can be obtained at this level. After that, the hidden layer outputs the calculation result through the output layer, if there is too big error between the final result and the expected result. The result of this operation will in turn be directed to the hidden layer through the output layer, and the hidden layer will decompose the operation result and restore the original signal, which will be corrected by each unit. After that, the data is imported into the input layer, and the whole operation process for the first time is started again, until the result of the whole operation process is satisfactory. Under the information-based financial mode, the precision of different financial risk early-warning algorithms in smart sharing financial management is shown in Figure 5.

By introducing the zero-mean normal prior distribution, the model achieves the same effect as adding the regular term to the error function of DNN model, thus avoiding the overfitting problem when modeling small data sets. Furthermore, the uncertainty of model estimation and prediction can be evaluated by the form of parameter posterior distribution and prediction distribution, thus making the model results more abundant. The system analyzes the data from multiple levels,

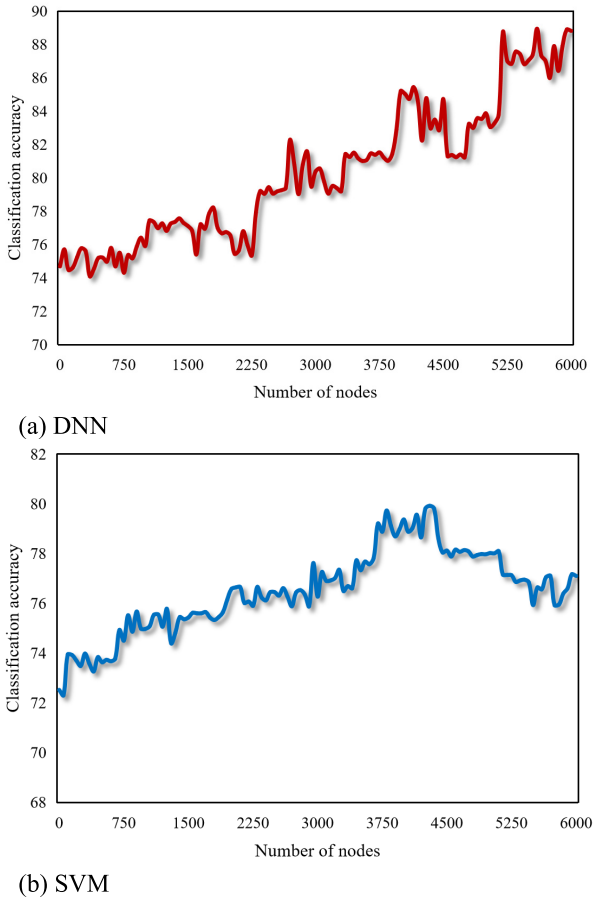

FIGURE 5. Prediction accuracy of different algorithms in smart financial management.

and at the same time has the ability to analyze the time series of indicators, so that supervisors can not only grasp the overall situation of regional monitoring data from a macro perspective, but also trace the key financial indicators in the whole life cycle from a micro perspective. Comparing the recall rate and average absolute error between the financial risk identification model in this article and SVM, the results are shown in Figure 6 and Figure 7.

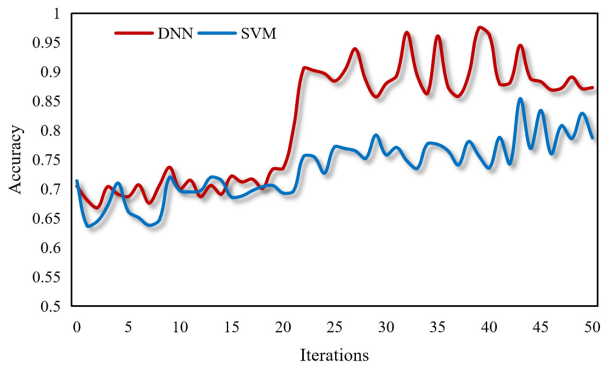

FIGURE 6. Accuracy comparison.

