Exploration on Financial Risk Management under Machine Learning Algorithms

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Abstract: Financial crises have a cyclical nature. In the context of economic globalization and the new normal, trade, industry, financial markets, capital markets, foreign exchange markets, real estate, etc., among countries have become interconnected through multiple channels. At the same time, it also leads to a very complex transmission chain of financial crises. If a financial crisis occurs, it would have a significant negative impact on the country, society, and people's lives. On the basis of establishing a system of financial risk warning indicators, this article used principal component analysis to reduce the dimensionality of the selected economic and financial index data. The main factors affecting the system's financial risk were extracted, and the comprehensive indicator values obtained through K-means clustering analysis were used to divide the risk level, thereby determining whether the risk warning state has been reached. In the statistical results of financial risk using the random forest method, the probability of financial risk in 2019 was 19%; the probability of financial risk in 2020 was 8%, and the probability of financial risk in 2021 was 5%. By strengthening the identification and prevention of financial risks, this article can provide a more comprehensive and accurate monitoring and evaluation of financial risks.

Keywords: Machine Learning Algorithms, Financial Risks, Random Forests, Principal Component Analysis, Risk Warning

1. Introduction

Currently, the international financial crisis is characterized by short cycles, strong destructiveness, strong systematicity, and strong contagion. A series of financial risks such as excessive currency issuance, excessive financial liberalization, lack of regulation, and high leverage have provided a breeding ground for the occurrence of financial crises. From a global perspective, the global economy has been hit by a strong rebound from the epidemic, with stagflation, high debt, global energy crisis, and rising non-performing loan ratios for banks, all of which have exposed the fragility of the global financial market. During this period, China's economic development showed signs of stagflation. In addition, with the continuous outbreak of the real estate market, the high debt between enterprises and local governments, as well as the introduction of

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the "double reduction" policy, all indicate that economic and financial development is facing dual pressures from both internal and external sources. In the new development pattern, the prevention and resolution of financial risks must be given top priority, and a bottom-line mentality must be strengthened, with a view to resolutely preventing the outbreak of systemic financial risks in a problem-oriented manner. In such a situation, it is of great significance to establish a comprehensive risk warning and prevention mechanism for the financial system and implement comprehensive risk monitoring.

It is necessary to deal with financial risks as early as possible, eliminate the signs of risks in the bud, and maintain the bottom line of avoiding systemic financial risks, which is a necessary measure to ensure financial security. Yang Zihui was continuously improving the financial risk warning index and improving the prevention system of systemic financial risks in China [1]. Gu Zheng believed that technologies such as big data, blockchain, and artificial intelligence can help improve the coverage of financial risk management and enhance the pertinence of financial risk management [2]. Taking regional financial risks as the starting point, Shen Li constructed a regional financial risk correlation network and utilized social network analysis techniques to reveal the overall correlation between regional financial risks. Through methods such as centralization and modularization, she explored the structural characteristics of regional financial risk networks and their impact on regional financial risk levels [3]. However, their research lacks necessary data support for the management and early warning of financial risks.

This article analyzed the liquidity risk, non-performing asset risk, and default risk of corporate and local government debt in the current financial market based on the development status of the financial market. In addition, the external impact risk of the financial market has led to an increase in local risks, thereby increasing the risk of financial crises and systemic financial risks. Therefore, strengthening research on this issue is of great significance. This article analyzed the causes of financial risks in China's banking system from two aspects: external and internal factors. From the perspective of external factors, China's macroeconomic cyclical fluctuations and imprudent financial regulatory policies are important reasons for the systemic financial risks in the Chinese banking industry; From the perspective of internal reasons, the inherent defects of the financial market itself, the inherent defects of the financial system, and the irrationality of financial market participants collectively contribute to the outbreak of systemic financial risks.

