Research Article

Systematic Financial Risk Identification and Dynamic Evolution Based on Deep Learning

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1. Introduction

Effectively measuring financial market systemic risk and identifying its time-varying characteristics will aid regulatory efficiency [1]. It breeds the belief in systematic financial risk capital employment and shapes the logic of thinking based on material value, which runs through the production-oriented systematic financial risk, under the concept of material-based economic development. There is little research on systemic risk worldwide, and it is frequently discussed in the context of financial crises, with no independent and comprehensive theoretical system in place [2]. Opportunities and risks coexist, and the increasingly open market emphasizes the importance of early warning of corporate systemic financial risks. A large amount of data has flooded into our field of vision since the dawn of the Internet era. Due to technical limitations in the past, people were unable to handle large amounts of data. People can now quickly process massive data thanks to the emergence of big data systems and the gradual maturity of distributed storage and distributed computing technology, and ANN (artificial neural network) [3, 4] and machine learning [5, 6] have also emerged.

An artificial neural network (ANN) is a large-scale distributed parallel processor made up of neurons. Deep learning (DL) [7] is a data representation and learning method. It is a neural network (NN) based on the human brain that can learn analytically. It interprets data by mimicking the human brain’s operating mechanism. ANN theory has been used to develop DL theory. Because systematic financial risk is a complex, gradual process with many internal factors, methods for early detection of systematic financial risk are constantly improving. Because of the complexity of systemic financial risk, it is impossible to express it using a simple linear function, and the relationship between related influencing factors and the occurrence of systemic financial risk crises is clearly nonlinear [8]. In this paper, deep learning is used to identify systemic financial risks, and a DNN (deep
neural network) classification model is built. The model is optimized to identify and monitor systemic financial risks using the improved loss function.

DL networks, in contrast to traditional NN, can handle low-level features to identify high-level results. ANN is a machine learning algorithm that simulates the structure of human brain neurons and has a large number of parameters that can model a large amount of data [9]. This method has a lot of computing power, can self-learn, and has a lot of fault tolerance [10]. ANN becomes a dynamic model because, unlike a univariate multivariable linear model or a probability model, it will learn to modify the network’s parameters on its own through continuous training. The use of DL not only improves financial risk management identification and analysis methods, but it also encourages empirical research to shift from linear to nonlinear, from a focus on parameter salience to a focus on model structure and dynamic characteristics. This paper investigates the identification and dynamic evolution of systemic financial risks using DL. The following are some of its innovations: (1) In this paper, the entire analysis, processing, and model-building process is viewed from the perspective of the application, and the DL network is trained using sample data. The trained DL method is used to identify the causative factors that have a significant impact on systemic financial risks, and then the constructed DL network’s prediction accuracy is tested with test samples, yielding a DL network model with early warning capability. (2) The importance of systemic financial risk to financial stability and the smooth operation of the entire macroeconomy cannot be overstated. As a result, this paper employs the DL model to conduct an empirical analysis of systemic financial risk identification. Furthermore, the model’s evaluation indicators in this paper all refer to widely accepted indicators in DL research, and the model’s actual performance is measured in a more scientific manner.

2. Related Work

2.1. Systemic Financial Risk. Based on a review of the relevant literature on banking crises, exchange rate crises, debt crises, and stock market crises, Wei L et al. designed an indicator system that covered the banking sector, foreign exchange market, bond market, and stock market. This variable is used to create a stress index that can be used to track financial stress and risk [11]. Ippolito F et al. summarized the characteristics in terms of shock factors and scale, and concluded that sudden events caused systemic financial risk, which eventually led to global and systemic financial turmoil. Commercial banks, other financial institutions, and even the entire macroeconomic system [12] are all affected. A M C B and others believe that systemic risk is complicated, owing to the large number of financial institutions, individual investors, a wide range of financial assets with large balance sheets, and a complicated creditor-debtor relationship, among other factors [13]. According to R Füss et al., accumulation is a feature of systemic risk, and accumulation means that risk spillovers from financial institutions and other financial institutions will continue to accumulate until systemic financial risks emerge [14]. Baghdadi L et al. used a network model to empirically analyze the Belgian banking system’s systemic risk [15].

