International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 1675-1694

https://doi.org/10.70517/ijhsa464147

Practical Application of Machine Learning Algorithms in National Economic Security Monitoring

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Abstract The study applies machine learning algorithms to the national economy, and selects one of the Extreme Learning Machine algorithms to be embedded in the field of financial risk prevention and control. The financial risk monitoring model and the financial risk warning model based on Extreme Learning Machine (ELM) are constructed to prevent and control financial risks. The ELM model is compared with other early warning models in terms of prediction performance to get a comprehensive evaluation of the ELM model. And then, the SHAP explanatory model is utilized to measure the degree of importance and impact of each financial risk warning feature. The ELM model is used to monitor China's financial risks from 2008-2021, analyze China's financial stress, and predict the possibility of China's outbreak of systemic financial risks in 2022-2023.The overall accuracy of the ELM algorithmic model is 0.990, which exceeds that of other early warning models. Among the top ten characteristic indicator variables in terms of importance, the closing price, the maximum price and the interbank 7-day pledged repo weighted interest rate are the indicators that pull the probability of risk warning, and the SZSE Composite Index, the S&P 500 Index, the foreign exchange reserves, the year-on-year growth rate of M2, and the Nikkei 225 Index are the indicators that reduce the probability of risk.In 2008-2013, the systemic financial risk was in the basic safety zone.In 2014- 2015 is in the alert zone. 2016-2017 is in the basic safety zone. 2018 is in the safety zone. 2019 is in the near-alert zone. 2020 enters the danger zone. 2021 is in the basic safety zone. 2022-2023 has a low probability of the outbreak of systemic financial risk.

Index Terms machine learning, extreme learning machine, risk detection, financial risk warning

I. Introduction

As a major practical problem faced by a country, the theoretical and practical studies related to national security have a long history. Traditionally, sovereign security, political security and national defense security based on military security constitute the main body of national security [1]. However, as peace and development became the theme of the times after World War II, the economic ties between the countries of the world have become increasingly close, the importance of comprehensive security has gradually appeared, and the national security issues in the fields of economy, culture, society, ecology and other areas have gradually entered the research field of vision of people [2]-[5]. In particular, the first oil crisis in the 1970s and the intense friction between the U.S., the Soviet Union, and the U.S. and Japan in the 1980s made more and more developed countries regard national economic security as the core of comprehensive security [6]-[8].

Since the 1990s, the deepening of economic globalization and the accelerated pace of China's integration into globalization have resulted in an overall good and rising state of economic security in which China finds itself, with the exception of 2009 and some strategic resources [9], [10]. However, compared with the “unintentional security” constituted by internal factors such as the market system, industrial level or unpredictable events, as well as external shocks such as changes in international economic rules and international capital flows, some countries have recently generalized the so-called “economic security”. Compared with the “unintentional security” constituted by internal factors and external shocks such as changes in international economic rules and international capital flows, some countries have recently generalized the so-called “economic security”, such as the use of long-arm jurisdiction by the U.S. and the opening of a state of emergency by the U.S., the setting up of a working group on economic security and safety of China by Japan, and the European Union (EU) suing the “source countries of false information”, which have greatly increased the complexity and severity of China's current and future national economic security situation. These constitute “intentional security”, which greatly enhances the complexity and severity of China's current and future national economic security situation [11]-[14]. Economic globalization, the rapid development of high technology, the application of e-commerce, the entry of the digital era, the economic competition and cooperation among countries is becoming more and more frequent, and often you have me and I have you, resulting in cross-border, cross-regional, and even global economic security problems are more and more [15]-[18]. Today, the focus of national security of all countries, has turned to economic security, no economic security, can not talk about national security, especially in this area often have a domino effect, instantly affect a piece. With the continuous development of national economies and the deepening of globalization, the issue of economic security has increasingly become a focus of attention. In order to guarantee the stability and sustainable development of national economies, all countries have adopted a series of monitoring measures to ensure economic security.

In today's complex and changing economic environment, financial risk is like a beast lurking in the dark, always threatening the stability and development of the economy. Financial risks usually include market risk, credit risk, operational risk, liquidity risk and so on [19]. Therefore, financial risk prevention and control is not only an important task for financial institutions, but also the focus of government regulators, especially when the market fluctuates frequently, it is a major event that concerns the immediate interests of every ordinary citizen [20]. In order to guarantee the stable operation of the financial system, the prevention and control of financial risk is essential. In the current economic situation, we must recognize the serious consequences of financial risks and take corresponding measures to guard the national economic security.

This paper analyzes the internal and external influencing factors of financial risk, and confirms the necessity of monitoring financial risk through in-depth study of the transmission mechanism of systemic financial risk. In order to monitor financial pressure in real time and track the pressure changes in the financial market, a financial risk monitoring model is established. The Extreme Learning Machine algorithm in the field of machine learning is introduced into financial risk early warning, and the financial risk early warning model based on ELM is constructed. The early warning performance of the ELM model is evaluated comprehensively, and then the ELM model is disassembled through the SHAP interpretation model. Finally, the ELM model is used to analyze the financial risk situation in China during the period of 2008-2021, and predict the probability of the outbreak of systemic financial risk from 2022 to 2023.

II. Overview

In the monitoring of national economic security, the current research focuses on the category of threat factors and the category of monitoring indicators. Literature [21] points out that the development of the shadow economy is a serious threat to national economic security, and it is necessary to limit the share of the shadow economy fundamentally from the system policy in order to protect national economic security. Literature [22] modifies the value of its indicator weights, while changes in the structure of the national economy are included in the scope of updating the monitoring indicators, and suggests that these indicators are no longer simply superimposed, but in the form of multiplication, with the addition of reference coefficients for a comprehensive assessment. The study proved to be effective for the monitoring and management of the country's economic security. Literature [23] mentions the selection of a suitable system of indicators as a key factor in monitoring the economic security of the country, on the basis of which threat indicators are identified and described before entering the monitoring process. And the study points out that under the modern economic development, economic security monitoring should be implemented with technology and mathematical modeling.

In terms of financial risk prevention and control, most of them are aimed at the financial risk of enterprises, and there is no research on the national financial risk prevention and control. Literature [24] uses the concept of upper and lower approximation of variable rough set algorithm to distinguish between the positive region and boundary region of the test samples, and carries out the weight determination under the K nearest neighbor algorithm, so as to realize the control of Internet financial risks. Literature [25] establishes a financial risk prevention model with deep learning and data mining technology, which mainly analyzes the five aspects of debt repayment, profitability, operation, growth, and cash flow capabilities to control the key factors of financial risk, and then realizes risk prevention and control.

III. Dynamic model for real-time monitoring of financial stress

III. A. Financial risk influences

The reasons for the generation of financial risks are complex, and there are numerous influencing factors that lead to the creation of systemic financial risks. To summarize, the factors affecting financial risk include both internal and external factors of the financial system.

III. A. 1) Internal factors

With regard to internal factors, the financial system has inherent instability, which is mainly caused by financial fragility, excessive financial liberalization, interconnectedness of the financial system, irrationality of market players, and the existence of moral hazard in financial markets.

First, financial vulnerability. The financial industry because of the high indebtedness of the characteristics of the industry so that it has “inherent vulnerability”, which is a natural characteristic of the financial industry. The inconsistency in the timing of the use and repayment of credit funds leads to the vulnerability of the banking sector, and asset price fluctuations and volatility interlinkages lead to the vulnerability of financial markets.

The second is excessive financial liberalization, excessive use of leverage instruments and lack of financial regulation. Excessive financial liberalization has led to a substantial increase in the complexity of financial markets, financial products and financial transactions, weakening the financial system's ability to absorb shocks and exacerbating the risks of the entire financial system, while systemic financial risks will intensify along with the relaxation or even absence of financial regulation.

Third, the correlation between financial institutions due to business, assets and liabilities, as well as risk homogenization.

Fourth, the irrationality of market players. In the financial market, such as the herd effect, price overshooting and other phenomena are difficult to be explained by the classic rationality assumptions of economics, and need to be considered from the perspective of sociology and psychology, and irrational psychological and behavioral factors into the analytical framework.

Fifth, there is widespread moral hazard within the financial system and a lack of self-regulation in the market. In the run-up to the subprime crisis in the United States, many financial institutions completely ignored the interests of shareholders and depositors and took risks in pursuit of short-term profits, and after the crisis, the internal control mechanisms and corporate governance of many financial institutions failed and did not play their due role of checks and balances, exacerbating the formation of systemic financial risks.

III. A. 2) External factors

With regard to external factors, the macroeconomic cycle and failures in policy regulation are the two main causes of systemic financial risks.