DNN can not only perfectly match the learned examples in the prediction of Internet financial data, but also perform well

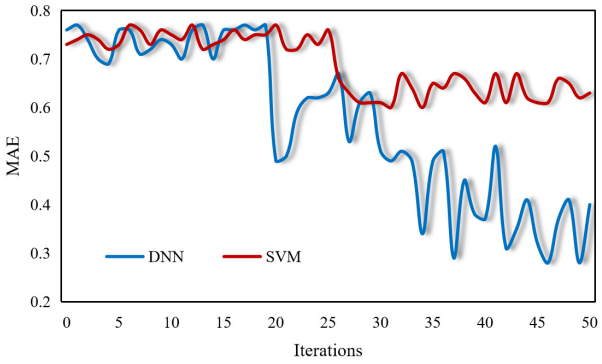

FIGURE 7. Comparison of average absolute error.

in the short-term rolling prediction of series. As a nonlinear system with large-scale parallel processing, DNN is modeled according to the intrinsic relationship of data itself, and has good adaptability, self-learning ability and strong anti-interference ability, so it can achieve satisfactory results in short-term prediction of series. The financial monitoring and pre-alarm system has the ability to import all statements in batches at one time by institution. In this stage, the system will automatically complete the forms check, compliance check, index split, data warehousing and other work, and the whole process does not need manual participation, with a high degree of automation.

DNN is mainly constructed according to the quantity of layers of neural network. It is a nonlinear mapping, and the transmission path is a process from low transmission to high transmission. The final conclusion of the model depends on the sample set to a certain extent. Therefore, the selection of sample sampling technology is very important for the successful establishment of a suitable Internet financial investment assessment model. The change of network is reflected by the change of network connection weight, while the change of numerical value is determined by the learning law of processing unit. Economic development and financial reform put forward urgent requirements for the construction of pre-alarm system of financial institutions' operational risks. Improving the financial ecosystem can effectively promote the reform of the financial system.

V. CONCLUSION

The application of DL in the financial risk pre-alarm system aims at integrating the data, information and policymaking in the market through big data, ML and DL, and realizing the intelligent correlation between data, assisting users to extract the key features between data, avoiding market risks and improving work efficiency and investment ability. In this article, a DL-based financial risk pre-alarm model is proposed. By introducing the zero-mean normal prior distribution, the over-fitting problem in modeling small data sets is avoided. The real data set is used to evaluate the performance of the proposed model, and the test results show that the proposed model has high prediction accuracy. According to the test

case analysis results of the financial risk pre-alarm system and the comparison of the actual function realization of the system, it can be found that the financial risk pre-alarm system can meet the actual needs of users, and for each part of the financial risk pre-alarm system, it basically meets the work needs of relevant users. If we want to use DL model reasonably, we need to correctly understand the application of DL in financial system, improve the principles and procedures of model program design, and try our best to reduce the probability of program errors. Secondly, it is necessary to improve the application system of DL, formulate relevant maintenance technical measures and manpower measures, introduce and train talents in corresponding fields, and speed up the transformation.