2.2. Financial Risk Identification. Hermansson et al. divided the state of the enterprise through certain criteria and judged whether the enterprise had a systemic financial crisis from the perspectives of systemic financial risk status, default, and bankruptcy law. Instability or violation of bankruptcy law, it can prove that the current state of the enterprise is a systemic financial risk crisis [16]. Karwowski M and others believe that the systemic financial risk crisis of a company refers to a state of insolvency, when the company’s funds are unable to maintain normal operations [17]. Ji H L et al. proposed a similar theory, which believed that with the transfer of actual power of enterprises, it proved that enterprises have fallen into operational difficulties and systemic financial risk crises [18]. Barnes K et al. proposed that when the company’s efficiency is not high and the funds cannot support the operation many times, it can be judged that there is a systemic financial risk crisis [19]. Rizwan M S et al. proposed that if the enterprise is in poor business conditions, various defaults, and bankruptcy, then the enterprise may have a systemic financial risk crisis [20]. Franzoni S et al. pointed out that there are various reasons for the emergence of systemic financial risk crises in enterprises, so their manifestations are also diverse. Judgment standard [21]. Tyler M et al. pointed out that the network model approach relies on financial institution data to assess the collateral externalities, tracking the response of a credit event or a liquidity crunch in the banking system, and can be used to measure financial institutions. The elasticity of the domino effect [22].

Based on related work, this paper defines the connotation of systemic financial risk, applies DL to systemic financial risk identification, and builds a DNN-based classification model. And use the improved loss function to optimize the model to identify and monitor systemic financial risks.

3. Methodology

3.1. Application Principle of DL in the Field of Financial Risk. DL is an effective machine learning algorithm for training deep NN, which can be used for high-level abstract modeling of various data. Broadly speaking, deep learning is a complex structure with multiple processing layers and nonlinear transformations. On the basis of various models and algorithms, deep learning can find suitable and effective features from complex data, which can achieve good results in solving practical problems. The training of DNN is the most important prerequisite for the practical application of the network, and the effect of its specific application depends on the training effect [23]. Corresponding to the actual DL network is the lower-level network. The lower-level network can automatically learn the statistical laws of data from a large number of trainings and judge events by using the back propagation algorithm. The training of DL network is completed in two stages. (1) Unsupervised layer-by-layer
training method is adopted to train each network level, which is carried out layer by layer. Then, the initial values of each layer and overall network parameters are obtained. (2) The supervised training method is used to adjust the parameters of the network. Through continuous learning, the characteristics of the network can be described more accurately, thus achieving a high level of identification and prediction.

When training multilayer NN, DL alleviates the local optimum problem of traditional NN algorithms, and its training process is independent of sample label information. The trained DL network can analyze the input data to identify the features represented by the input layer and then form the output layer via implicit multilayer assignment and feedback in the middle. DL is a deep network with many hidden layers. DL can be abstracted from the features of the bottom multidimension into features with fewer dimensions, eventually reaching the top-level representation, which is similar to human brain processing. Each data feature is learned by the DL model, which then feeds the new feature into the next layer. New features are created in this process by transforming the learned data features into specific feature transformations [24]. Its main task is to process large amounts of data, learn features through training, and learn data with supervision or unsupervised learning using a multilayer perceptron learning model. Multilinear data transformations make up the model’s layers. The higher the level, the more accurate the data features can be expressed. The structure of DL network and artificial neuron is shown in Figure 1.

Compared with traditional methods, DL’s pattern recognition method is different in that DL can automatically learn features from big data instead of using artificially designed features. Good features can greatly improve the performance of the recognition system. Compared with traditional machine learning methods, the deep architecture with multilayer abstract structure has stronger learning ability. Compared with the machine with depth of \( k + 1 \), the learning machine with depth of \( k \) needs multiple computing units to express a functional relationship. The performance of DL model is better than that of simple regression model, while the performance of classifier is better than that of individual learner. There are many layers in the DL network. In the traditional NN, because the back propagation algorithm is used for error adjustment, there will be the problem of error diffusion when there are many layers, which will lead to the decline of the training accuracy. The DL method can avoid this problem by adjusting the algorithm. Automatic encoder is the simplest kind of DL, which is a network designed by the hierarchical structure of ANN. For a given network, the input and output are assumed to be the same, then the network is trained and the parameters in the network are adjusted to obtain the weight of each layer.