First, the impact of the macroeconomic cycle is reflected in the following: on the one hand, in the period of economic recession, enterprises and households are prone to financial problems, leading to an increase in the total amount of non-performing loans of financial institutions, deterioration of the overall quality of assets, a serious blow to the confidence of investors and depositors in the financial system, and in extreme cases there will be a panic selling of assets and a run on the bank, due to the existence of interconnectedness of the financial institutions, therefore, the risk will continue to “snowball” in the entire financial system, contagion and expansion. Due to the interconnectedness of financial institutions, the risk will continue to “snowball” in the entire financial system, spreading, contagious and expanding, and ultimately triggering systemic financial risks and financial crises. On the other hand, due to the requirements of the financial industry such as capital adequacy regulation, loan loss provisioning and fair value accounting standards, its pro-cyclicality has become more and more obvious, which is specifically reflected in the fact that the financial system has been increasing the supply of credit in the period of economic upturn, and decreasing the supply of credit in the period of economic downturn, which strengthens the fluctuation of the economic cycle and contributes to the development of the financial crisis.

Secondly, macroeconomic policy mismanagement has also been recognized as an important factor contributing to systemic risk. Government intervention is also prone to lead to systemic financial risks because macroeconomic operations follow their own internal laws, and although government intervention can temporarily smooth out cyclical fluctuations in the economy in the short term, in the long term it disrupts the mechanism of spontaneous economic regulation, which makes it easier for systemic financial risks to accumulate.

III. B. Systemic financial risk transmission mechanisms

By combing, analyzing and interpreting the relevant theories on systemic financial risk mentioned above, and combining them with China's actual situation, it is further proposed that the transmission mechanism of systemic financial risk formation and impact on the real economy within a country is shown in Figure 1.

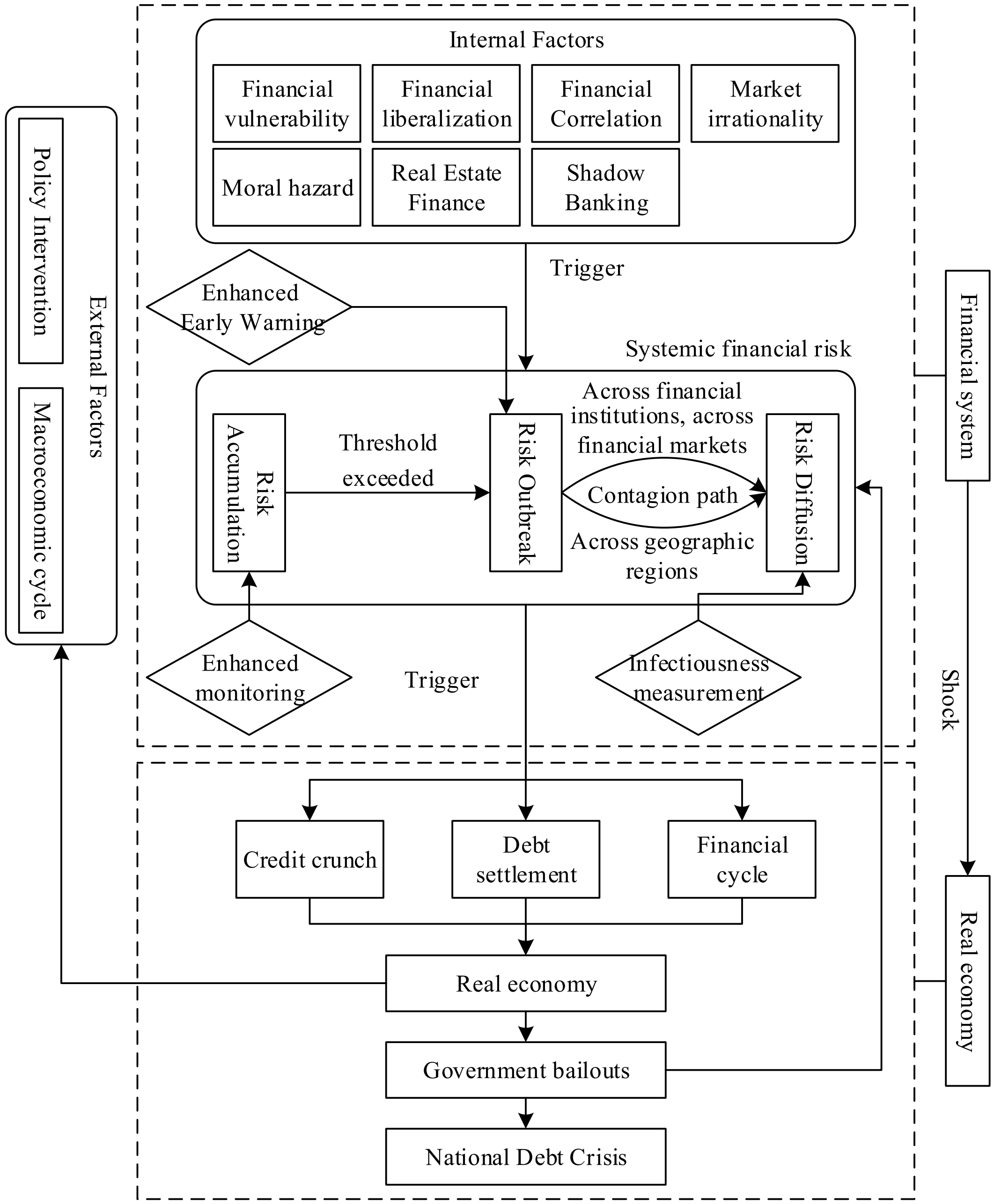


Figure 1: Systemic financial risk transmission mechanism

As can also be seen from figure 1, effective monitoring and early warning of systemic financial risk is particularly important, given that systemic financial risk will cause damage to the entire financial system and impact on the real economy. According to the formation and evolution mechanism of systemic financial risk, in the stage of financial risk accumulation, the focus should be on strengthening the monitoring of risk, in order to timely grasp the trend of change and evolution of risk. At the same time, on the eve of the outbreak of a systemic crisis when the accumulation of risks exceeds the threshold, early warning of the crisis should be strengthened, so that risk prevention and mitigation measures can be taken in advance.

III. C. Financial risk monitoring model

III. C. 1) Model fundamentals

In order to monitor financial stress in real time and track the changing stress conditions in the financial market in a more timely manner, high-frequency data containing high-frequency information are incorporated into the model, and high-frequency data are directly correlated with low-frequency data observation frequencies, so that key information at different data frequencies can be effectively utilized. In this chapter, the daily frequency is used as the time scale, the model is constructed based on the daily data, and the low-frequency (e.g., monthly) indexes are recorded as missing values if there are no corresponding observations, and Kalman filtering method is used to ensure that the model estimation is not affected by individual missing values. Let $\mathrm{x_t}$ denote the financial stress index at moment t, and $\mathrm{x_t}$ is an unobservable variable, which is assumed to obey the $\mathrm{AR(p)}$ process of dynamic change, i.e.:

$$x_t = \rho_1 x_{t-1} + \rho_2 x_{t-2} + \cdots + \rho_p x_{t-p} + e_t \tag{1}$$

where e_t is the white noise new interest with variance 1. Let y_t^i denote the i th observable variable at moment t, with linear dependence on x_t, as well as on the exogenous variables and the lag term of y_t^i:

$$y_t^i = c_i + \beta_i x_t + \delta_{i1} w_t^1 + \cdots + \delta_{ik} w_t^k + \gamma_{i1} y_{t-D_i}^i + \cdots + \gamma_{in} y_{t-nD_i}^i + u_t^i \tag{2}$$

where w_t is an exogenous variable and u_t^i is the contemporaneous continuous uncorrelated new interest. The lag of the $\mathrm{y_t^i}$ lag term is an integer multiple of D_i, and D_i is the number of days in each observation period, related to the frequency of the observed variable y_t^i (e.g. $D_i = 7$ if the frequency of y_t^i is weekly). In practice, typically D_i is time-varying, e.g. a month may have 28, 29, 30 or 31 days. For simplicity of representation, this paper implicitly assumes that D_i in equation (2) is fixed.

