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Early Warning of Financial Risk in China's Banking Sector Using Support Vector Machines

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Abstract

In this study, a credit risk early warning model is constructed for the Chinese banking industry based on the support vector machine (SVM) and kernel principal component analysis (KPCA). Monthly data from January 2008 to December 2024 are used to train the model, and then the credit risk level of the Chinese banking industry from January 2009 to December 2025 is predicted. Kernel Principal Component Analysis (KPCA) is used to pre-process the original features for dimensionality reduction and extract the key risk factors; subsequently, Support Vector Machine (SVM) is used as the core model to carry out the early warning modelling of credit risk in China's banking industry and compared with BP neural network and Logit regression model for validation. Preliminary experiments show that SVM exhibits a high degree of accuracy and stability in credit risk prediction, especially during periods of large market fluctuations, and is able to identify potential risk signals early. Furthermore, the trend of credit risk levels in the Chinese banking sector varies over time. Finally, this study recommends that Chinese government agencies and the banking sector remain vigilant against potential risks such as speculative bubbles in the capital market and continue to improve risk prevention mechanisms within the banking sector.

Keywords: banking industry; systemic risk; support vector machine; kernel principal component analysis; risk early warning

JEL code: C45; G21

1. Introduction

In recent years, the development of the global financial market and the trend of globalization have made the links between financial institutions increasingly close, and commercial banks play a very key role in the financial system. One of the main reasons for the outbreak of the international financial crisis in 2008 was the spread of systemic risks within the entire financial system and among the real economy. In China's financial system, the banking sector occupies a dominant position. Because systemic risk is characterized by global, contagious, and negative externalities, once the systemic risk of the banking sector occurs, the whole financial system and even the real economy of China will suffer catastrophic damage (Hongwei F & Bingkun, H., 2024). Therefore, it is necessary to construct a theoretically and practically feasible early warning model of systemic risk in the banking industry to avoid the occurrence of systemic risk and ensure the good and orderly operation of the economy and finance.

Li, S., Wang et al. (2013) suggest that past financial crises have shown that banking crises are usually at the centre of financial crises. The banking systemic risk is a complex non-linear phenomenon rooted in the diversity and uncertainty of risk sources, the diversity of contagion channels and their interrelationships, and the complexity and evolutionary nature of the structure of the banking system. Therefore, bank stability is the key to maintaining financial stability. Cavalcante et al. (2016) proposed that the financial market is a nonlinear, high-latitude, and noisy dynamic system. Zhi, S. et al. (2017) suggested that traditional statistical methods are not suitable for analyzing complex, high-latitude and noisy financial market data series. In recent years, artificial neural network models have been continuously applied to financial risk and financial crisis early warning research. Although artificial neural network models, such as back propagation neural network (hereinafter referred to as BP neural network model) trained according to the error back propagation algorithm, do not have strict limitations on the data distribution, sample size, etc., and are suitable for the treatment of uncertainty, multidimensional input variables and other problems, they do not have the ability to model complex environments and multidimensional data accurately; therefore, artificial neural network modelling is not suitable to analyse complex environments and multidimensional data. Support Vector Machines (SVM) is a machine learning algorithm proposed by Cortes and Vapnik (1995) based on statistical learning theory, and its basic idea is to determine the optimal classification hyperplane by minimizing the structural risk and maximizing the classification interval. The basic idea is to determine the optimal classification hyperplane by minimizing the structural risk and maximizing the classification interval, and to map the samples from the original space to the high-dimensional feature space by adopting a nonlinear mapping function, and then perform linear regressionism is suitable for solving the problem of classifying data with small samples, nonlinearities, and high dimensions, and it obtains a good generalization performance in a limited number of learning modes. Therefore, it is feasible to apply the SVM model to early warning of financial risks.

The purpose of this paper is to construct and comparatively validate the SVM credit risk early warning model based on monthly data of China's banking industry from 2008 to 2024, in order to improve the accuracy and stability of risk early warning.

In this paper, we will screen credit risk indicators from two dimensions of internal vulnerability and external shocks in the banking industry, use kernel principal component analysis (KPCA) to non-linearly dimensionalize the original features, construct a risk early warning system using the support vector machine (SVM) model optimised by genetic algorithms, and make a side-by-side comparison with the BP neural network and logit regression model. The empirical part is developed based on the monthly macro, industry, and market data of China's banking industry from January 2008 to December 2024, aiming to provide methodological support for the establishment of an efficient risk early warning mechanism in China's banking industry.

2. Review of the literature

First, the traditional early warning method for financial risk is the early warning model. The probabilistic FR model proposed by Frankel and Rose (1996) has become an early warning model for predicting the probability of future crises. Based on this model, Frankel and Rose used the panel data of 105 developing countries from 1971 to 1992 for currency crisis early warning, and the results showed that although the model could accurately predict the in-sample data, the prediction of out-of-sample financial crises was unstable. Sachs et al. (1996) proposed a cross-sectional regression model, i.e. the STV model, which used the cross-sectional data of 20 emerging market countries to conduct a linear model and explains how the contagion of the 1994 Mexican financial crisis caused financial crises in related countries. Kaminsky et al. (1997) propose the KLR signaling early warning model, which monitors a number of abnormal indicators that may trigger a crisis and sets a threshold based on the distribution of the indicator data; if the indicator exceeds the threshold, it indicates that a crisis will occur within the next 24 months. Although the KLR signaling model is easy to implement, its results are overly dependent on indicator thresholds and do not fully utilise the original dynamic information.