The DL algorithm corrects the weight and deviation of each neuron layer by judging whether the error function of the whole NN drops fastest. The iteration is calculated as follows.

\[
X_{k+1} = X_k - a_k b_k
\]  

Among them: \( X_k \) represents the weight and local difference of the network, \( X_{k+1} \) represents the weight and deviation after iterative calculation, \( a_k \) represents the speed of NN learning, and \( b_k \) represents the gradient of the error function. The output error of the neuron \( p \) in the output layer is expressed as:

\[
e_{kp}(n) = d_{kp}(n) - y_{kp}(n)
\]

The sum of error energy of each neuron in the output layer is expressed as:

\[
E(n) = \frac{1}{2} \sum_{p=1}^{n} e_{kp}^2(n)
\]

DL self-coding algorithm is used to obtain initial nonrandom parameters through hierarchical training, which greatly improves the training efficiency of DL and avoids falling into local minimum. DL is a set of nonlinear modules that includes training parameters in all training links and uses function approximation to express the intrinsic relationship and essential characteristics of data. The DL network is a two-way system. Train the identification parameters from the lower layer to the higher layer and the recurrence parameters from the top layer to the lower layer first. Two-way adjustment is performed in this manner, and the network parameters can finally achieve the best expression effect. The financial market is a dynamic system that is noisy and nonparametric. Whether it is various policy adjustments issued by regulatory agencies, inquiry letters for listed companies, or announcement information from various enterprises, the financial field is full of text information. These factors invariably influence the financial market, so combining natural language processing tools to deal with such complex data can aid market analysts in maintaining a firm grip on the situation. The ever-changing bottom systematic financial risk makes high-level decisions. Systematic financial risk data, and new and effective feature representations are learned automatically from the changing systematic financial risk data, resulting in an intelligently constructed systematic financial risk identification standard with broad applicability. DNN is also a process of feature judgment and self-learning when it comes to identifying systemic financial risks. As the complexity of financial data grows, so does the demand for analysis, so the use of deep learning has become a research frontier in the field of financial risk management and identification.

3.2 Dynamic Evolution and Supervision of Systemic Financial Risk. Systemic risk refers to the occurrence of similar risk events in multiple banking and financial institutions, resulting in risk losses for all banking and financial institutions operating or holding such products, engaging in this business, and related to it. Serious consequences could jeopardize the financial system, as well as economic and social stability. Systemic risk has four characteristics: a broad range of influence, rapid infection, significant damage, and accumulation prior to an outbreak. The risk that an economic
Macrofinancial risk includes systemic risk. Concentration risk, which evolves from quantity to quality and accumulates over time, is usually the cause of its characteristics. It will spread quickly, widely, and cause significant losses once it breaks out, which is a key factor in triggering the financial crisis. Individual financial risks generate some systemic financial risks, while multihead contagion, systemic joint development, double expansion, and chain reaction generate others, resulting in the “butterfly effect” and “El Nino” phenomenon. When we look at financial crisis and systemic financial risk in the long run, we can see that financial crisis is a concept of an equilibrium point, whereas systemic risk is a process of an equilibrium point moving. From systemic financial risk to financial crisis, it is a process of economic and financial development and evolution, with systemic financial risk serving as a kind of probability and financial crisis serving as a concrete manifestation of that probability. The three mechanisms that cause systemic financial risks in the financial system are as follows: first, the systemic financial risks of the evolution of the state-owned financial system. Second, the market financial system’s evolution poses a systematic financial risk. Third, there is a systematic financial risk associated with the state-owned financial system’s interaction with the market financial system’s evolution.