III. C. 2) State space representation of the model

When estimating the model, the above model should first be rewritten in state-space form as follows:

Measurement Equation:

$$y_t = C + Z_t \alpha_t + \Gamma_t w_t + \varepsilon_t \tag{3}$$

Transfer equation:

$$\alpha_{t+1} = \mu_{s_t} + T\alpha_t + R\eta_t \tag{4}$$

$$\varepsilon_t \sim (0, H_t), \eta_t \sim (0, Q), t = 1, \ldots, \overline{T} \tag{5}$$

where y_t is a vector of observed variables for $N \times 1$, α_t is a vector of state variables for $m \times 1$, C and μ_{s_t} are intercept terms, w_t is a vector of priors containing k trend terms and $N \times n$ lagged terms of the dependent variable, and ε_t and η_t are vectors of stochastic perturbations to the measurement and transfer equations containing u_t and e_t. T is the last period of the time series observation. T, R and Q are constant matrices, but since D_i of t is time-varying, so are Z_t, Γ_t and H_t.

y_t^i denotes the i nd variable with a daily frequency, but most variables, although changing daily, are not actually observed every day. Thus, let $\tilde{y}_t^i$ denote the same variable observed at a lower frequency, and the relationship between $\tilde{y}_t^i$ and y_t^i depends largely on whether y_t^i is a stock or flow variable.

If y_t^i is a stock variable, since it is a stock quantity at a particular point in time, at any moment t, y_t^i can be observed, in which case $\tilde{y}_t^i = y_t^i$. y_t^i cannot be observed, in which case $\tilde{y}_t' = NA$, where NA denotes missing data. The value observed at a frequency is equal to the sum of the corresponding daily values in the observation period, i.e:

$$\tilde{y}_t' = \begin{cases} \sum_{j=0}^{D_i - 1} y_{t-j}^j & y_t^t \text{ is observed} \\ NA & Other \end{cases} \tag{6}$$

III. C. 3) Model setup

In accordance with the AIC and SBIC information criteria, the lag order of the dynamic factor model is set at order 1. At the same time, the streamlined model form is used in this chapter because the higher order lag form leads to more complex expressions and more difficult estimation of parameter ρ_p. The observed variables Yield, Bond, Stock, NEER, Houseprice and CSI are recorded as $\tilde{y}_t^1$, $\tilde{y}_t^2$, $\tilde{y}_t^3$, $\tilde{y}_t^4$, $\tilde{y}_t^5$ and $\tilde{y}_t^6$, respectively, and the lag values of the three monthly variables are recorded as $\tilde{y}_{t-M}^4$, $\tilde{y}_{t-M}^5$ and $\tilde{y}_{t-M}^6$, and the model is established in the form of Eq. (7) to Eq. (10), and the maximum likelihood method is used to estimate the model:

$$\begin{bmatrix} \tilde{y}_t^1 \\ \tilde{y}_t^2 \\ \tilde{y}_t^3 \\ \tilde{y}_t^4 \\ \tilde{y}_t^5 \\ \tilde{y}_t^6 \end{bmatrix} = \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ u_t^1 \\ u_t^2 \\ u_t^3 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \gamma_4 & 0 & 0 \\ 0 & \gamma_5 & 0 \\ 0 & 0 & \gamma_6 \end{bmatrix} \begin{bmatrix} \tilde{y}_{t-M}^4 \\ \tilde{y}_{t-M}^5 \\ \tilde{y}_{t-M}^6 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \tilde{y}_t^4 \\ \tilde{y}_t^5 \\ \tilde{y}_t^6 \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} x_t \\ u_t^1 \\ u_t^2 \\ u_t^3 \end{bmatrix} = \begin{bmatrix} \rho & 0 & 0 & 0 \\ 0 & \gamma_1 & 0 & 0 \\ 0 & 0 & \gamma_2 & 0 \\ 0 & 0 & 0 & \gamma_3 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ u_{t-1}^1 \\ u_{t-1}^2 \\ u_{t-1}^3 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_t \\ \gamma_t^1 \\ z_t^2 \\ z_t^3 \end{bmatrix} \tag{8}$$

Among them,

$$\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \sim N\left(\begin{bmatrix} 0_{6\times1} \\ 0_{4\times1} \end{bmatrix}, \begin{bmatrix} H_t & 0 \\ 0 & Q \end{bmatrix} \right), H_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4t}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5t}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{6t}^2 \end{bmatrix} \tag{9}$$

$$Q = \begin{cases} \begin{bmatrix} 1-\rho^2 & 0 & 0 & 0 \\ 0 & \sigma_1^2 & 0 & 0 \\ 0 & 0 & \sigma_2^2 & 0 \\ 0 & 0 & 0 & \sigma_3^2 \end{bmatrix} & \rho \neq 1 \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \sigma_1^2 & 0 & 0 \\ 0 & 0 & \sigma_2^2 & 0 \\ 0 & 0 & 0 & \sigma_3^2 \end{bmatrix} & \rho = 1 \end{cases} \tag{10}$$

IV. Machine learning-based financial risk early warning models

IV. A. Extreme Learning Machines

IV. A. 1) Single hidden layer forward neural network

Extreme learning machine is a special kind of single hidden layer forward neural network [26], [27], therefore, before introducing the theory of extreme learning machine, it is necessary for us to introduce the principles and advantages of single hidden layer forward neural network.

Single implicit layer forward neural network has been widely used in many research fields, with very strong function fitting ability [28], which can theoretically approximate any nonlinear function, and compared with the traditional statistical measures, it has better learning ability, and it can adapt to the complex characteristics of the data through the training of a large amount of data.

For single hidden layer forward neural networks, error-based backpropagation is one of the more common algorithms, the principle of which is shown in Fig. 2.

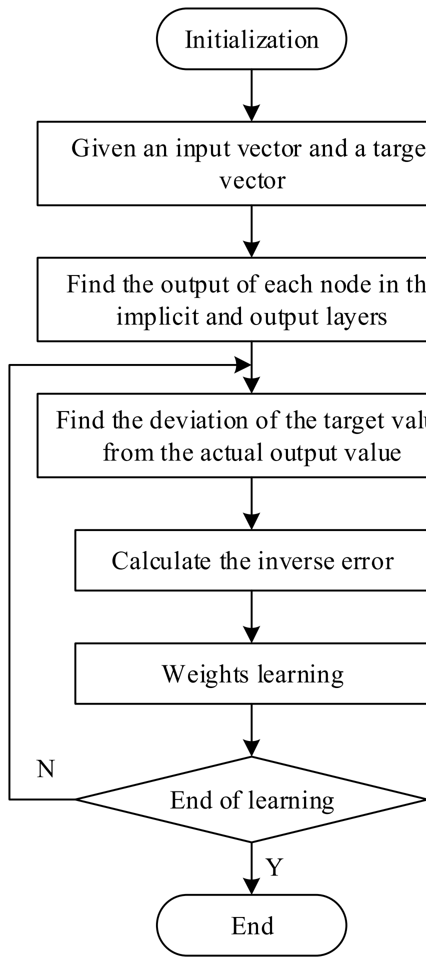


Figure 2: Neural network principle

For the training set $\{X,T\}=\{x_j,t_j\}$ with N sample, where $x_j \in R^p$ and $t_j \in R^q$ denote the input and output vectors of the j th sample, respectively, the variable p denotes the dimension of the input vector, and q denotes the dimension of the target output vector. In a standard single hidden layer forward neural network, p input nodes and q output nodes are connected through n_h hidden layer neurons.

The model is mathematically represented as:

$$\sum_{i=1}^{n_n} \beta_i g\left(w_i^T x_j + b_i\right) = t_j \tag{11}$$

where $w_i \in R^p$ is the input weight vector of the connection between the input node and the i nd implicit layer node. b_i is the bias of the i th implicit layer node. $\beta_i \in R^q$ is the output weight vector connecting the i th implicit layer node. g represents the activation function of the implied layer node.

Using matrix representation, Eq. (11) can be expressed as:

$$H\beta = T \tag{12}$$

Among them:

$$H = \begin{pmatrix} g\left(w_1^T x_1 + b_1\right) & \cdots & g\left(w_{n_h}^T x_1 + b_{n_h}\right) \\ \vdots & \ddots & \vdots \\ g\left(w_1^T x_N + b_1\right) & \cdots & g\left(w_{n_h}^T x_N + b_{n_h}\right) \end{pmatrix} \tag{13}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{n_h}^T \end{bmatrix}, T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix} \tag{14}$$

Matrix H is the hidden layer output matrix. In general, the process of training a single hidden layer feedforward neural network is to find suitable $\hat{w}_i$, $\hat{b}_i$, $\hat{\beta}_i\left(i = 1,\cdots,n_h\right)$ to satisfy the constraints:

$$\begin{aligned} &\left\| H\left(\hat{w}_1,\ldots,\hat{w}_{n_h},\hat{b}_1,\ldots,\hat{b}_{n_h}\right)\hat{\beta} - T \right\| \\ &= \min_{w_i,b_i,\beta_i} \left\| H\left(w_1,\ldots,w_{n_h},b_1,\ldots,b_{n_h}\right)\beta - T \right\| \end{aligned} \tag{15}$$

In that case, it is equivalent to obtaining the minimum value of the cost function:

$$E = \sum_{j=1}^{N} \left(\sum_{i=1}^{n_i} \beta_i g\left(w_i \cdot x_j + b_i\right) - t_j \right)^2 \tag{16}$$

Let W be the set of parameters $\hat{w}_i$, $\hat{b}_i$, $\hat{\beta}_i\left(i = 1,\ldots,n_h\right)$. In order to find the minimum value of $\left\| H\beta - T \right\|$, it is necessary to find the optimal W to minimize the formula, and the most commonly used method is the gradient-based BP neural network algorithm. This algorithm is trained according to error back propagation and adjusted W to reach the optimal value through iterations:

$$W_k = W_{k-1} - \eta \frac{\partial E(W)}{\partial W} \tag{17}$$

Of these, η is learning efficiency.