Then there is the risk warning research of the artificial neural network model. Kim et al. (2004) used the BP neural network model to conduct early warning research on the Korean economic crisis based on the Korean Composite Stock Price Index during the 1997 economic crisis. The experimental results show that the BP neural network model can accurately warn of the financial crisis. Fioramanti (2008) used data related to sovereign debt from 1980 to 2004 to compare the artificial neural network (ANN) model with traditional parametric and nonparametric models. The results showed that ANN can predict crisis events in a timely manner. Yu et al. (2010) proposed a multirange neural network model based on the empirical mode decomposition method, using the exchange rate of the Korean won and the Thai baht against the US dollar as indicators of the economic volatility level of South Korea and Thailand, respectively. Empirical results showed that, compared to the traditional neural network model, the model has higher prediction accuracy. Credit risk early warning models have evolved from early Logit regression and BP neural networks to support vector machines (SVMs) and richer machine learning methods. Logit regression has been the benchmark model for early warning due to its good interpretability and ease of implementation (Abdou & Pointon, 2011); BP neural networks have strong fitting capabilities for credit risk through multilevel nonlinear mappings that do not depend on distributional assumptions (Khashman, 2011); BP neural networks have a strong ability to fit credit risk through multilevel nonlinear mapping. Iturriaga and Sanz (2015) constructed a neural network model combining multilayer perceptron and self-organising mapping to study the bank bankruptcy problem in the US. The model can predict the likelihood of bankruptcy three years in advance and has a higher prediction correctness rate compared to traditional models.

Shin et al. (2005) investigated the effectiveness of SVM applied to corporate bankruptcy early warning problems and found that with the reduction of the number of training sets, the correctness of SVM's early warning rate and the generalisation performance are better than that of the BP artificial neural network model. Based on SVM, Ahn et al. (2011) constructed an Early Warning System (EWS) to monitor the financial market based on the assumption of investors' herd behaviour. The results show that SVM is an effective early warning model. Hu et al. (2012) used the SVM and BP neural network to build a credit risk assessment model for small and medium enterprises (SMEs) based on the perspective of supply chain finance and found that the SVM credit risk assessment model is more effective and superior under the condition of small samples through comparison. Li et al. (2013) found that in recent years, SVM has become the mainstream choice in bank risk early warning research due to its superior generalization performance in small samples and high-dimensional settings and has demonstrated high accuracy and stability in systematic risk prediction. Pandey et al. (2023) stated in their study: 'we propose a kernel principal component analysis model for multivariate time series forecasting, where the training and prediction schemes are derived from the multiview formulation of restricted kernel machines.'

In the research on early warning of credit risk in the banking industry, the capital adequacy ratio is recognised as the core indicator for measuring bank resilience. "One of the most important indicators of bank resilience is its capital adequacy ratio (Dipendra Karki, 2019); the nonperforming loan ratio directly reflects the asset quality. Ali Polat (2018) proposed that nonperforming loans (NPLs) are important variables on a macro scale for the financial stability of the country as well as microscale for banks profitability itself. "The LDR is often used as an indicator of a bank's risk level, with a high ratio suggesting that the bank is taking on more risk because it has less cash reserves on hand to cover unexpected losses." (Trepp, 2022). A. Bolarinwa (2023) proposed that the higher value of liquidity ratio makes bank more liquid and less vulnerable to failure." "The cost-to-income ratio is one of the most vital metrics in banking, providing insight into a financial institution's efficiency. It serves as a key indicator of operational performance, giving both investors and regulators a clear view of how well a bank is managing its expenses in relation to its income." (Analyst Interview, Oct 11 2024).

Al-Romaihi and Kumar (2024) state, “The results show that non-oil real GDP growth and inflation significantly reduce NPLs, indicating that stronger economic conditions improve borrowers’ ability to repay loans.” Buch et al. (2016) find that “The countries that reduced their NPL ratio experienced faster GDP growth, invested more, and enjoyed better labour market outcomes. ' The Journal of Financial and Quantitative Analysis (2019) asserts that 'Fiscal deficits represent an important variable for aggregate credit risk of banks, revealing the ability of governments to kerb bank losses in bad states, either with direct cash infusions or with macroeconomic stabilisation policies'. S&P Global Market Intelligence (2025) emphasises: 'The PMITM is widely seen as an accurate and timely indicator of business conditions that helps analysts and economists to correctly anticipate changing economic trends in official data series such as gross domestic products (GDP), industrial production, employment and inflation.' Finally, Wu and Ramos (2024) warn that “Chinese banks’ substantial exposure to commercial real estate poses a risk to lenders if demand does not pick up”.

ECB (2012) finds that 'real M1 growth generally tends to decline further in the first year of recession' when recessions coincide with banking crises. Shin (2013) observes that 'the growth of broad money (M2), reflecting household and corporate deposits, is much less variable over the cycle', making it a reliable indicator of aggregate liquidity conditions. Aizenman and Noy (2013) note that 'financial development is generally proxied by the ratio of private credit to GDP and by the ratio of stock market capitalisation to GDP', underscoring the depth of equity markets as a barometer of systemic risk. Investopedia (2014) explains that “higher price-to-earnings ratios typically indicate higher growth expectations, low risk and efficient earnings,” highlighting the value of P / E in detecting potential market overvaluation and stress.