2. Exploring Methods for Financial Risk Management

A. Machine Learning

Machine learning is an interdisciplinary problem involving multiple disciplines such as statistics, mathematics, and information theory, and its definition has always been controversial. The main research object of machine learning is artificial intelligence, which is the foundation of artificial intelligence and improves the performance of algorithms by learning from past experiences. Machine learning refers to the study of automatically improving computer algorithms through experience. According to the definitions of pioneers and the current applications of machine learning in various fields, the definition of machine learning can be summarized as: machine learning is a technology that helps humans make intelligent decisions by learning from past experiences or data. With the continuous progress of hardware and computer technology, some bottleneck problems faced by artificial intelligence in its development have been solved, which is also the reason why artificial intelligence has become increasingly popular in recent years.

Overall, in supervised learning, the training data would contain labeled information, which means that when training the sample data, the corresponding category or regression results of the sample would be known. Therefore, in the learning process, it would be like being supervised, rather than blindly learning. Supervised learning methods are mainly used for classification and regression, among which the most representative algorithms are logistic regression, Bayesian, support vector machine, decision tree, etc. Compared with supervised learning methods, unsupervised learning methods are more based on the feature vectors of each sample. Therefore, they are called "birds of a feather flock together" rather than classification, and their representative algorithms include Apriori, K-Means, and hierarchical clustering.

The semi supervised learning algorithm is actually a supervised learning method and has become a hot topic in recent years. Its main goal is to lack labeling information in a large number of samples, which makes it impossible to use supervised methods. However, it hopes to maximize the utilization of labeling information. Therefore, semi supervised learning is a good compromise between the two methods. Reinforcement learning is a method of learning optimal strategies that enable an ontology to take corresponding actions under certain conditions and current conditions, in order to achieve maximum benefits. Representative algorithms include dynamic programming method, time series difference method, Monte Carlo method, etc.

B. Financial Risks

(1) Financial risk classification

Financial risk refers to the uncertain factors faced by market participants in financial activities. Financial risks can be classified according to different classification methods [4-5]. From the perspective of the causes of risks, financial risks can be divided into static risks and dynamic risks. The probability distribution of dynamic financial risk varies over time, so it is basically unpredictable [6].

According to the essential characteristics of risk, it can be divided into two types: institutional and non-institutional [7-8]. Systemic financial risk refers to the risk caused by macro factors, which can have a certain impact on the overall economic environment and financial system. Non systematic financial risks caused by micro factors such as target setting and decision-making errors of financial activity participants may have an impact on the financial products obtained by some financial entities. Therefore, diversification or portfolio investment can be used to control or eliminate these risks. This article analyzed risk from four aspects: the impact of exchange rates, interest rates, stock and derivative product prices, and other factors on market risk [9]. Credit risk refers to a series of impacts caused by changes in the borrower's credit rating and ability to fulfill obligations [10-11]. The main manifestations of business risks are institutional defects and operational risks caused by human factors. Liquidity risk refers to a comprehensive impact caused by a lack of liquidity in the market [12]. The risk classification method is shown in Table 1.

Table 1. Risk Classification Method

Serial number	Dividing reasons	**Categorize**
1	Root causes of risks	Static financial risk
		Dynamic financial risk
2	Nature of risk	Systemic financial risks
		Non systemic financial risks
3	Risk drivers	Market risk
		Credit risk
		Operational risk
		Liquidity risk
		Legal risks

(2) Financial risk management steps

Financial risk management is divided into four stages: financial risk identification, financial risk measurement, financial risk disposal, and financial risk management evaluation and adjustment [13].

The identification of financial risks is the first step in financial risk management. For participants in the financial market, financial risk identification is a cross temporal identification, which means that it is not limited to current and single risks, but rather takes into account both potential and cross risks [14-15]. The first is to identify financial risks; the second is to analyze the characteristics and causes of financial risks.

Financial risk measurement is an important part of financial risk management, and the core of financial risk measurement is the selection of financial risk measurement models [16]. Financial risk measurement refers to the process of quantifying financial risks in financial risk assessment through model selection, model construction, and information and data collection.