IV. A. 2) Principles of Extreme Learning Machines

As the most common method of iteratively adjusting the parameters in the network, the standard BP neural network algorithm based on gradient descent has a long computation time, poor generalization performance, and the accuracy usually cannot reach a high standard in real classification problems, and these defects have become a bottleneck affecting the development of feedforward neural network applications based on gradient descent.

Based on the problems described above, a novel single hidden layer forward neural network model has emerged, which is the Extreme Learning Machine (ELM), an improvement of the back propagation algorithm, which is able to enhance the learning efficiency and simplify the setting of learning parameters. Extreme Learning Machine is believed to contain some mechanisms of biological learning, and its name implies that it crosses the barrier between traditional machine learning and biological learning. Extreme Learning Machines have become an important method for nonlinear modeling due to their good performance, and they are usually used to deal with problems such as binary classification, multiclassification, and multivariate regression. Extreme learning machines have been continuously developed and improved to become independent learning systems that contain a complete theory and are linked to other machine learning methods.

Comparing the standard BP neural network and the extreme learning machine, they are similar in that they are both forward neural network structures with a single hidden layer, and the main difference is that the former utilizes back-propagation for learning, which requires iterative updating of weights and thresholds, whereas the latter relies on increasing the number of nodes in the hidden layer to achieve the purpose of learning. Compared to traditional forward neural networks, extreme learning machines have superior learning efficiency, and many models based on extreme learning machines can be trained in a very short period of time, which is faster than most traditional single-hidden layer neural network learning algorithms. In most cases, extreme learning machines have better adaptability to different sample data. In addition, limit learning machines are less likely to fall into dilemmas such as local optimization and overfitting, and can directly obtain optimal solutions.

The structure of a standard limit learning machine is shown in Figure 3.

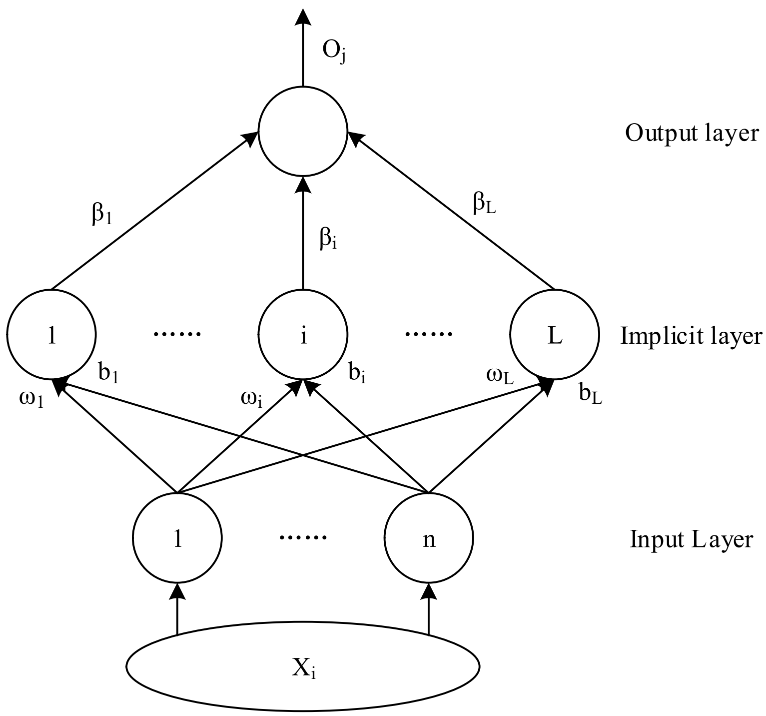


Figure 3: Extreme learning machine structure

The limit learning machine randomly initializes the weights and deviations from the input layer to the hidden layer according to a certain probability distribution to obtain a unique optimal solution, even if the hidden layer nodes are randomly generated, the limit learning machine maintains the approximation ability of a single hidden layer forward neural network, while the weights from the hidden layer to the output layer are obtained by solving a least squares problem.

For a standard network of extreme learning machines, assuming N arbitrary sample $\left(X_i, t_i\right)$, where $X_i=\left[X_{i1}, X_{i2}, \ldots, X_{in}\right]^T \in R^n$, $\left[t_{i1}, t_{i2}, \ldots, t_{in}\right]^T \in R^m$, a neural network with L hidden layer nodes can be represented as:

$$\sum_{i=1}^{L} \beta_i h\left(W_i \cdot X_i+b_i\right)=O_j,(j=1, \ldots, N) \tag{18}$$

where, $h(x)$ is the activation function, $W_i=\left[w_{i1}, w_{i2}, \ldots, w_{in}\right]^T$ is the input weights, β_i is the output weights, b_i is the bias of the i th hidden layer unit, $W_i \cdot X_i$ is denoted as the inner product of W_i and X_i, and O_j is the output of the system. The goal of the extreme learning machine is to minimize the output error of the network, which can be expressed as:

$$\sum_{j=1}^{N}\left\|O_j - t_j\right\| = 0 \tag{19}$$

That is, there exist β_i, W_i and b_i such that $\sum_{i=1}^{L}\beta_i\left(W_i * X_j + b_i\right) = t_j$, $\left(j = 1,\ldots,N\right)$, can be matrix-represented as $H\beta = T$.

$$H = \begin{pmatrix} h\left(\omega_1 \cdot x_1 + b_1\right) & \ldots & h\left(\omega_L \cdot x_L + b_L\right) \\ \vdots & \cdots & \vdots \\ h\left(\omega_1 \cdot x_N + b_1\right) & \cdots & h\left(\omega_L \cdot x_N + b_L\right) \end{pmatrix}_{N\times L} \tag{20}$$

$$\beta = \begin{pmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{pmatrix}_{L\times m} \quad T = \begin{pmatrix} T_1^T \\ \vdots \\ T_N^T \end{pmatrix}_{N\times m} \tag{21}$$

where H is the output of the hidden layer node, h is the output weight, and T is the desired output.

The training process of the extreme learning machine can be simply described as the process of solving the linear system $\left(H\beta = T\right)$, and so it is derived:

$$\hat{\beta} = H^{+}T \tag{22}$$

where H^{+} is the Moore-Penrose generalized inverse matrix of matrix H. After computing to obtain β, a network training of an extreme learning machine is realized.

IV. B. Extreme Learning Machine Early Warning Model Setting

The purpose of this subsection is to utilize the machine learning method based on extreme learning machine for early warning identification of systemic risk status and influencing factors in Chinese financial stock market.

The accumulation and outbreak of systemic risk in the stock market is a nonlinear and complex process, and the characteristics of the extreme learning machine can overcome the shortcomings of traditional early warning methods in model setting and make more accurate predictions, while also effectively avoiding the interference of some human factors. Therefore, this paper will utilize the advantages of the extreme learning machine and try to apply the extreme learning machine to the stock market systematic risk state identification and classification.

The modeling steps of the early warning model based on the extreme learning machine can be summarized as follows:

(1) Sample classification

Before constructing the machine learning model, the dataset is firstly divided into training set and testing set. In order to make the Extreme Learning Machine model have high prediction accuracy, a large number of relevant data sets need to be used to train the model, and it is required that the training data should not be too small and should have a certain degree of representativeness.

In this paper, a total of 168 months of data from January 2008 to December 2021 are selected as the sample dataset of the model, and a total of 132 months of data are classified as the training set and 36 months of data are classified as the test set. The optimal extreme learning machine warning model is constructed by training the training set, and then the effect of the extreme learning machine model is verified based on the test set data.

(2) Create and train an extreme learning machine warning model

In the process of creating and training an extreme learning machine model, parameter setting is a very critical part. Reasonable parameter setting largely determines the effect of the model, which is mainly to adjust the activation function and the number of neurons in the hidden layer in the extreme learning machine algorithm. In addition, the data should be preprocessed before model creation.