Casabianca et al. (2019) document that “current account deficits deteriorate as we approach the crisis”, highlighting the role of external imbalances in banking distress. Bianchi et al. (2013) show that 'the government faces a trade-off between the benefits of keeping reserves as a buffer against rollover risk and the cost of having larger gross debt positions', underscoring the precautionary function of reserve accumulation.ion. Coudert et al. (2011) find that “exchange rate flexibility increases more than proportionally with global financial stress”. In the external trade channel, Kaminsky and Reinhart (1999) report that “import growth remains below that of normal periods throughout the postcrisis period”, while “exports consistently underperform (relative to normal times) during this period,” linking trade contractions to crisis dynamics. Finally, Caballero (2012) shows that 'bonanzas in all flows increase the probability of crises when the windfall occurs jointly with a lending boom', underscoring the systemic risk posed by sudden surges in FDI relative to GDP.

3. Methodology and data selection.

In this section, we explain the methodologies mentioned in the literature review and the corresponding variables.

3.1 SVM model

Based on the first part, Cortes and Vapnik (1995) proposed that SVM model is a machine learning algorithm based on statistical learning theory, and its basic idea is to determine the optimal classification hyperplane by minimizing the structural risk and maximizing the classification interval, and to map the samples from the original space to the high-dimensional feature space by employing a nonlinear mapping function, and then perform a linear regression. Based on this, we will show and explain the formulas we use in this section. Cortes and Vapnik (1995) also emphasized that support vector networks are a new type of learning machine for solving binary classification problems. The machine conceptually implements the following idea: nonlinearly map the input vector to a high-dimensional feature space. A linear decision surface is constructed in this feature space. The special properties of the decision surface ensure that the learning machine has a high generalisability.

3.1.1 SVM classification principle

First, we assume that the classification decision function is:

$$f(x) = w^T \varphi(x) + b \tag{3.1}$$

where, in (3.1), $\varphi(x): R^n \to R^{nh}$ is the nonlinear mapping function; $w \epsilon R^n$ is the weight coefficient; and $b \epsilon R$ is the bias value; T is for transpose. Next, the following quadratic optimization problem needs to be solved.

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \tag{3.2}$$

The constraints are: $y_i[w^T \varphi(x) + b] \geq 1 - \xi_i, \xi_i \geq 0, i = 1,2 \ldots N$

where, C denotes the penalty parameter, which is used to control the degree of penalty for misclassification of samples; ξ_i denotes the slack variable that allows misclassification; N denotes the number of training samples.

Next, we will introduce the Lagrange coefficients:

$$minL = \frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\lambda_i \ \ [y_i(w^T\varphi(x) + b) - 1] \tag{3.3}$$

$\lambda_i \epsilon R$ denotes the Lagrange multiplier. After that we take the first order partial derivatives of the Lagrangian function to obtain:

$$\frac{\partial L}{\partial b} = 0 \rightarrow w = \sum_{i=1}^{N}\lambda_i \, y_i\varphi(x_i) \tag{3.4}$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{N}\lambda_i \, y_i \tag{3.5}$$

Substituting formulas (3.4) and (3.5) into (3.3) yields the dyadic form of the quadratic optimisation function.

$$max\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j k\left(x_i, x_j\right) \tag{3.6}$$

The constraints are: $\sum_{i=1}^{N}\lambda_i \, y_i = 0, 0 \le \lambda_i \le C, i = 1,2, \dots, N$

Where, α_i is the Lagrange multiplier, derived from the pairwise variables obtained from the derivation of the multiplier α_i after introducing the original optimization problem with constraints into the Lagrange function. Each training sample i corresponds to a α_i, which characterizes the influence or weight of that sample on the final decision boundary. y_i is the sample label. $k\left(x_i, x_j\right)$ is the kernel function, defined as $k\left(x_i, x_j\right) = \varphi(x_i)^T\varphi(x_j)$, i.e., the points in the original space are mapped to the high-dimensional feature space before making the inner product.

The two-category decision function for the linearly indistinguishable case can be obtained through formula (3.6) as:

$$f(x) = sign\left(\sum_{i=1}^{N}\sum_{j=1}^{N}\lambda_i y_i k\left(x_i, x_j\right) + b\right) \tag{3.7}$$

Radial Basis Function (RBF) is chosen as the kernel function of SVM model. The RBF kernel function is generally expressed as follows:

$$k\left(x_i, x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\gamma^2}\right) \tag{3.8}$$

where $\gamma > 0$, is the width parameter of the RBF.

3.1.2 Hard Spacing Maximization and Optimal Separation Hyperplane

For linearly divisible data, the goal of SVM is to find a hyperplane in the feature space that maximizes the minimum distance (a.k.a., the interval) from the two classes of samples to that hyperplane. Let the decision function be:

$$f(x) = w^T\varphi(x) + b$$

Then the hard interval SVM solves the following quadratic programming problem (Wang et al., 2017):

$$\min\frac{1}{2} w^T w,$$
$$s.t.\ \ y_i(w^T\varphi(x_i) + b) \geq 1,\ \ i = 1,2,\ldots,N \tag{3.9}$$

where $w \in R^n$ is the weight vector, $b \in R$ is the bias, and $y_i \in \{+1, -1\}$ is the true label of the ith sample. This constraint ensures that all samples lie outside at least two parallel interval boundaries.

3.1.3 Soft Interval and Relaxation Variables

For data containing noise or not fully linearly separable, SVM introduces $\xi_i \geq 0$ slack variables and a penalty parameter $C > 0$ to obtain a soft interval model (Hsu, Chang & Lin, 2003):

$$min_{w,b,\xi_i}\ \frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i\,,$$
$$s.t.\ \ y_i(w^T\varphi(x_i) + b) \geq 1 - \xi_i,\ \ \xi_i\ \geq 0\ \ i = 1,2,\ldots,N. \tag{3.10}$$

where, $\sum\xi_i$ penalizes samples that violate the interval or are misclassified; a larger C indicates a stricter penalty for misclassification and a narrower interval; a smaller C allows more classification errors in exchange for a wider interval.