An important aspect of financial risk management is financial risk management [17]. The disposal of financial risks can be divided into pre disposal and post disposal according to different timing. Preprocessing of losses, also known as control methods, involves selecting appropriate risk management techniques, monitoring and warning them [18]. The financial method of post loss processing refers to the inspection and adjustment of existing risk management techniques, selection of corresponding risk remedial measures, and offsetting compensation.

The evaluation and adjustment of financial risks is an important link in financial risk management [19].

The evaluation and adjustment of financial risk management is a supplement and improvement to the first three steps of financial risk management [20-21].

As China's economy enters a new normal, its economic development has entered a new cycle stage [22]. At present, in the process of China's development, there are various types of risks, including risks in the macroeconomic operation, sharp fluctuations in the stock market, and foam in the real estate market. China's finance and macroeconomic situation are relatively weak, and its ability to resist risks is also relatively weak. The outbreak of financial crises can easily trigger systemic financial risks [23]. With the gradual recovery of the national economy, it would gradually become stable. However, with the continuous deepening of China's economic restructuring and the increasing number of uncertain factors in the external economic environment, it is particularly important to control risks when making macro decisions. Therefore, when formulating relevant policies, the following issues should be fully considered [24]. One is to reasonably guide the rational investment of social capital and curb the disorderly and excessive influx of capital in the financial and real estate markets, blindly raising the value of social assets, and other situations. Necessary financing constraints should be implemented for enterprises with high asset liability ratios and a tendency towards financial speculation. Secondly, it is necessary to further deepen the reform of the financial industry and improve the systems and systems of the financial market, in order to completely eliminate various illegal and improper trading activities. The third is to strengthen the coordination and coordination of national macroeconomic policies, and create a good economic environment to reduce financial risks, thereby maintaining the stability and development of the financial market. At the same time, systemic financial risks are constantly accumulating, and their own particularity and complexity often make them overlooked. Therefore, there is an urgent need to improve the framework of China's macro prudential management system. At the macro level, breaking through individual financial institutions requires more attention to the complex relationships between Chinese financial institutions. Exploring a systematic financial risk regulatory system that is suitable for China's national conditions has important practical significance for monitoring and preventing risks in the Chinese financial system [25-26].

(3) Financial risk model

On this basis, a systematic financial risk warning model is constructed by constructing three machine learning methods: BP (Back Propagation) neural network, random forest, and CNN (Convolutional Neural Network).

1) BP neural network algorithm model

By using traditional fully connected feedforward neural networks and utilizing the learning ability of BP neural networks, the parameters of the neural network can be adjusted. When the training results of the network deviate from the predicted results, the BP neural network would continuously adjust the network parameters and thresholds based on the gradient of the loss function and the learning rate, until the output of the training set matches the expected results or the number of training meets the requirements.

2) Random forest algorithm model

Due to the fact that discontinuous output can cause overfitting of specific noise, it may be worse when dealing with regression problems than classification problems. However, random forest technology often achieves better results in solving complex problems due to its integrated learning characteristics. In response to the multi category problem of "systematic financial risk warning" and the complexity of the optimal space (high correlation of financial data and obvious chaotic characteristics), the random forest algorithm has more application value.

3) CNN algorithm model

CNN is a type of neural networks with forward feedback characteristics in BP neural networks. This article intended to draw inspiration from human visual cognitive mechanisms and utilize CNN to transform fully connected neurons into local connections between convolutional kernels, in order to achieve weight sharing and parameter reduction. The characteristic of weight sharing is that on the one hand, it can reduce a lot of weights, making it easy to learn and train; on the other hand, weight sharing can avoid network overfitting caused by too many parameters and improve generalization ability. On this basis, the CNN adopted can effectively automatically learn features from massive data to effectively solve the problem of feature loss caused by traditional PCA dimensionality reduction, and can promote similar data to achieve better classification results.

However, in the process of rapid economic growth in China, due to its procyclical nature, all participating entities have a blind and optimistic attitude towards future development, which has led to the accumulation of financial risks. In China, because of the high profits of the real estate industry, a large amount of capital flows into it. On the one hand, this would have a certain impact on the real economy. On the other hand, there would be a large amount of capital inflows, which would keep the house price rising, thus making the foam of the real estate market bigger and bigger. With the rapid development of internet finance, the boundaries of traditional finance have become increasingly blurred, and mixed operation has exacerbated the fragility of China's financial system, while excessive financial innovation has triggered a "thunderstorm" in the financial field.