(3) Simulation test

After establishing and training the extreme learning machine warning model, simulation test can be carried out. The data input of the test set will be tested and examined to get the corresponding prediction results and accuracy. In this paper, the simulation test is carried out by Matlab software.

(4) Evaluate the model performance

When the final prediction results are obtained, the predicted values of the test are compared with the real values according to the evaluation criteria. In this paper, the performance of the extreme learning machine model is mainly evaluated based on the classification accuracy obtained from the experiment. If the model performance is not satisfactory, the model parameters can be adjusted again.

The steps of the extreme learning machine model are shown in Figure 4.

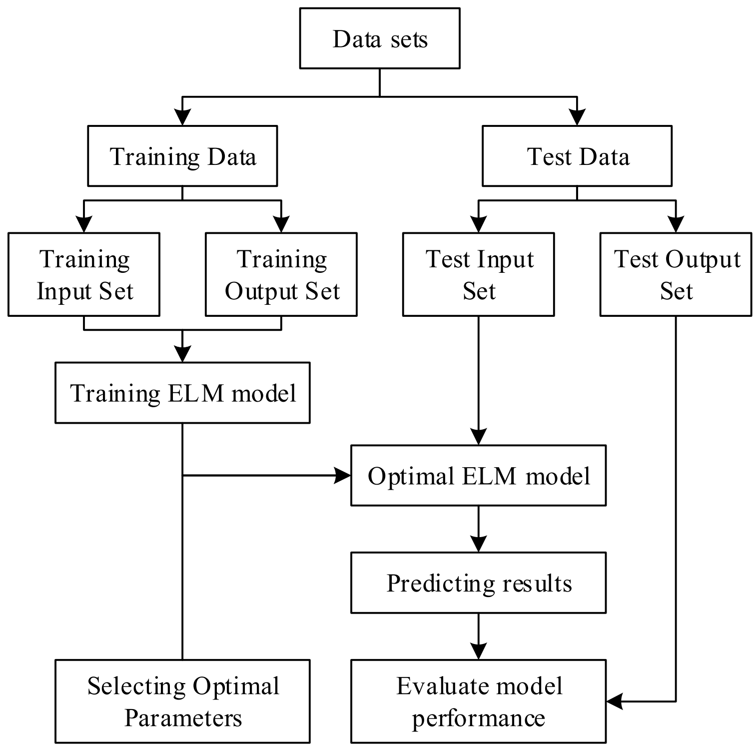


Figure 4: ELM model process

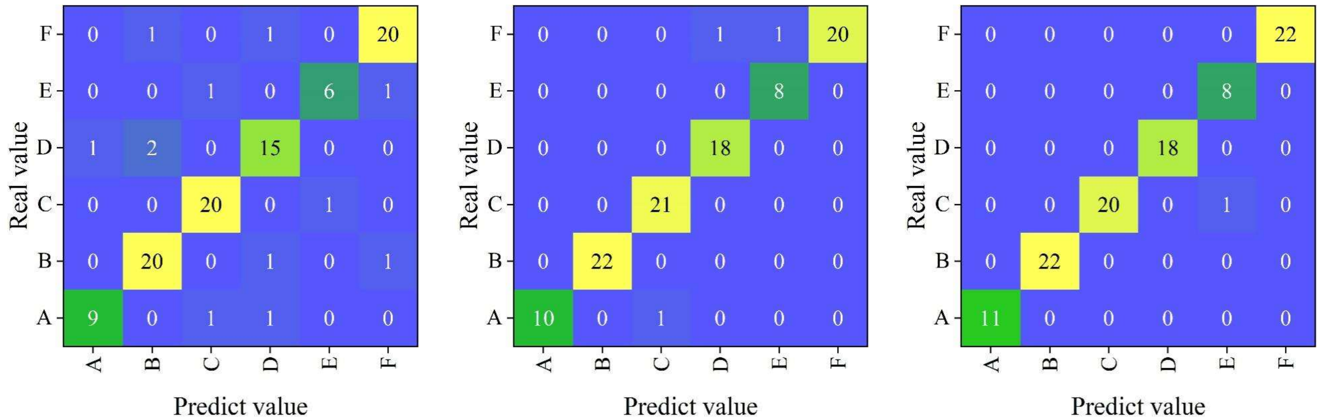
V. Model early warning analysis

V. A. Comprehensive model evaluation

The prediction of financial risk state in this paper is essentially a multi-classification problem, so the confusion matrix is used for the performance measure of the classifier, and the three models, BPNN, Random Forest and ELM in this paper, are evaluated and analyzed. For multi-classification problems, the confusion matrix can describe and compare the real situation of the model and the prediction results, and the confusion matrix can also be used to evaluate more intuitively the advantages and disadvantages of the classification effect of the three types of network models used in this paper. The confusion matrices for each of the BPNN, Random Forest and ELM network models are shown in Fig. 5, where A~F represent the six financial risk levels of safety, basic safety, concern, caution, alert and danger, respectively.

Based on the obtained confusion matrix, this paper adopts the accuracy rate, check all rate, check accuracy rate, specificity (TNR), and F1 as the performance evaluation indexes of the specific multi-classifier network model, and obtains the classification performance evaluation results of the BPNN, Random Forest, and ELM network models for the six financial risk categories in this paper as shown in Table 1.

In terms of model accuracy, the accuracy of the three types of machine learning algorithm models is at a high level, with the overall accuracy ACC of the ELM algorithm model amounting to 0.990, the Random Forest model coming second, with an accuracy ACC of 0.971, and the BPNN network model with the lowest accuracy but still as high as 0.882, which indicates that the three types of machine learning algorithm models selected in this paper have a good accuracy and credibility in the study of early warning of systemic financial risks have good accuracy and credibility in terms of systemic financial risk early warning research.



(a) BPNN confusion matrix (b) RF confusion matrix (c) ELM confusion matrix

Figure 5: BPNN, RF and ELM network model confusion matrix

The BPNN, Random Forest, and ELM network models likewise have large differences in classification performance for individual systemic financial risk states. (1) In the A risk class, i.e., the safe state, ELM has the highest Recall value of 0.921, and Random has the lowest Recall value of only 0.896, and the three models have the same performance in the checking accuracy Precision. In terms of specificity TNR, the BPNN model is consistent with ELM, and the F1 value of ELM is also the highest, so for A risk class, the classification performance of ELM model is the best. (2) In the B risk level, i.e., the basic safety state, the values of the four evaluation indexes of the ELM model are all 1, the Random Forest model is the second highest, and the BPNN model is only slightly inferior to the Random Forest in terms of the specificity TNR, so for the B risk level, the classification performance of the ELM model is the best. (3) In the C risk level, i.e., the state of concern, the values of the four evaluation indexes of the random forest model are higher than or equal to the other two models, and the BPNN model is superior to the ELM model, so it is considered that the predictive output of the random forest model is the best in this level. (4) In the D risk level, i.e., the cautious state, the evaluation values of the four indicators of the ELM model are all 1, which is better than the BPNN and Random Forest model, and the Random Forest model is only slightly lower than the BPNN model in the specificity TNR, so for the D risk level, the ELM model is also considered to have the best performance. (5) In the E risk level, i.e., alert status, the evaluation index values of the three models are the same, all of them are 1, indicating that the three models have the same performance in the classification of alert risk status. (6) In F risk level, i.e., hazardous state, Random Forest and ELM models have the same Recall value, Precision value, and F1, and the TNR of ELM model is lower than that of Random Forest model by 0.003, while the BPNN model performs the worst in these evaluation index values, so that Random Forest model has the best performance in F risk level.

In summary, it can be seen that the ELM model has the best performance among the three types of network models compared in this paper, both in terms of the overall accuracy of the model and the performance on individual risk levels. Therefore, it is considered that the systematic financial risk early warning model based on ELM model constructed for the machine learning-based systematic financial risk early warning research studied in this paper has the best applicability.

Table 1: Comparison of model index evaluation results

Model	Risk level	Accuracy	Recall	Precision	TNR	F1
BPNN	A	0.818	0.912	1.000	0.975	0.924
	B	0.909	1.000	0.936	0.957	0.968
	C	0.952	1.000	0.914	0.942	0.922
	D	0.833	1.000	0.937	0.929	0.965
	E	0.750	1.000	1.000	1.000	1.000
	F	0.909	0.922	0.931	0.923	0.944
RF	A	0.909	0.896	1.000	0.952	0.915
	B	1.000	1.000	0.936	0.963	0.968
	C	1.000	1.000	0.958	0.967	0.975
	D	1.000	1.000	0.937	0.925	0.965

	E	1.000	1.000	1.000	1.000	1.000
	F	0.909	0.955	0.934	0.943	0.962
ELM	A	1.000	0.921	1.000	0.975	0.967
	B	1.000	1.000	1.000	1.000	1.000
	C	0.952	0.953	0.948	0.933	0.942
	D	1.000	1.000	1.000	1.000	1.000
	E	1.000	1.000	1.000	1.000	1.000
	F	1.000	0.955	0.934	0.940	0.962

V. B. Analysis of explanatory models

Although the machine learning model has better prediction performance and accuracy than the linear model when making predictions, it also loses the interpretability of the linear model, that is, there is a "black box" problem [29].