The evolution process of systemic risk is very complicated and full of mystery. It usually explodes suddenly after a long period of accumulation, quickly infecting the whole financial system and causing a disastrous financial tsunami. Systemic financial risks generally go through four stages: germination, accumulation, outbreak, and disposal. Therefore, the measurement of systemic financial risk mainly includes three dimensions: financial market cycle, correlation between financial institutions, and tail risk of financial institutions. A typical evolution process of systemic financial risk is microsubject’s profit expectation is optimistic-risk preference is rising-investment position is increased-risk exposure is expanded-leverage ratio is high-vulnerability of financial institutions is rising-systemic risk is fermenting continuously … The financial system is getting closer to
the edge of collapse. Therefore, correctly identifying the sources of systemic financial risks and estimating the risks are of great significance for ensuring national financial stability and promoting economic development. To accurately identify systemic financial risks, it is necessary to proceed from the inherent logic of its formation and focus on several groups of important relationships. First, balance the relationship between stable growth and risk prevention. Second, balance the relationship between promoting innovation and preventing risks. Third, balance the relationship between opening up and risk prevention. At the same time, effectively preventing financial risks is a systematic project, which requires the cooperation of government supervision departments, real economy departments, financial institutions, and other parties.

3.3. Identification of Systemic Financial Risks. To identify risks, it is important to understand that most are developed over time, from potential reserves to gradual emergence. For risk early warning operations, understanding this process is critical. Risks are generally divided into three stages. The dangers of the primary naive stage 2nd stage of comprehensive risk management. At the end of the risk transformation process. The matrix is used to describe the financial institution risk correlation network in this paper. The correlation coefficients of unexpected volatility of financial institutions are the matrix's elements. The systematic risk values of various institutions and industries are calculated by solving the eigenvalues of the correlation matrix. Each stage of risk has its own set of “three processes.” The latent process of risk, the process of risk generation, and the process of risk evolution are all part of the first stage. The approaching process of risk, the gradual emergence process of risk, and the destruction process of risk are all part of the second stage. The process of risk out of control, the process of risk withdrawal and liquidation, and the process of risk termination and transfer are all part of the third stage. Self-learning is a feature of DL, and it can even conduct unsupervised learning in a large database. However, DL will not be able to fully exploit its own advantages if the data is insufficient. To avoid errors caused by a lack of systematic financial risk indicators, DL should be trained on as much data as possible. To some extent, the systematic financial risk indicators labeled in this paper can reduce errors. The DL model construction framework and data processing flow of this paper are shown in Figure 2.

In order to identify the systemic financial risks in different regions, reduce, control, and absorb the systemic financial risks, the regional financial risks must be graded and judged. Through rating evaluation, we can know the degree of systemic financial risk of a country or region, and then get the overall evaluation, that is, whether the evaluated object is in a relatively safe, certain risk, cautious risk, high risk, and extreme risk state. Because one of the characteristics of the formation of systemic risk is the accumulation of the whole system risk, the set systemic risk value of the industry is the average of the systemic risks of institutions in the industry. The systemic risk of a financial institution is the sum of other systemic risks related to but not includ-

\[
\begin{align*}
X_j &= \frac{1}{m} \sum_{i=1}^{m} X_{ij} (i = 1, 2, \ldots, N) \\
S_j^2 &= \frac{1}{m-1} \sum_{i=1}^{m} (X_{ij} - \bar{X}_j)^2 (i = 1, 2, \ldots, N)
\end{align*}
\]

Then, the coefficient of variation of each index is:

\[
V_j = \frac{S_j}{\bar{X}_j}
\]

The coefficient of variation is normalized to obtain the weight of each indicator:

\[
W_j = \frac{V_j}{\sum_{j=1}^{n} V_j}
\]

Use a distributed representation of the original input as a feature and a binary indicator variable as a target that indicates whether the hedging trade should continue. Given parameter weight \( W \) and bias \( b \), the probability that transaction \( x \) belongs to class \( i \) is:

\[
P(Y = i|x, W, b) = \text{softmax}(Wx + b) = \frac{e^{Wx + b_i}}{\sum_{i} e^{Wx + b_i}}
\]

A negative log-likelihood function is adopted as the loss function in supervised fine-tuning. Assuming that \( y^* \) is the true classification of the input \( x' \), the loss function has the following form:

\[
L(W, b, x) = - \sum_{i=1}^{N} \log(P(Y = y'|x', W, b))
\]