The disorderly cross-border regulation by Chinese financial regulatory agencies has led to frequent occurrences of regulatory arbitrage. The Western countries led by the United States have joined forces to wage a trade war against China, impose blockades and sanctions on China, and due to the pandemic, the world economy has fallen into recession, which has also had some impact on China's economy. The current international situation in China is becoming increasingly complex, resulting in many uncertain factors in the Chinese financial system, which may trigger financial risks in the system. However, the emergence of systemic financial risks is a gradual accumulation process, so the outbreak of risks has certain precursors. By studying systemic financial risks and establishing warning models, risk outbreaks can be prevented and controlled. Therefore, using deep level dynamic factor models to accurately and timely measure and warn of China's systemic financial risks has important theoretical and practical significance.

3. Financial Risk Management Experiment

(1) Indicator design concept

This article constructed a systematic financial risk warning indicator system consisting of two primary dimensions: macro dimension and market dimension. The market dimension is further divided into five sub market dimensions: banking market, securities market, insurance market, real estate market, and foreign exchange market.

Macroscopic dimensions include GDP (Gross Domestic Product) growth rate, inflation rate, consumer confidence index, fixed assets investment growth rate, macroeconomic climate index, fiscal deficit and real interest rate indicators.

In addition, the non-performing loan ratio and deposit to loan ratio of banks are selected. The banking market is represented by the reserve requirement ratio of RMB (Renminbi) deposits and the growth rate of bank credit, and the securities market is represented by the average price to earnings ratio of stocks, securitization rate, and stock market volatility; the insurance market is represented by the comprehensive loss ratio, insurance depth, and insurance density, and the real estate market is represented by the growth rate of real estate investment, real estate price, national housing prosperity index, and the proportion of real estate development investment; the foreign exchange market is represented by the real effective exchange rate index, foreign exchange reserve growth rate, current account balance, and external debt liability ratio.

In estimating the expected return on stocks, there are:

$$g_h = Rf + G_i * (E(Rm) - Rf) \quad (1)$$

Among them, g_h is the expected return on the stock, and Rf is the risk-free interest rate.

(2) Data preprocessing

This article established a systematic financial risk warning indicator system that includes 25 economic and financial indicators from the perspectives of Wind database, China Banking and Insurance Regulatory Commission website, People's Bank of China website, National Bureau of Statistics website, etc. In this article, there were differences in the frequency of the collected raw data, which were divided into monthly data, quarterly data, and annual data. For the sake of accuracy and completeness of subsequent empirical results, 25 quarterly data of economic and financial indicators from 2018 to 2021 were selected as the standard dataset for frequency conversion of non quarterly indicator data. In academic research, it is common for some data sets to be missing due to unpublished data or untimely statistics. The data quality problem caused by missing data can to some extent affect the accuracy of subsequent model construction. Therefore, how to handle missing values in data is very important.

Currently, there are two main methods for handling missing values, namely data substitution and model prediction. The former can be replaced by means, such as mean difference interpolation, mean interpolation of the same class, random interpolation of mean of the same class, or approximate substitution, such as nearest interpolation and K-adjacent values. The latter uses other variables to predict missing values in the model, including regression prediction, maximum likelihood estimation, grayscale prediction, and random forest. When dealing with the problem of missing data, two main strategies are adopted: firstly, when the number of indices is too large, the corresponding indices are deleted; the second is to use the mean interpolation method to fill in another index when its quantity is insufficient. In addition, in order to standardize the 25 economic and financial indicators selected in this article, a reverse transformation method is used to normalize the negative index:

$$Y_{mn} = c/X_{mn} \quad (2)$$

Among them, c represents the normal number, and m represents 25 indicators.