SHAP is a post-hoc model interpretation method, which is based on the cooperative game theory proposed by Shapley, and introduces Shapley's value to calculate the “marginal contribution” of features to the model output, so as to explain the black-box model from the global or local level. SHAP can be used to explain the black-box model in the context of machine learning modeling. The SHAP explanation model can be used to explain machine learning modeling results, where all features are considered as “contributors” to the model results, and the importance and influence of each feature on the model results can be measured.

The code in this section is based on Python's SHAP library to implement the SHAP explanatory model, which utilizes a tree-specific interpreter to obtain the contribution of each feature to the probability of risk warning, i.e., the Shapley value. The SHAP model implements the Shapley absolute mean as a measure of the significance of each feature indicator variable in the risk warning situation, and the results are shown in Table 2.

Table 2: Shapley absolute mean of the characteristic indicator variable

Number	Characteristic indicator	Shapley absolute mean
1	GDP (X1)	0.23992681
2	CPI (X2)	0.30113435
3	M2 (X3)	0.45833431
4	Domestic Credits (X4)	0.15160358
5	1-year LPR (X5)	0.13526179
6	P/E (X6)	0.33865923
7	Market value (X7)	0.30003963
8	SZI (X8)	0.57301069
9	ChinaBond Composite Index (X9)	0.24500023
10	1-week and 1-year SHIBOR Spread (X10)	0.11361415
11	7-day Interbank Repo Rate (X11)	0.41483434
12	Real Estate Climate Index (X12)	0.34853534
13	Gold Price(X13)	0.20846858
14	Oil Price (X14)	0.32365568
15	Foreign Exchange Reserve (X15)	0.48462158
16	REER (X16)	0.14130889
17	DJIA (X17)	0.40197149
18	N225 (X18)	0.40659892
19	S&P500 (X19)	0.49417495
20	VIX (X20)	0.76047199
21	USDX (X21)	0.43340279
22	Open (X22)	0.14591535
23	Close (X23)	2.16620467
24	High (X24)	0.53250194
25	Low (X25)	0.40048658
26	Volume (X26)	0.37297756

The results of Shapley's absolute mean are sorted by size and the importance ranking of the characteristic indicator variables is shown in Figure 6. It can be observed from the figure that the top ten characteristic indicator variables in terms of importance are, in order, closing price (X23), VIX panic index (X20), SZSE composite index (X8), maximum price (X24), S&P 500 index (X19), foreign exchange reserves (X15), year-on-year growth rate of M2 (X3), US dollar index (X21), inter-bank 7-day pledged repo weighted rate (X11) and Nikkei 225 (X18), with importance indicator values (Shapley's absolute mean) of 2.1662, 0.7605, 0.5730, 0.5325, 0.4942, 0.4846, 0.4583, 0.4334, 0.4148, and 0.4066, respectively. Among them, the closing price and the highest price belong to the technical indicator dimension of the VIX Panic Index, S&P 500 Index, US Dollar Index and Nikkei 225 Index are the characteristic indicator variables of the external market dimension, and their importance rankings are 2nd, 5th, 8th and 10th respectively, indicating that the importance level of the characteristic indicator variables of the external market dimension is not significant, which means that the external market is the most important indicator for early warning of systematic risk. The high importance level and overall high ranking of the variables characterizing the external market dimension indicate that changes in the external market are an important influence on the level of systemic risk in China's stock market. Foreign exchange reserves and the interbank 7-day pledged repo weighted rate belong to the foreign exchange market and money market dimensions, and their importance rankings are 6th and 9th respectively, indicating that the foreign exchange market and the money market also affect the level of systemic risk in the Chinese stock market.

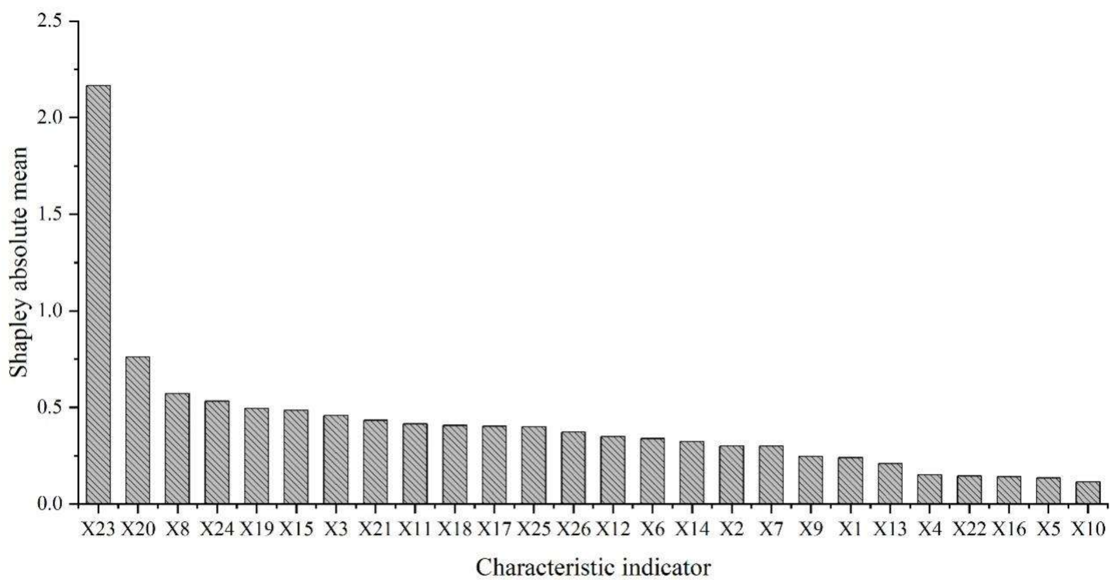


Figure 6: Importance ranking of characteristic indicators

Since the above importance level can only reflect the relative importance level of each characteristic indicator variable affecting the systemic risk of the stock market, and cannot show the direction of the role of each characteristic indicator variable on the probability of early warning of systemic risk, therefore, based on the SHAP model, we draw the decomposition chart of Shapley value to analyze the probability of pulling or reducing the warning probability of systemic risk of each characteristic indicator variable, and after the black box of SHAP model After the black box decomposition of SHAP model, the dynamic change of Shapley value year by year is shown in Fig. 7, which is the main feature indicator that pulls and reduces the probability of early warning risk.

Among the top 10 characteristic index variables in importance, the closing price (X23), the highest price (X24) and the 7-day pledged repo weighted rate (X11) are the indicators that pull the risk warning probability, and the larger the corresponding eigenvalue, the higher the risk warning probability. The VIX Fear Index (X20) and the US Dollar Index (X21) are not indicators that can significantly pull or reduce the risk warning probability, but their importance is high, indicating that the VIX Fear Index and the US Dollar Index will have an impact on the systemic risk of China's stock market in the external market dimension, but whether the risk warning probability is in the direction of pulling or decreasing needs to be analyzed on a case-by-case basis. The SZSE Composite Index (X8), the S&P 500 Index (X19), foreign exchange reserves (X15), the year-on-year M2 growth rate (X3) and the Nikkei 225 Index (X18) are all indicators that reduce the probability of risk, and the larger the corresponding eigenvalues, the smaller the warning probability of risk (i.e., the smaller the corresponding eigenvalues, the larger the warning probability of risk). It indicates that the S&P 500 and Nikkei 225 indexes play a pull-down role on the warning probability of systemic risk of the Chinese stock market in the external market dimension, i.e., the smaller the corresponding eigenvalue is, the larger the warning probability of systemic risk of the stock market is. The SZSE

Composite Index, foreign exchange reserves and M2 year-on-year growth rate play a lower role in the stock market dimension, foreign exchange market dimension and macroeconomic dimension, respectively, in the early warning probability of stock market systemic risk, i.e., the smaller the corresponding eigenvalues are, the larger the early warning probability of stock market systemic risk is.