3.1.4 Pairwise Problems and Support Vectors

Introducing the Lagrange multiplier $\alpha_i \geq 0$ transforms the original problem into dyadic form:

$$max\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j k\left(x_i, x_j\right),$$

$$s.t.\ \sum_{i=1}^{N} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1,2, \ldots, N \tag{3.11}$$

where $k\left(x_i, x_j\right) = \varphi(x_i)^T \varphi(x_j)$ is the kernel function. Only those samples with $\alpha_i \geq 0$ are called support vectors, which together determine the decision boundary; the final weight vector can be reconstructed as:

$$w = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i)$$

3.1.5 Kernel functions and nonlinear mappings

To be able to better handle the nonlinear problem, the SVM replaces $\varphi(x_i)^T \varphi(x_j)$ with $k\left(x_i, x_j\right)$ and the classification function becomes:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i k\left(x_i, x_j\right) + b$$

3.2 Data selection

In this section we explain the selection of the relevant risk indicators and explain the selected intervals of the data as well as some of the corresponding treatments.

3.2.1 Early warning indicators of risk in the banking sector

The selection of risk early warning indicators in the banking industry should have the principles of science, adaptability and standardization, be in line with international practice, and be able to comprehensively reflect the actual situation of the Chinese banking system. Through the second part of the literature review I have sorted out a large amount of literature related to crisis early warning indicators for the banking system. Therefore, here I design a system of indicators to measure the risk of China's banking sector in terms of both external shocks and internal vulnerabilities of the banking sector. This indicator system includes monthly data for 22 indicators, which are mainly from the People's Bank of China, the China Banking and Insurance Regulatory Commission, the National Bureau of Statistics, stock exchanges, and stock websites. The sample period is January 2008-December 2024. I will show the selected indicators and their economic significance below.

Internal bank vulnerability:

(1) Capital Adequacy Ratio (x_1): reflects a bank's ability to compensate for risky losses; too low a ratio indicates that the bank's solvency is poor and its ability to withstand external risks is weak.

(2) NPL ratio (x_2): reflecting the vulnerability of banks, a large number of non-performing loans can affect the economy and the financial system.

(3) Deposit to loan ratio (x_3): too high may show insufficient deposit repatriation in the short term, too low indicates more idle deposits, ample liquidity but limited profit margins.

(4) Liquidity ratio (x_4): too low a level may be exposed to the risk of illiquidity and difficulty in servicing debt in a timely manner.

(5) Cost to income ratio (x_5): The lower the ratio, the lower the cost consumption per unit of revenue and the higher the operational efficiency.

External shocks in the banking sector:

(6) GDP growth rate (x_6): a core indicator of how well the economy is doing as a whole and how well it is doing. Too high an indicator suggests that the economy may be overheating, creating inflationary pressures. Too slow an indicator suggests that the economy is in recession or stagnation, with increased risks to social functioning.

(7) inflation rate (x_7): too high will create hyperinflation, which will disrupt the price system and resource allocation. Too low a level will lead to weak economic growth and trigger a debt crisis.

(8) fixed asset investment growth rate (x_8): Reflecting the state of investment in economic activity, a decrease in the volume of investment is often a precursor to a financial crisis.

(9) fiscal deficit/GDP (x_9): measures fiscal sustainability and the strength of the expansion. The larger the fiscal deficit, the faster government fiscal spending grows and the less resilient it is to risk

(10) business sentiment index growth rate (x_{10}) : reflect overall operator confidence and economic vitality.

(11) real estate investment growth rate (x_{11}): too high is easily caused by rapidly rising house prices, market bubbles and climbing leverage.

(12) M1 growth rate (x_{12}): a direct reflection of the highly liquid monetary aggregates in the economy.

(13) M2 growth rate (x_{13}): excessive levels signal an over-injection of money across society, which, if demand does not keep up, can cause inflation in the medium to long term and may exacerbate credit expansion and leverage risks. Too slow implies a tightening of the money supply and higher medium to long-term financing costs, which could lead to disruptions in corporate investment and project financing and dampen potential capacity expansion and economic growth.

(14) credit growth rate/GDP growth rate (x_{14}): measures the extent to which the rate of credit expansion matches the rate of economic growth. Too high of a rate can easily trigger a borrowing bubble.

(15) stock market capitalization/GDP (x_{15}): reflects the depth and maturity of the stock market relative to the national economy. Too high means the stock market is in a bubble and prone to crash.

(16) P/E ratio (x_{16}): reflects stock market bubbles, and capital market bubbles are precursors to crises

(17) current account balance/GDP (x_{17}): excessive could be a drag on domestic demand growth and could also create pressure for exchange rate appreciation.

(18) foreign exchange reserve growth rate (x_{18}): the higher the rate of foreign exchange reserves, the greater the resilience to risk.

(19) exchange rate volatility (x_{19}): a measure of the magnitude of daily or cyclical fluctuations in the exchange rate of the local currency against foreign currencies, which can affect the price level.

(20) import growth rate (x_{20}): the higher the value of imports, the more active foreign trade is.

(21) export growth rate (x_{21}): the higher the value of exports, the more active foreign trade is.

(22) Foreign Direct Investment (FDI)/GDP (x_{22}): higher OFDI indicates a better general economic environment.