REFERENCES

[1] R. Gerrard, M. Hiabu, I. Kyriakou, and J. P. Nielsen, "Communication and personal selection of pension saver's financial risk," *Eur. J. Oper. Res.*, vol. 274, no. 3, pp. 1102–1111, May 2019.
[2] X. Huang and F. Guo, "A kernel fuzzy twin SVM model for early warning systems of extreme financial risks," *Int. J. Finance Econ.*, vol. 26, no. 1, pp. 1459–1468, Jan. 2021.
[3] L. Zhu, M. Li, and N. Metawa, "Financial risk evaluation Z-Score model for intelligent IoT-based enterprises," *Inf. Process. Manage.*, vol. 58, no. 6, Nov. 2021, Art. no. 102692.
[4] L. Bonnafous, U. Lall, and J. Siegel, "An index for drought induced financial risk in the mining industry," *Water Resour. Res.*, vol. 53, no. 2, pp. 1509–1524, Feb. 2017.
[5] F. C. Bagliano and C. Morana, "It ain't over till it's over: A global perspective on the great moderation-great recession interconnection," *SSRN Electron. J.*, vol. 49, no. 49, pp. 4946–4969, 2017.
[6] S. Kaufmann, S. Frühwirth-Schnatter, and H. K. van Dijk, "Editorial introduction on complexity and big data in economics and finance: Recent developments from a Bayesian perspective," *J. Econ.*, vol. 210, no. 1, pp. 1–3, May 2019.
[7] J. F. Kölbel, T. Busch, and L. M. Jancso, "How media coverage of corporate social irresponsibility increases financial risk," *Strategic Manage. J.*, vol. 38, no. 11, pp. 2266–2284, Nov. 2017.
[8] E. S. Meyer, G. W. Characklis, and C. Brown, "Evaluating financial risk management strategies under climate change for hydropower producers on the great lakes," *Water Resour. Res.*, vol. 53, no. 3, pp. 2114–2132, Mar. 2017.
[9] X. An and H. Gu, "Optimization decision model of enterprise financial risk management with random demand," *Boletin Tecnico/Tech. Bull.*, vol. 55, no. 2, pp. 155–161, 2017.
[10] J. Huang, "Analysis of corporate financial risk management under the new accounting standards based on the fair value model," *Boletin Tecnico/Tech. Bull.*, vol. 55, no. 19, pp. 54–63, 2017.
[11] J. Liang and J. Wang, "A study on the financial risk and legal supervision of P2P lending model in the context of Internet finance," *Revista de la Facultad Ingenieria*, vol. 32, no. 14, pp. 628–634, 2017.
[12] F. Dai and F. Xu, "Research on financial risk prewarning of Chinese manufacturing listed companies based on panel logit model," *Revista de la Facultad Ingenieria*, vol. 32, no. 16, pp. 594–600, 2017.
[13] S. Only, "Analysis on the enterprise financial risk based on interactive data association rule mining technology," *Boletin Tecnico/Tech. Bull.*, vol. 55, no. 6, pp. 772–781, 2017.
[14] H. Yoshikawa and K. Goda, "Financial seismic risk analysis of building portfolios," *Natural Hazards Rev.*, vol. 15, no. 2, pp. 112–120, May 2014.
[15] S. G. Anton, "Who manages financial risk? An empirical examination of risk management practices in the Romanian metallurgical industry," *Metalurgija*, vol. 52, no. 4, pp. 518–520, 2013.
[16] P. M. R. Bento, J. A. N. Pombo, M. R. A. Calado, and S. J. P. S. Mariano, "A bat optimized neural network and wavelet transform approach for short-term price forecasting," *Appl. Energy*, vol. 210, pp. 88–97, Jan. 2018.
[17] G. Adosoglou, G. Lombardo, and P. M. Pardalos, "Neural network embeddings on corporate annual filings for portfolio selection," *Expert Syst. Appl.*, vol. 164, Feb. 2021, Art. no. 114053.
[18] X. Sun and Y. Lei, "Research on financial early warning of mining listed companies based on BP neural network model," *Resour. Policy*, vol. 73, Oct. 2021, Art. no. 102223.
[19] G. T. Ribeiro, A. A. P. Santos, V. C. Mariani, and L. dos Santos Coelho, "Novel hybrid model based on echo state neural network applied to the prediction of stock price return volatility," *Expert Syst. Appl.*, vol. 184, Dec. 2021, Art. no. 115490.
[20] J. Lu and X. Chen, "Risk model of financial supply chain of Internet of Things enterprises: A research based on convolutional neural network," *Comput. Commun.*, vol. 183, pp. 96–106, Feb. 2022.
[21] P. Macmillan, "Economic capital & financial risk management for financial," *Rsc Adv.*, vol. 4, no. 42, p. 22129, 2014.
[22] W. W. Cooper, A. T. Kingyens, and J. C. Paradi, "Two-stage financial risk tolerance assessment using data envelopment analysis," *Eur. J. Oper. Res.*, vol. 233, no. 1, pp. 273–280, Feb. 2014.
[23] H. Yi, "Analysis of the influencing factors of university financial risk based on structural equation model," *Revista de la Facultad de Ingenieria*, vol. 32, no. 4, pp. 659–665, 2017.
[24] E. Y. Chan and N. U. Saqib, "Online social networking increases financial risk-taking," *Comput. Hum. Behav.*, vol. 51, pp. 224–231, Oct. 2015.
[25] Q. Yang, Y. Wang, and Y. Ren, "Research on financial risk management model of Internet supply chain based on data science," *Cogn. Syst. Res.*, vol. 56, pp. 50–55, Aug. 2019.