Combining the results obtained from the Shapley trend chart with historical stock market crisis events, further analysis of the characteristic indicators affecting stock market systemic risk reveals that the smaller the foreign exchange reserves, the greater the likelihood of stock market systemic risk. The smaller the year-on-year growth rate of China's M2, the greater the likelihood of systemic risk in China's stock market, indicating that the systemic risk of China's stock market is closely related to the domestic economic situation and monetary policy.

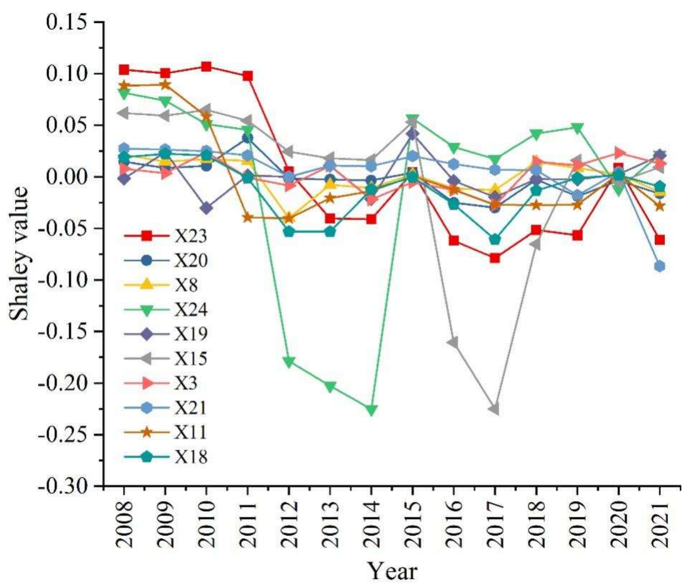


Figure 7; Shapley value trend diagram from 2008-2021

V. C. Early warning analysis of financial risks

V. C. 1) Composite Early Warning Index Measurement

The NSR calculation of the aforementioned indicators, theoretically, indicates safety when the value of the early warning indicator falls within the threshold range, while falling outside the threshold range indicates the possibility of a crisis. In the early warning system, only the GDP growth rate and the domestic and foreign real interest rate deviation have upper and lower thresholds because: although the higher the GDP growth rate the stronger the ability to withstand risks, too fast a growth rate will lead to unbalanced economic growth. And the domestic and foreign interest rate differentials, whether the domestic interest rate is too high or too low, can cause the investment environment to become dysfunctional. Other early warning indicators are based on their own correlation, with positive correlation indicators sending out early warning signals when they are greater than a threshold, and vice versa for safety. Negative correlation indicators send early warning signals when they are less than the threshold, and vice versa.

Since the noise signal ratio is negatively correlated with the early warning capability, when the NSR is greater than 1, it means that the noise in the signal issued by the early warning indicator is more than the correct signal, and should be eliminated. Based on this principle, in the early warning system of this paper, the NSR of deposit growth rate and one-year bank deposit yield is greater than or equal to 1, which should be eliminated. After that, when the value of the indicators in the early warning system exceeds the critical value, the early warning signal is issued, and the early warning signal takes the value of 1. When the value of the indicators is safe, the early warning signal takes the value of 0, and the signal status of the indicators in each year is shown in Table 3.

Table 3: Signal state of the warning indicator

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
X1	0	0	1	0	0	0	0	1	0	0	0	0	1	0
X2	1	0	0	0	1	0	1	0	0	1	0	1	0	1
X3	0	1	0	1	0	1	0	1	0	0	0	1	1	0

X4	0	0	0	0	1	0	0	1	0	0	1	0	1	1
X5	1	0	0	0	1	0	1	0	1	0	0	0	0	0
X6	0	0	1	0	0	0	0	0	0	1	0	0	1	1
X7	1	0	0	1	0	0	1	1	0	0	0	1	0	1
X8	0	0	0	0	0	1	0	1	0	0	0	0	1	0
X9	0	1	0	0	0	0	0	1	1	0	1	1	0	0
X10	1	0	0	0	0	0	1	0	0	1	0	0	1	0
X11	0	0	1	0	0	0	0	1	0	0	0	0	1	1
X12	0	0	0	1	1	0	0	0	0	0	1	0	1	0
X13	1	0	0	0	1	1	0	0	1	0	0	1	0	1
X14	1	0	0	0	0	0	0	1	0	1	0	0	1	0
X15	0	1	1	0	0	0	0	0	0	0	1	1	1	1
X16	0	0	0	1	0	0	1	0	1	0	0	0	0	0
X17	0	0	0	0	1	0	0	1	0	0	0	1	1	0
X18	0	0	1	0	0	0	0	1	0	1	0	0	0	0
X19	1	0	0	0	0	1	0	0	0	0	0	1	1	0
X20	0	1	0	1	0	0	0	1	0	0	0	1	0	1
X21	0	1	0	1	0	0	1	0	1	0	0	0	1	0
X22	0	0	0	0	0	1	0	1	0	1	0	1	1	0
X23	1	0	1	0	1	0	0	0	0	0	1	0	1	0
X24	0	0	0	1	0	1	0	0	0	0	0	1	0	1
X25	0	1	0	0	0	0	1	0	1		0	0	1	0
X26	0	0	0	0	1	0	0	1	0	1	0	0	0	1

The thresholds of the aforementioned relevant indicators, the optimal NSR and the signal values of the warning indicators in each year are calculated, and the warning index of systemic financial risk in each year is obtained as shown in Table 4. According to the relevant research, China's economic operating conditions are now categorized into safety zone, basic safety zone, alert zone, danger zone and deep danger zone, and the following conclusions can be drawn:

From the data from 2008 to 2013, the systemic financial risk early warning index is at a low level, most of the early warning indicators are in a safe state, and the economic conditions are all in the basic safety zone.The early warning index in 2014 (0.44752) broke through 0.4, and fell into the alert zone.The early warning index in 2015 (0.59065) was close to 0.6, still in the alert zone but close to the danger zone The warning index in 2016 (0.39955) was slightly less than 0.4, in the basic safety zone but still near the caution zone. 2017 and 2018 saw a decline in the warning index, falling into the basic safety zone and the safety zone, respectively. 2019 saw the warning index reach 0.43846, which approximates the boundary value of the caution zone. 2020 saw a surge in the warning index (0.66247), which breaks through the danger zone, representing the possibility of systemic financial risk within 12 months.

The value of the financial early warning index in 2021 is 0.34054, which is in the basic safety zone, and the probability of the outbreak of systemic financial risks in China from 2022 to 2023 is not high from a forecasting point of view, and the overall pressure is relatively small. As far as the signals of each early warning index are concerned, macroeconomic indicators such as GDP and CPI growth rates and most foreign exchange market indicators are more stable, while other indicators are lighted. Combined with China's real economic conditions and financial market dynamics at this stage, the real estate sector policies are gradually tightening, and the possibility of rising real estate risks in the future is extremely high. In terms of fiscal risk, local government debt under the pressure of macroeconomic downturn has always been the main source of debt crisis. In terms of balance of payments and financial markets, the uncertainties in Sino-US relations and the Russia-Ukraine situation have led to turbulence in the capital and foreign exchange markets. The complex international environment, coupled with the internal supply structure transformation, also requires monitoring in terms of tail risks.

Table 4: Systemic financial risk warning index

Year	Systemic financial risk warning index
2008	0.25125
2009	0.31456
2010	0.32985

2011	0.29468
2012	0.24586
2013	0.32674
2014	0.44752
2015	0.59065
2016	0.39955
2017	0.30356
2018	0.19354
2019	0.43846
2020	0.66247
2021	0.34054

V. C. 2) Comparative analysis of risk warning and financial composite stress indices

In order to better measure the predictive ability of the systemic financial risk early warning index, this paper analyzes the financial stress index by constructing it in comparison with the risk early warning results, so as to verify the model effectiveness. The national economy is an indivisible whole, can not use a single economic indicator to measure the pressure situation facing the financial system, so this paper adopts the financial composite stress index composition method and stress index index index selection, first of all, the money market, foreign exchange market, asset bubbles and other four subsystems of the financial stress index construction, the index selection as shown in Table 5, based on which reference to the IMF report synthesized financial composite pressure index.

Table 5: Financial comprehensive pressure index

Sub-system financial pressure index	Variable name	Variable number
Monetary market pressure index	Interbank lending rate	Y1
	Money supply (M2/GDP)	Y2
	Deposit and loan ratio	Y3
	Actual interest rate	Y4
Exchange market pressure index	Actual exchange rate	Y5
	Foreign exchange rate	Y6
Asset bubble pressure index	Stock price index	Y7
	Real estate development comprehensive economic index	Y8
Other pressure index	CPI	Y9
	Industrial added value growth rate	Y10
	Investment growth rate of fixed assets	Y11
	Export growth rate	Y12

The trends of the financial composite stress index and the four subsystem stress indices are analyzed, and the stress index trends are shown in Figure 8, where FCPI, CM, EMPI, ABP, and OPI denote the Financial Composite Stress Index, Money Market Stress Index, Foreign Exchange Market Stress Index, Asset Bubble Stress Index, and Other Stress Indices, respectively.