3.2.2 KPCA and input vectors

Given the complex non-linear correlations among risk indicators in the banking industry, direct use of the original 22 monthly indicators may miss important information. In this study, the monthly data from January 2008 to December 2024 are first mapped into a high-dimensional feature space using radial kernel principal component analysis (KPCA) to transform the underlying nonlinear structure into a linearizable form. Subsequently, the samples in this high-dimensional space are decomposed by conventional PCA to extract the most representative linear principal components. The results show that the first 14 kernel components have a cumulative variance contribution ratio of 80.33%, which can adequately capture the key vulnerability signals within the industry, as well as the information of external shocks. Therefore, this study uses these 14 kernel components as the input vector of the SVM model.

3.2.3 Banking industry risk classification and output vector

I selected the monthly closing price data of the CSI Bank Stock Index (stock code: 399986) for the time interval January 2008-December 2024 to reflect the asset price level of the Chinese banking system. Volatility is calculated from the closing price data and is used to classify the risk level of the Chinese banking sector. Here, we draw on the methodology of Yang. X et al. (2015) to classify the risk levels.

In this sample, the mean value of the index volatility of CSI Bank, $\mu = 0.0645$, and the standard deviation is $\sigma = 0.0306$. defines that when the index volatility is at $[\mu - 1.28\sigma, \mu + 1.28\sigma]$, there is no systematic risk in China's banking industry, which is the risk level I; when the index volatility is at $[\mu + 1.28\sigma, \mu + 1.65\sigma]$ or $[\mu - 1.65\sigma, \mu - 1.28\sigma]$, the China's banking sector has mild systemic risk, that is, risk level II; when the index volatility is at $[\mu + 1.65\sigma, \mu + 2.33\sigma]$ or $[\mu - 2.33\sigma, \mu - 1.65\sigma]$, China's banking sector has serious systemic risk, risk level III; when the index volatility is at $[-\mu + 2.23\sigma, +\infty]$ or $[-\infty, \mu - 2.33\sigma]$, China's The probability of a systemic crisis in the banking sector is extremely high and the risk level is IV.

At the end, the thresholds and desired output vectors are determined. When the risk level is I, the Chinese banking industry is considered to be in a safe state, and the threshold value is labelled 0001; when the risk level is II, the Chinese banking industry is considered to be in a mild risk state, and the threshold value is labelled 0010; when the risk level is III, the Chinese banking industry is considered to be in a heavy risk state, and the threshold value is labelled 0100; when the risk level is IV, the Chinese banking industry is considered to be in a risk state, and the threshold value is labelled 1000.

4. Application

First, we perform SVM modelling here. We use the feature subset composed of 14 principal kernel components of 191 samples from January 2008 to December 2024 as the input vector of the SVM model, and the threshold of the systemic risk level of the banking industry as the expected output vector of the SVM to perform risk warning modelling.