Before conducting principal component analysis, this article used KMO (Kaiser Meyer Olkin) test and Bartlett spherical test. The applicability of KMO test and Bartlett test values is shown in Table 2. The KMO coefficient for the sample data was 0.7, indicating that the applicability of this factor was "very applicable"; the Bartlett spherical test method was "applicable" in factor analysis. Therefore, the test results showed that the data in this article met the requirements of PCA.

Table 2. Application of KMO Test and Bartlett Test Values

Test category	Numeric Range	Categorize
KMO value=0.7	[0.8,1)	Most applicable
	[0.6,0.8)	Very applicable
	[0.4,0.6)	Applicable
	[0.2,0.4)	Barely applicable
	[0,0.2)	Not applicable
BarlettTest of Sphericity	⩽0.05	Applicable

4. Exploration Results of Financial Risk Management

In order to more intuitively see the changes in the comprehensive evaluation indicators in 2019, the comprehensive evaluation indicators in this article are shown in Figure 1. There were significant differences in the comprehensive evaluation indicators in different months, indicating that the situation of systemic financial risk was also different in different periods.

The prediction results of the systematic financial risk status for the four quarters of 2019 using the BP neural network model are shown in Table 3. For the first quarter of 2019, it was the most applicable; for the second quarter of 2019, it was very applicable.

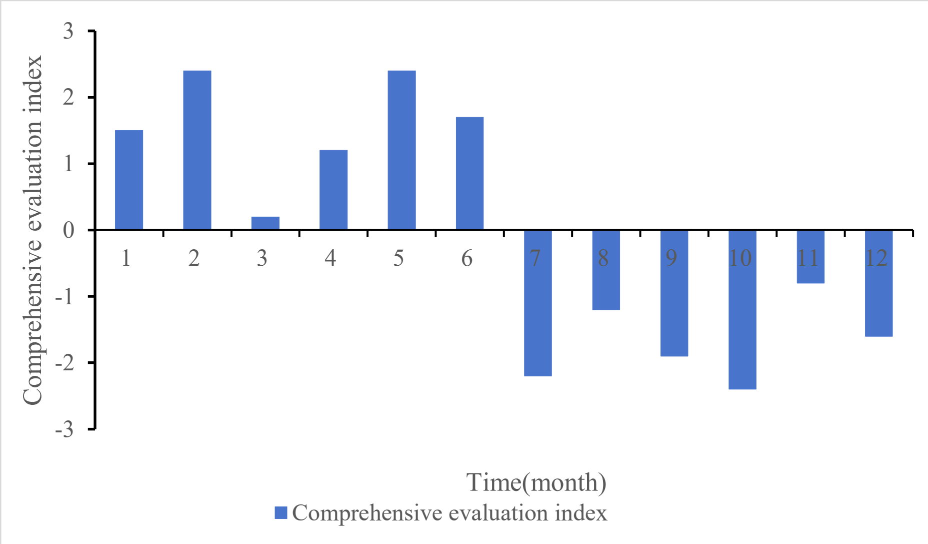

Fig 1. Comprehensive Evaluation Indicators in this Article

Table 3. Prediction Results of Systemic Financial Risk Status for the Four Quarters of 2019 Using BP Neural Network Model

Time	Categorize
First quarter of 2019	Most applicable
Second quarter of 2019	Very applicable
Third quarter of 2019	applicable
The fourth quarter of 2019	Barely applicable

The training and validation set curves of the CNN network model are shown in Figure 2. As the number of training samples increased, the loss functions of both the sample set and the confirmation set showed a decreasing trend, indicating that the network was convergent on this sample set and may enter local extremum.