Each training effect will show different convergence in DL model training, so it is necessary to train many times and choose the result with the best training effect. Pretraining is used to find a distributed representation of data that can explain and amplify changes in the data that are important for classification. The pretraining process can help overcome the problem of gradient disappearance by creating a feature detection layer, avoiding the propagation of error information in multilayer networks, and creating a feature detection layer through a series of nonlinear transformations. Although training data can be used to determine an
accuracy rate, the data’s accuracy is questionable. It is necessary to test the test data at this time, and an accuracy rate, known as the effective accuracy rate, will be determined. Deep confidence networks and stacked denoise automatic encoders are two popular methods for pretraining. Because both strategies aim to reduce the generated model’s log likelihood, their results are usually comparable. A stacked denoise automatic encoder is used to perform the pretraining. The distributed representation of input samples is learned by a denoising automatic encoder. The following are the definitions for the accuracy rate, recall rate, and comprehensive index F1 in this paper:

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (9)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (10)
\]

\[
F1\text{-}score = \frac{2}{\left(\frac{1}{P}\right) + \left(\frac{1}{R}\right)} = \frac{2 \times P \times R}{P + R} \quad (11)
\]

Traditional methods have some shortcomings in determining the critical value of financial stress index. For example, the selection of standard deviation multiple k value is subjective to some extent, and different k values selected by different studies will directly lead to different empirical results. Therefore, this paper uses the estimation method of extreme quantile to determine the critical value of financial stress index, so as to achieve the research purpose of identifying the risk period. However, the more hidden layers there are, the better the training results will be, and the determination of the number of hidden layers needs to conform to the reality. The initial value of the number of hidden layers in this paper is 18 nodes. In order to solve the over-fitting problem of DNN model, a dropout layer is set behind each hidden layer of DNN. During the training process, dropout will remove hidden layer neurons and their corresponding connection weights according to a certain probability. Because it is randomly removed, each mini-batch is training a different NN, and the probability of hidden neuron removal obeys Bernoulli distribution with a given dropout rate. The crisis warning signals sent by this model are shown in Table 1. It should be noted that the score value of factor state is determined based on risk experts’ previous experience, so it can only be completed by risk assessment agencies separately according to different objects using this method. Because each factor is determined by a number of related risks and factors, the risk assessment agency should also take into account changes in the status and function of risk sub-factors when determining the grade. The financial pressure index is treated as a random variable, and sample data that exceed this threshold are treated as extreme values, allowing the generalized Pareto distribution to fit the statistical characteristics of the systemic financial crisis. The variance risk premium, which is easily influenced by time-varying risk preferences, is the individual risk based on the rate of return. The tail risk quantile of a probability distribution is non-stackable and insensitive to loss scale. The value of volatility has a long-term memory, allowing it to continuously monitor the impact of exogenous shocks on risk events and better reflecting the risk status or income uncertainty of financial

![Figure 2: DL model construction framework and data processing flow.](image-url)
assets during a stress period. This paper conducts risk technical monitoring through risk assessment, risk signal transmission, risk signal identification, intermediate control and information feedback, and information transmission technology, using basic analysis. The basic research stage is risk analysis, the behavior effect research stage is information transmission and risk technology monitoring, and the intermediate operation process is the application technology research stage.

### 4. Result Analysis and Discussion

Some existing systematic financial risk identification and monitoring methods provide a good theoretical basis for us to build an identification and early warning model. However, the existing methods require high data and are based on the explanation of postevent risk events, so the monitoring of risks often has no good early warning effect. This paper adopts DL-based systematic financial risk identification and early warning model. In this paper, firstly, SMOTE sampling is carried out for the whole sample, and then lattice search is carried out for the above parameters to find out the optimal hyperparameter. Then, the model is trained and evaluated by 50% cross validation. In the empirical analysis, whether the risk probability value reaches the multimeeting, the crisis will break out, which involves setting the probability threshold of the systematic financial crisis. If the threshold is set too low, all possible crises will trigger the probability threshold, and crises will be identified. However, if the threshold is set too low, it may send out a risk warning signal in the noncrisis period, causing unnecessary panic in the financial market and leading policy departments to make some unnecessary or even counterproductive adjustment policies. If the threshold is set too high, the crisis will be identified only when the probability of outbreak is extremely high, and some risks may be missed, resulting in serious consequences. The statistics of classification results using this method are shown in Table 2.