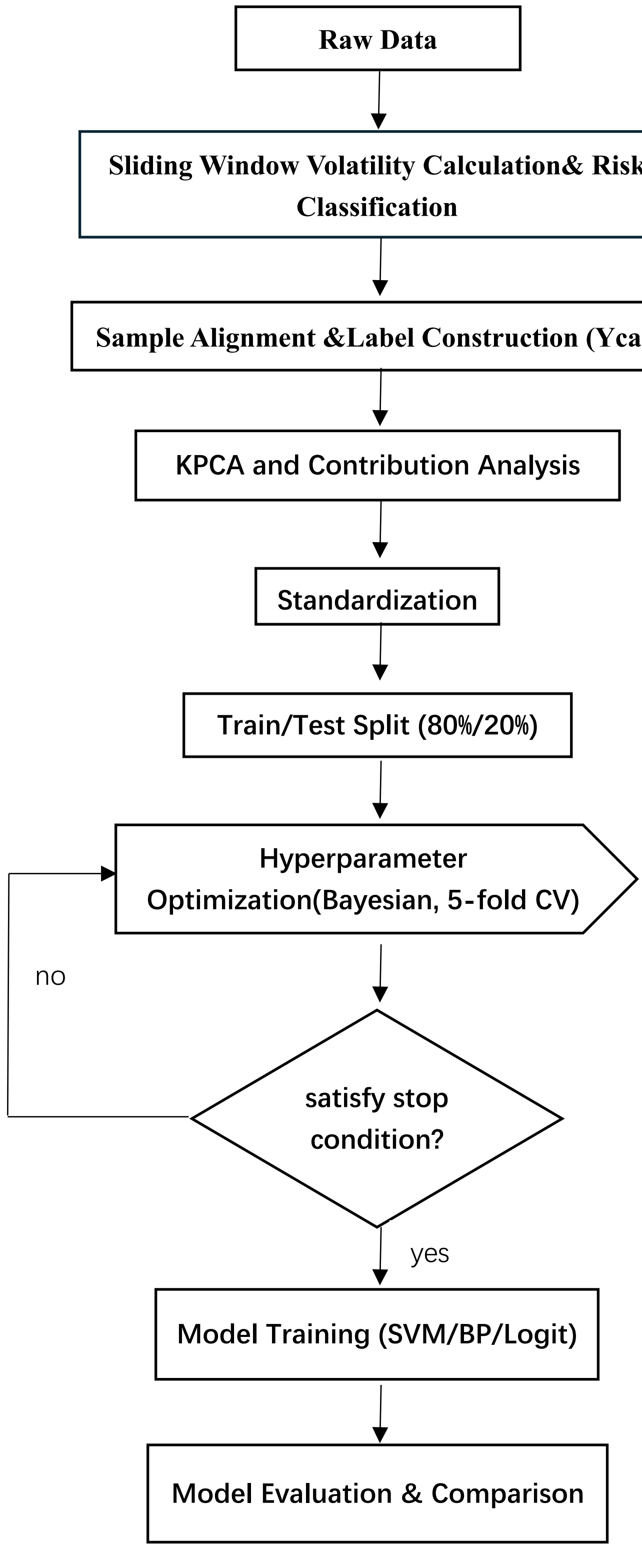
4.1 SVM model construction

Classify the samples. Use a 12-month sliding window to calculate the volatility of the CSI bank index logarithmic return, and divide it into four risk levels (I~IV) with $\mu \pm 1.28\sigma, \pm 1.65\sigma, and\ \pm 2.33\sigma$, and obtain the time series label Ycat. Align the feature matrix X with the volatility label, remove the first window+1 observations, and form the final total number of samples N (N=191). Then use 80% of the samples (153 samples) as the training set and 30% of the samples (38 samples) as the test set. The optimal SVM model is constructed by training the training set and then the general performance of the SVM model is verified based on the test set data.

Then perform parameter optimisation. The Z characteristic after the reduction in KPCA dimensionality in the training set (calculate the RBF kernel using the median heuristic γ and take the first principal components numPC = 6). Then, under the 5-fold cross-validation framework, combined with Bayesian optimisation (expected-improvement plus), BoxConstraint and KernelScale are automatically searched, with classification accuracy as the goal, to obtain the optimal hyperparameters C_opt and σ_opt.

Finally, modeling and performance evaluation are performed. On the basis of SVM, the optimal parameter combination obtained in the second step is used to build the model, and then the test set is used for testing.

Figure 4.1 SVM modelling flowchart



4.2 Parameter optimization

The key parameters of the SVM model include the penalty parameter C and the scale parameter of the radial basis function (KernelScale, denoted as σ). In order to avoid the subjectivity of empirical values, this paper uses Bayesian Optimization in MATLAB to automatically search for both. After 5-fold cross-validation and Bayesian optimization (expected-improvement-plus), the article searches for the optimal hyperparameters on the features obtained by KPCA dimensionality reduction (numPC=6) and performs about 40~50 iterations. The penalty parameter of the final model is $C = 486.2$, which means that the model has a strong penalty for classification errors, which helps to avoid excessive underfitting through cross-validation while ensuring training accuracy. The kernel scale parameter is $\sigma = 9.108$, and the corresponding γ is about 6×10^{-3}, which means that the RBF kernel remains smooth over a relatively large distance range. Combined with the feature distribution after KPCA dimensionality reduction, it can balance the flexibility and generalization ability of the decision boundary.

4.3 Early warning model construction and comparison

In this section, we use Matlab2024b. The article constructs three multi-classification warning models - SVM based on RBF kernel, single hidden layer BP neural network and Logistic regression with Ridge regularization - to compare their classification performance on the training set and test set. On the feature Z after KPCA dimension reduction, a multiclass SVM with the ECOC framework is used; the hyperparameters are automatically searched by Bayesian optimisation under 5-fold cross-validation, and the penalty parameter C and the kernel scale parameter σ are finally determined. By training and learning the training set data, the optimal SVM model is constructed and then the generalisation performance of the training model is tested using the test set data to obtain the model performance indicators. Then, a feedforward network with a single hidden layer is established, and the number of hidden layer nodes is determined by parameter adjustment; For BP, the number of training rounds is set to 200, the learning rate $\eta = 0.01$, and the activation functions are tansig (hidden layer) and purelin (output layer). For Logit regression, under the ECOC framework, the multi-classification problem is split into multiple groups of binary classification, and linear logistic regression with Ridge regularization of $\lambda = 0.1$ is used without additional hyperparameter optimization.

Table 4.1 The correctness of early warning for different models (%)

Modelling Alerts	Training Sets	Test Set
SVM	96.078	94.737
BP	95.425	92.105
Logit	89.542	89.474

4.4 Early warning results and empirical analysis

Since financial risks generally exist with a lag, here the existing data are brought into the constructed SVM early warning model to predict the risk level of the banking sector from January 2009 to December 2024, and to obtain the early warning outputs from January 2009 to December 2024 as well as the corresponding risk level and risk status.

Here, I divide the trend of changes in China's banking risks into the following four stages:

Table 4.2 Banking sector risk phase I: 2009.02-2010.07

Sample period	Early warning period	Early warning output	Risk level	Risk status
2008/2/1	2009/2/1	1000	IV	**Crises**
2008/3/1	2009/3/1	1000	IV	**Crises**
2008/4/1	2009/4/1	1000	IV	**Crises**
2008/5/1	2009/5/1	1000	IV	**Crises**
2008/6/1	2009/6/1	1000	IV	**Crises**
2008/7/1	2009/7/1	1000	IV	**Crises**
2008/8/1	2009/8/1	1000	IV	**Crises**
2008/9/1	2009/9/1	1000	IV	**Crises**
2008/10/1	2009/10/1	1000	IV	**Crises**
2008/11/1	2009/11/1	1000	IV	**Crises**
2008/12/1	2009/12/1	1000	IV	**Crises**
2009/1/1	2010/1/1	1000	IV	**Crises**
2009/2/1	2010/2/1	0100	III	**Heavy risk**
2009/3/1	2010/3/1	0001	I	Safety
2009/4/1	2010/4/1	0001	I	Safety
2009/5/1	2010/5/1	0001	I	Safety
2009/6/1	2010/6/1	0001	I	Safety
2009/7/1	2010/7/1	0001	I	Safety