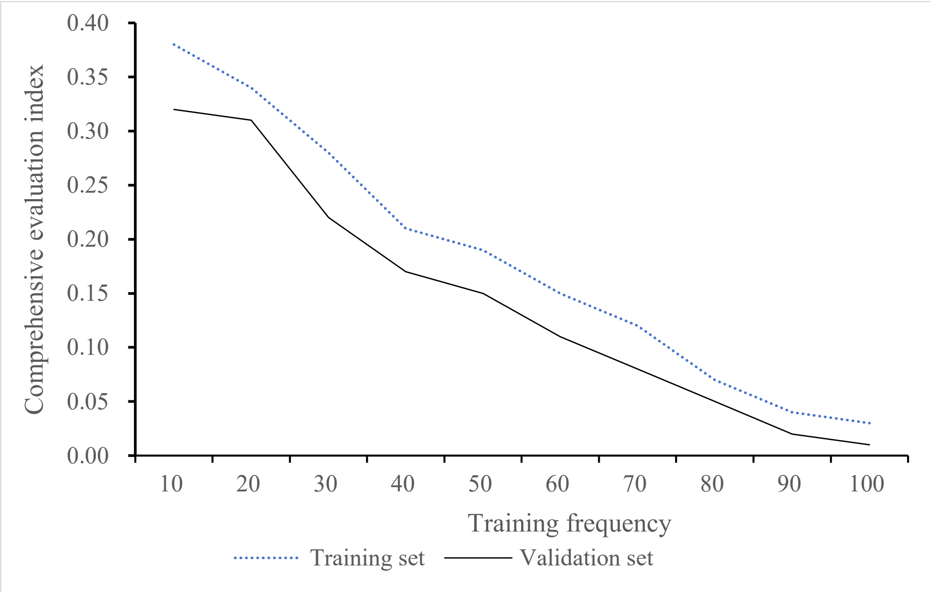

Fig 2. Training and Validation Set Curves of CNN Model

The statistical results of financial risk using the random forest method are shown in Figure 3. The average probability of financial risk in 2019 was 19%, in 2020 it was 8%, and in 2021 it was 5%.

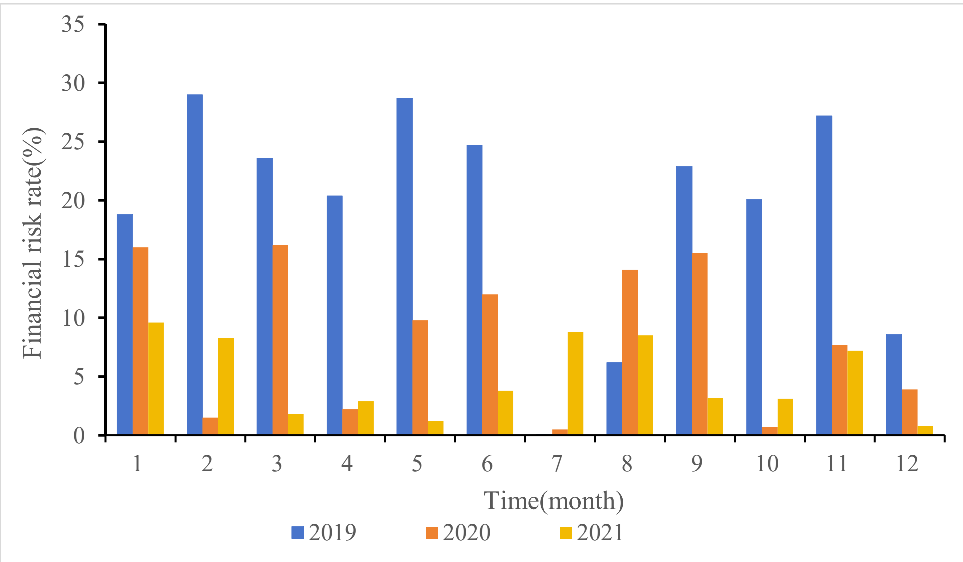

Fig 3. Statistical Results of Financial Risk Using Random Forest Method

5. Conclusions

This article analyzed the mechanism of systemic financial risk from three perspectives: theoretical connotation, current situation analysis, and cause exploration, and further enriched its theoretical research, thus forming a relatively complete and complete theoretical research system. This project planned to construct three machine learning algorithms based on BP neural network, random forest, and CNN for early warning. However, this article uses relatively basic machine algorithms. Therefore, in future research, this article can further improve and improve the model to improve its prediction accuracy.

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