Combined with the above analysis, the performance of this model is high. When the performance of the model itself needs to be more dependent, choosing this model is the best solution. The model in this paper is compared with the random forest model and the logistic regression model. The recall comparison results are shown in Figure 3. The accuracy comparison results are shown in Figure 4.

The results show that this model can get 93.2% recall rate and 95.4% accuracy rate. The results are better than the compared models. The function of the index system in this paper is to express the characteristics of regional overall financial risks. These indicators can reflect the characteristics of the region. The characteristics of normal areas and crisis areas are different, which is what DL network needs to learn from sample training, and also the premise of case identification and analysis. Using DL method, we need to describe the characteristics of regional finance through data, so we choose various indicators to reflect the financial situation, first of all, train, and then conduct early warning analysis on the case regional finance. In the multi-index comprehensive evaluation, it is necessary to forward the reverse indicators, so as to ensure that all indicators tend to be consistent with the development trend of systemic risk. In this paper, the reverse indicators are positively processed by taking the corresponding reciprocal. On the other hand, in order to eliminate the influence of different dimensions on the research results and prevent the magnitude difference between data from being too large, it is necessary to standardize the monitoring indicators. By studying the causes of systemic financial risks, we can determine which financial variables can be used for the assessment and identification of systemic financial risks, and then use historical data for statistical analysis to determine the variables significantly related to systemic financial risks as the leading indicators of risk outbreak. In the process of evaluating the results of many classification models in the past, only the model accuracy was used as an index. However, with the increasing complexity of the problems to be dealt with and the emergence of various abnormal situations, the effectiveness and practicability of the model cannot be objectively evaluated only by the accuracy of the model. In this paper, the indicators widely used in DL are used to evaluate the model. Draw the F1 values of random forest model, logistic regression model, and this model into line charts, as shown in Figure 5.

The number of variables at the input level should be determined first in the training process, which is determined by the index system. Second, the number of hidden layers and the number of variables in each layer must be determined. This is a challenge in training as well. We need

| Serial number | Determine if there is a crisis | Determine whether to send a signal | Result |
|---------------|-------------------------------|-----------------------------------|--------|
| 1             | Systemic financial crisis     | Send out crisis warning signal    | Valid signal |
| 2             | There was no systemic financial crisis | Send out crisis warning signal | Type 1 error |
| 3             | Systemic financial crisis     | No crisis warning signal was sent | Type II error |
| 4             | Systemic financial crisis     | Failure to send crisis warning signal in time | Type III error |

| Serial number | Accuracy | Precision | Recall | F1-score | AUC |
|---------------|----------|-----------|--------|----------|-----|
| K-fold_ 1     | 0.941    | 0.869     | 0.854  | 0.814    | 0.899 |
| K-fold_ 2     | 0.973    | 0.893     | 0.892  | 0.857    | 0.945 |
| K-fold_ 3     | 0.978    | 0.885     | 0.889  | 0.898    | 0.936 |
| K-fold_ 4     | 0.964    | 0.917     | 0.951  | 0.946    | 0.967 |
| K-fold_ 5     | 0.958    | 0.935     | 0.946  | 0.954    | 0.917 |
constant training and testing to determine the network parameters suitable for systematic financial risk early warning in order to get a good network model. The specific process entails continuously modifying the network structure, training times, step length, and other parameters in order to obtain the most accurate network model. Divide the training data into five equal parts and set one aside as test data each time. SMOTE sampling is done first for the other four pieces of data, and then the model is trained to determine the model’s parameters. Finally, the evaluation index is calculated by verifying the model on the test set. By reducing the dimensions of the basic indicators, principal component analysis overcomes human subjectivity, calculates their respective weights based on the objective authenticity of the data, and generalizes the basic indicators into several main influencing factors; the above influencing factors can contain most of the information of the original data with little distortion. The scores of each principal component are divided by the eigenvalues of the corresponding principal components and then multiplied by the variance contribution rates of the principal components to accumulate the values, in order to obtain the final weight of the principal components, based on the eigenvalues and variance contribution rates of each principal component of the rotated load matrix. To determine whether DL is accurate in detecting systemic financial crises, it is necessary to identify samples that have not undergone training, or test samples. The training errors of different models are shown in Figure 6.
The training accuracy reflects the accuracy of network identification. It can be seen from Figure 6 that after many trainings, the error rate of DL network is significantly reduced. And among the three models, the model in this paper has the fastest decreasing speed and the smallest error.