In the first stage, from February 2009 to July 2010, the level of systemic risk of China's banking industry was high and in a crisis period. Due to the low level of nationalization of China's banking industry at that time, it was less directly impacted by the 2008 US subprime mortgage crisis, but affected by the contagion effect of the crisis, China's macro-economy was still affected. The volume of imports and exports dropped significantly, and risk indicators such as the bond market, stock market, and real estate market were all rising and had a comprehensive impact on China's banking industry through the real economy channel. Wong (2010) proposed that in the face of the crisis, the Chinese government launched the "Four Trillion" investment stimulus plan in November 2008 and supported the real economy through loose monetary policy. Major banks expanded credit countercyclically: in the first 11 months of 2009, new loans were 9.2 trillion yuan, far exceeding the official target of 5 trillion yuan. Liu Mingkang (2009), chairman of the China Banking Regulatory Commission, pointed out that China's banking industry was limited by the crisis, its profitability and capital adequacy ratio remained the world's leading, and its nonperforming loan ratio declined. In general, although there were hidden systemic risks during this period (accelerated credit expansion), the banking system performed well and did not trigger a systemic crisis.

In the second stage, from August 2010 to June 2014, the systemic risk of China's banking industry was relatively small. China was hit by the international financial crisis and the European sovereign debt crisis. Although China faced the risk of insufficient aggregate demand and shrinking asset bubbles, the financial system was still operating steadily and had not reached the serious risk state of triggering a financial crisis. Since the implementation of the "four trillion" stimulus plan in 2008, China's money market liquidity has been sufficient, and the two sides have entered a downward channel. Foreign exchange reserves have continued to increase and the macroeconomic situation and environment have temporarily improved. During this period, China's banking industry was in a "safe" state. As the tightness of the liquidity in the interbank market eased, the pressure on the banking industry decreased.

Table 4.3 Banking Risk Phase III: 2014.07-2016.12

Sample period	Early warning period	Early warning output	Risk level	Risk status
2013/7/1	2014/7/1	0001	I	Safety
2013/8/1	2014/8/1	0001	I	Safety
2013/9/1	2014/9/1	0001	I	Safety
2013/10/1	2014/10/1	0001	I	Safety
2013/11/1	2014/11/1	0001	I	Safety
2013/12/1	2014/12/1	0010	II	**Slight risk**
2014/1/1	2015/1/1	0010	II	**Slight risk**
2014/2/1	2015/2/1	0100	III	**Heavy risk**
2014/3/1	2015/3/1	0100	III	**Heavy risk**
2014/4/1	2015/4/1	0100	III	**Heavy risk**
2014/5/1	2015/5/1	0100	III	**Heavy risk**
2014/6/1	2015/6/1	0010	II	**Slight risk**
2014/7/1	2015/7/1	0001	I	Safety
2014/8/1	2015/8/1	0001	I	Safety
2014/9/1	2015/9/1	0001	I	Safety
2014/10/1	2015/10/1	0001	I	Safety
2014/11/1	2015/11/1	0001	I	Safety
2014/12/1	2015/12/1	0001	I	Safety
2015/1/1	2016/1/1	0001	I	Safety
2015/2/1	2016/2/1	0001	I	Safety
2015/3/1	2016/3/1	0001	I	Safety
2015/4/1	2016/4/1	0001	I	Safety
2015/5/1	2016/5/1	0001	I	Safety
2015/6/1	2016/6/1	0001	I	Safety
2015/7/1	2016/7/1	0001	I	Safety
2015/8/1	2016/8/1	0001	I	Safety
2015/9/1	2016/9/1	0001	I	Safety

2015/10/1	2016/10/1	0001	I	Safety
2015/11/1	2016/11/1	0001	I	Safety
2015/12/1	2016/12/1	0001	I	Safety

The third stage, July 2014-December 2016. He, M. et al. (2022) mentioned that speculative trading began to pour into the Chinese stock market in the second half of 2014. In June-July 2015, the stock index collapsed, with the Shanghai Composite Index falling from 5174 points to 3373 points and thousands of stocks hitting the daily limit. This "stock market crash" triggered the government to rescue the market, but it also exacerbated the market panic. The study found that during the 2015 stock market crash, the systemic risk of financial institutions increased sharply, and the market was concerned about financial chain reactions. He and Guo (2022) pointed out that the 2015 stock market crash caused "violent turbulence in the financial market", and the government and the market were highly alert to systemic risk events, and even worried about the outbreak of a domestic financial crisis. Nivorozhkin et al. (2022) also found using the SRISK indicator that the systemic risk of banks increased significantly during the 2015-2016 stock market decline. According to statistics from the China Banking and Insurance Regulatory Commission, by the end of 2015, China's national banking nonperforming loans reached 1.27 trillion yuan, the provision coverage ratio continued to decline, and the credit risk of the banking industry continued to rise. In 2016, foreign exchange reserves continued to flow out, overcapacity was serious, and the GDP growth rate slowed down.

The fourth stage is from January 2017 to December 2024. During this period, all predictions of the systemic risk of China's banking industry by the SVM model fell into the "safe" range (level I), which fully reflects the situation of sufficient liquidity, sound asset quality, and efficient risk disposal in the banking system under the synergy of multiple policies such as macroprudential management, structural monetary policy (targeted reserve requirement ratio cuts, re-lending, etc.) and fiscal policy to stabilise growth. Even when the impact of the COVID-19 pandemic was the most severe in 2020-2021, through targeted credit support and flexible regulatory tools, China's banking industry still maintained a low nonperforming loan ratio and sufficient provision coverage, and there was no accumulation or outbreak of systemic risks, reflecting strong resilience and security.