In terms of the currency market, the ABP has been fluctuating around 0 from 2008 to mid-2019, and peaked in the first quarter of 2020 with a surge in the outbreak of the new crown epidemic, after which it began to fall back and fluctuate slightly. In terms of the foreign exchange market, the EMPI reached a great value in 2015 and 2017, corresponding to the sharp depreciation of the RMB after the “811” exchange rate reform in 2015, and the emerging foreign exchange market turbulence affected by political factors after 2016. In terms of asset bubble conditions, the ABP continues to be at a high level in 2010, 2014 and 2015, and reaches its maximum value in 2020 when both the stock market and the real estate market are hit by the epidemic. In terms of other stress indices, they reach great values in 2013, 2014 and 2020, corresponding to China's macroeconomic development. In terms of China's Financial Composite Stress Index (FCPI), with 1 as the critical value: from 2008 to 2013, the financial system in general was less stressed and the system was more stable. 2013 broke through the critical value, especially due to the impact of the stock market turbulence and the real estate price escalation in the same year, and the stress index reached an extreme value. 2016 was less stressed before 2016, and 2016 again broke through the critical value. 2017 The stress index fluctuates but generally returns to a lower level during the period from 2017 to 2019. 2020 sees a surge in the stress index due to the impact of the new crown epidemic, which is characterized by depressed macroeconomic conditions, depressed financial markets, and volatile trade markets. As the epidemic is gradually brought under control and the economies of various countries return to the right track, the stress index declines and China's financial market stabilizes.

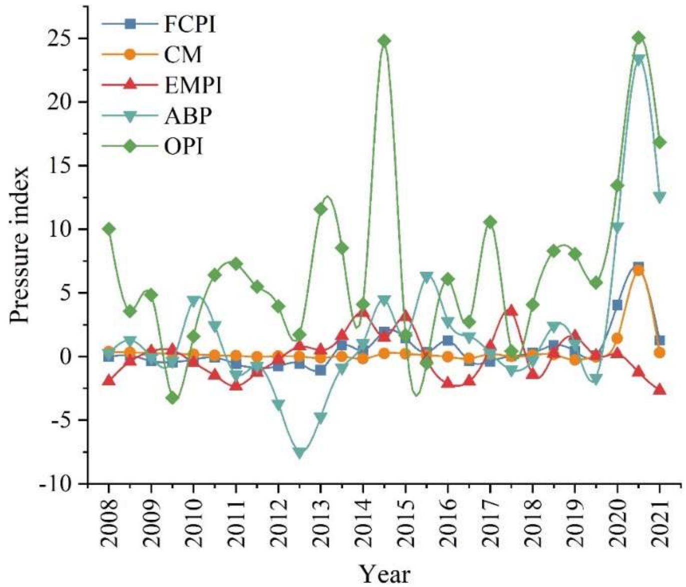


Figure 8: Pressure index diagram

VI. Financial risk prevention and control model

Based on the early warning analysis and prediction of China's financial system made by the financial risk detection and early warning models in Chapters 2 and 3, relative financial risk prevention and control methods are proposed.

VI. A. Sound early warning mechanisms for systemic financial risks

The systemic risk early warning mechanism should be based on a macro and global perspective, and should provide timely monitoring of risks in different industries, risks in key areas, risk contagion between industries, and overall financial risks in the market. The current risk situation in China is complex and critical, and it is imperative for regulators to take the lead in establishing a systemic financial risk monitoring and early warning mechanism. Under this monitoring and early-warning mechanism, regulations on systemic financial risk prevention should be formulated so that the response to systemic financial risks and financial crises is standardized, certain, orderly, predictable and transparent.

VI. B. Risk prevention and control of priority areas

Systemic risks in China are currently concentrated in the real estate sector and local government debt. China has now carried out risk prevention and control work in these two key areas. For the healthy and stable development of the real estate sector, a housing mechanism that combines renting and purchasing, multi-principal supply and multi-channel guarantee should be promoted as soon as possible. Local government debt should be tightly controlled, with increased restraints in terms of the sources of debt funding, where the funds go, how the debt is borrowed, and blacklists of risk-warning cities.

VI. C. Preventing risk contagion between different industries

The correlation between the banking sector and the real estate and real economy sectors, as well as the correlation between the internal financial market and the foreign economic environment, is very strong and increases significantly when the financial risk situation deteriorates. Therefore, this paper suggests focusing on monitoring real-time changes in inter-sectoral correlations and identifying cross-sectoral channels and modes of financial risk transmission, so that risk isolation measures can be implemented in a timely manner after a crisis occurs to avoid amplifying risk losses. In preventing the contagion of risks, the focus should be on the transmission of risks between the real estate industry and the banking sector, local government debt and the financial sector, and the shadow banking system.

VI. D. Establishment of risk response mechanisms for systemically important financial institutions

Systemically important financial institutions are characterized by the large number of industries involved, the complexity of their financial operations and the huge size of their assets. The subprime mortgage crisis in the United

States has demonstrated that the occurrence of operational risks or the closure and bankruptcy of such institutions will bring about incalculable shocks to the market, and is highly likely to trigger systemic risks. The supervision and risk prevention of such institutions should start from two aspects. First, special regulatory conditions should be established and differentiated requirements should be imposed on systemically important institutions. For example, on top of the general regulatory requirements currently in place, higher requirements should be set for important regulatory indicators such as capital adequacy ratio, liquidity coverage ratio, net stable funding ratio and provision coverage ratio. Secondly, on the basis of the existing regulatory requirements and crisis management mechanisms in various industries, a special risk management mechanism tailored to the situation of systemically important institutions should be established, so as to prevent systemic risks resulting from temporary difficulties in responding to crises within the institutions.

VI. E. Establishment of a comprehensive risk relief and compensation system

According to the theory of risk management, risk management should be carried out in a timely manner after the occurrence of risks. Risk relief compensation system is one of the methods in risk management. At present, the international market has securities investor compensation system, deposit compensation system, life insurance policyholder compensation system as an important way to resist financial risks and stabilize market operation.

Risk compensation mechanism has two major advantages: one is to protect individual investors, to avoid the risk of investor asset shrinkage, emotional panic, aggravate the market chaos; the second is to help financial institutions in the impact of liquidity risk, operational difficulties, insurance surrender rate rise and other chaotic conditions, this can protect the interests of both sides of the financial market transactions, maintain the order of the financial market compensation mechanism for the defense against risk has a This compensation mechanism can protect the interests of both parties in the financial market and maintain the order of the financial market, which is of great significance for risk prevention.

VII. Conclusion

The article constructs a financial risk detection model to detect financial early warning indicators in real time after in-depth study of financial risk influencing factors and transmission mechanism. The Extreme Learning Machine (ELM) algorithm in machine learning is used to construct the financial risk early warning model.

(1) The performance of the ELM model in this paper is compared with other risk warning models, and the overall accuracy of the ELM algorithm model is 0.990, which exceeds that of the random forest model (0.971) and the BPNN network model (0.882.) The ELM model achieves the optimal results in the four risk levels of A, B, D, and E. The ELM model is also used to detect the financial risk indicators in real time, and to detect the financial risk indicators in real time.

(2) The Shapley absolute mean of the top ten importance-ranked characteristic indicator variables ranges from [0.4066,2.1662]. The closing price, the highest price and the interbank 7-day pledged repo weighted rate are the indicators that pull the probability of risk warning, while the SZSE Composite Index, the S&P 500 Index, the foreign exchange reserves, the year-on-year growth rate of M2, and the Nikkei 225 Index are the indicators that reduce the probability of risk.During 2008-2013, the systemic financial risk is in the basic safety zone. 2014 (0.44752) fell into the alert zone. 2015 (0.59065) is in the alert zone. 2016 (0.39955) is in the basic safety zone. 2017 and 2018 were in the basic and safe zones, respectively. 2019 (0.43846) is close to the boundary value of the alert zone. 2020 (0.66247) breaks through the danger zone. 2021 (0.34054) is in the basic safety zone, which is used to predict a low probability of systemic financial risk outbreaks from 2022 to 2023.

(3) China's financial composite stress index and subsystem stress indices were both hit by the 2020 New Crown epidemic, with a surge in each stress index. As the epidemic was brought under control, the stress indices fell back and the financial market stabilized.

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