According to the DL model, the probability of occurrence of systemic financial crisis is identified, and the mean value of the predicted probability sequence of systemic financial risk is obtained, and the probability values which deviate from the mean value by $k$ times are calculated, respectively. The calculated probability values are used as risk prediction thresholds, respectively, and then the noise-signal ratios in different situations are calculated, respectively, and the probability values corresponding to the lowest noise-signal ratios are used as risk prediction thresholds. The advantage of this threshold determination method is that to some extent, it solves the problem of subjectively setting the risk probability threshold as $k$ times of the predicted probability sequence in the existing research, without comparing and selecting the appropriate $k$ value. The weighted average method is used to calculate the systemic stress index. The larger the final synthesized systemic financial risk index, the greater the systemic financial risk. On the contrary, it means that the smaller the systemic financial risk is. The
model performance metrics are all based on the comparison between the recognition results of samples and the actual results. Among them, the most basic model accuracy represents the same proportion of labels and real situations in recognition results, and reflects the overall classification results of the model. In order to verify the practical feasibility of this model, the three models are tested again, and the recognition error results are shown in Figure 7.

When using DL network model for case analysis, it is necessary to ensure that the input level indicators in the case area are consistent with those during training. Therefore, according to the data of the case area, the indicators in this index system are calculated as input values. Then, the recognition result can be obtained by calculation. Furthermore, it is analyzed and summarized according to the recognition results. According to the needs of the model, a threshold value is determined for each selected risk index according to its historical data. When a risk indicator exceeds its corresponding critical value at a certain time point or within a certain period of time, it means that the indicator sends out a risk signal; otherwise, it does not send out a risk signal. The more signals there are, the more likely a country or a macro market will have a risk or crisis in the future.

In the experiment, compared with random forest model and logistic regression model, this model has the smallest recognition error and the highest accuracy. And the model in this paper can get 93.2% recall rate and 95.4% accuracy rate. In this chapter, many experiments have been conducted, and the experimental results have verified that the model in this paper has good performance and certain practical assumptions.

5. Conclusions

Banks and financial institutions will suffer losses as a result of systemic risks, and the economy and society will suffer greatly as a result. The potential systemic financial risks will cause incalculable losses to China and even the global economic system, especially during a period of high-quality economic development. As a result, identifying and detecting systemic financial risks is a problem that China’s economic development must address. This paper provides a framework study on the theory and practice of systemic financial risk from the perspectives of its meaning, evolution process, identification, and detection. Also, based on DL, create a systematic financial risk identification model. The comprehensive detection signal that can reflect China’s systemic financial risks in recent years is calculated after determining the critical value of the indicators used in the model and describing the signal state of each indicator variable, and the signal state and changes are further analyzed. DL, for example, has a strong mining learning ability, which allows it to more accurately mine the rules hidden in the deep layer of data, and is better suited to financial markets with large scale, high dimension, and streaming data characteristics. The use of DL not only helps to improve recognition methods in this field, but it also helps to optimize the algorithm for deep networks and solve invalid training problems, which advances traditional empirical application research methods. The experimental results show that this model can achieve a recall rate of 93.2 percent and an accuracy rate of 95.4 percent. It also has a high level of accuracy, as well as some feasibility and practicability. The purpose of this paper is to identify and track systemic financial risks in China’s economic development.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors do not have any possible conflicts of interest.

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References

[1] B. Gao, “The use of machine learning combined with data mining technology in financial risk prevention,” Computational Economics, vol. 1, pp. 1–21, 2021.

[2] K. Safarzynska, “Financial stability at risk due to investing rapidly in renewable energy,” Energy Policy, vol. 108, no. 9, pp. 12–20, 2017.

[3] D. Yao, Z. Zhi-li, Z. Xiao-feng et al., “Deep Hybrid: Multi-Graph Neural Network Collaboration for Hyperspectral Image Classification,” Defence Technology, 2022.

[4] W. Cai, B. Zhai, Y. Liu, R. Liu, and X. Ning, "Quadratic polynomial guided fuzzy C-means and dual attention mechanism for medical image segmentation," Displays, vol. 70, article 102106, 2021.

[5] J. Zhou, Y. Wang, and W. Zhang, "Underwater image restoration via information distribution and light scattering prior,"
J. Zhou, D. Zhang, and W. Zhang, "Underwater image enhancement method via multi-feature prior fusion," Applied Intelligence, vol. 1, pp. 1–23, 2022.

Z. Huang, Y. Liu, C. Zhan, C. Lin, W. Cai, and Y. Chen, "A novel group recommendation model with two-stage deep learning," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 3, 2021.

A. N. Berger, W. S. Frame, and V. Ioannidou, "Reexamining the empirical relation between loan risk and collateral: the roles of collateral liquidity and types," Journal of Financial Intermediation, vol. 26, pp. 28–46, 2016.

E. Luciano and C. Wihlborg, "Financial synergies and systemic risk in the organization of bank affiliates," Journal of Banking & Finance, vol. 88, no. 3, pp. 208–224, 2018.

K. Tissaoui, "Forecasting implied volatility risk indexes: international evidence using Hammerstein-ARX approach," International Review of Financial Analysis, vol. 64, no. 7, pp. 232–249, 2019.

L. Wei, G. Li, X. Zhu, X. Sun, and J. Li, "Developing a hierarchical system for energy corporate risk factors based on textual risk disclosures," Energy Economics, vol. 80, no. 5, pp. 452–460, 2019.

F. Ippolito, J. L. Peydró, A. Polo, and E. Sette, "Double bank runs and liquidity risk management," Journal of Financial Economics, vol. 122, no. 1, pp. 135–154, 2016.

M. C. Beaulieu, M. H. Gagnon, and L. Khalaf, "Less is more: testing financial integration using identification-robust asset pricing models," Journal of International Financial Markets, Institutions and Money, vol. 45, pp. 171–190, 2016.

R. Füss and D. Ruf, "Bank systemic risk exposure and office market interconnectedness," Journal of Banking & Finance, vol. 133, article 6311, 2021.

L. Baghdadi, R. Bellakhal, and M. A. Diaye, "Financial participation: does the risk transfer story hold in France?" British Journal of Industrial Relations, vol. 54, no. 1, pp. 3–29, 2016.

C. Hermansson, "Can self-assessed financial risk measures explain and predict bank customers' objective financial risk?" Journal of Economic Behavior & Organization, vol. 148, pp. 226–240, 2018.

M. Karwowski, "The risk in using financial reports in the study of airline business models," Journal of Air Transport Management, vol. 55, no. 8, pp. 185–192, 2016.

H. L. Ji and P. Phillips, "Asset pricing with financial bubble risk," Journal of Empirical Finance, vol. 38, pp. 590–622, 2016.

K. Barnes, A. Mukherji, P. Mullen, and N. Sood, "Financial risk protection from social health insurance," Journal of Health Economics, vol. 55, no. 9, pp. 14–29, 2017.

M. S. Rizwan, M. Moinuddin, B. L’Huillier, and D. Ashraf, "Does a one-size-fits-all approach to financial regulations alleviate default risk? The case of dual banking systems," Journal of Regulatory Economics, vol. 53, no. 3, pp. 1–38, 2017.

S. Franzoni and C. Pelizzari, "Rainfall financial risk assessment in the hospitality industry," International Journal of Contemporary Hospitality Management, vol. 31, no. 3, pp. 1104–1121, 2019.

M. Tyler, "Financial crises and risk premia," Quarterly Journal of Economics, vol. 132, no. 2, pp. 765–809, 2017.