5. Conclusion

This paper builds a banking risk warning model based on SVM and compares the warning results with the regression results of the BP neural network model and the Logit regression model. In addition, this article analyses the risk status of China's banking industry from February 2009 to December 2024 based on the SVM warning model and obtains the following research results:

(1) From the empirical analysis in the fourth part, it can be seen that the SVM model has a significantly higher risk prediction accuracy than the other two models. The efficiency and stability of SVM in multiclassification warning problems are verified.

(2) Warning results truly reflect the actual situation and economic conditions at that time. From February 2009 to July 2010, the risk level of China's banking industry was in a crisis state; from August 2010 to June 2014, the risk of China's banking industry was relatively small and was in a safe state; from July 2014 to December 2016, the risk of China's banking industry rose and experienced a stock market crash, which caused the risk status of China's banking industry to go through two stages: mild risk and severe risk; from January 2017 to December 2024, all predictions of the SVM model for the systemic risk of China's banking industry fell into the "safe" range (level I). Even when the impact of the new crown epidemic was the most severe in 2020-2021, through targeted credit support and flexible regulatory tools, China's banking industry still maintained a low nonperforming loan ratio and sufficient provision coverage, and there was no accumulation or outbreak of systemic risks, reflecting strong resilience and security.

Importance of policy and practical implications

(1) This study shows that the SVM early warning model can not only accurately capture crisis precursors but also maintain a low false alarm rate during normal periods and has strong practical value.

(2) Regulators and banks can incorporate this method into their daily monitoring system and combine it with macroprudential assessment indicators and structural

monetary tools to achieve dynamic "point-to-point" supervision of systemic risks.

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Appendix

The state of risk in China's banking sector

InputSample	WarningPeriod	PrewarnOutput	RiskLevel	RiskState
2008/2/1	2009/2/1	1000	IV	Crises
2008/3/1	2009/3/1	1000	IV	Crises
2008/4/1	2009/4/1	1000	IV	Crises
2008/5/1	2009/5/1	1000	IV	Crises
2008/6/1	2009/6/1	1000	IV	Crises
2008/7/1	2009/7/1	1000	IV	Crises
2008/8/1	2009/8/1	1000	IV	Crises
2008/9/1	2009/9/1	1000	IV	Crises
2008/10/1	2009/10/1	1000	IV	Crises
2008/11/1	2009/11/1	1000	IV	Crises
2008/12/1	2009/12/1	1000	IV	Crises
2009/1/1	2010/1/1	1000	IV	Crises
2009/2/1	2010/2/1	0100	III	Heavy risk
2009/3/1	2010/3/1	0001	I	Safety
2009/4/1	2010/4/1	0001	I	Safety
2009/5/1	2010/5/1	0001	I	Safety
2009/6/1	2010/6/1	0001	I	Safety
2009/7/1	2010/7/1	0001	I	Safety
2009/8/1	2010/8/1	0001	I	Safety
2009/9/1	2010/9/1	0001	I	Safety
2009/10/1	2010/10/1	0001	I	Safety
2009/11/1	2010/11/1	0001	I	Safety
2009/12/1	2010/12/1	0001	I	Safety
2010/1/1	2011/1/1	0001	I	Safety
2010/2/1	2011/2/1	0001	I	Safety
2010/3/1	2011/3/1	0001	I	Safety

2010/4/1	2011/4/1	0001	I	Safety
2010/5/1	2011/5/1	0001	I	Safety
2010/6/1	2011/6/1	0001	I	Safety
2010/7/1	2011/7/1	0001	I	Safety
2010/8/1	2011/8/1	0001	I	Safety
2010/9/1	2011/9/1	0001	I	Safety
2010/10/1	2011/10/1	0001	I	Safety
2010/11/1	2011/11/1	0001	I	Safety
2010/12/1	2011/12/1	0001	I	Safety
2011/1/1	2012/1/1	0001	I	Safety
2011/2/1	2012/2/1	0001	I	Safety
2011/3/1	2012/3/1	0001	I	Safety
2011/4/1	2012/4/1	0001	I	Safety
2011/5/1	2012/5/1	0001	I	Safety
2011/6/1	2012/6/1	0001	I	Safety
2011/7/1	2012/7/1	0001	I	Safety
2011/8/1	2012/8/1	0001	I	Safety
2011/9/1	2012/9/1	0001	I	Safety
2011/10/1	2012/10/1	0001	I	Safety
2011/11/1	2012/11/1	0001	I	Safety
2011/12/1	2012/12/1	0001	I	Safety
2012/1/1	2013/1/1	0001	I	Safety
2012/2/1	2013/2/1	0001	I	Safety
2012/3/1	2013/3/1	0001	I	Safety
2012/4/1	2013/4/1	0001	I	Safety
2012/5/1	2013/5/1	0001	I	Safety
2012/6/1	2013/6/1	0001	I	Safety
2012/7/1	2013/7/1	0001	I	Safety
2012/8/1	2013/8/1	0001	I	Safety

2012/9/1	2013/9/1	0001	I	Safety
2012/10/1	2013/10/1	0001	I	Safety
2012/11/1	2013/11/1	0001	I	Safety
2012/12/1	2013/12/1	0001	I	Safety
2013/1/1	2014/1/1	0001	I	Safety
2013/2/1	2014/2/1	0001	I	Safety
2013/3/1	2014/3/1	0001	I	Safety
2013/4/1	2014/4/1	0001	I	Safety
2013/5/1	2014/5/1	0001	I	Safety
2013/6/1	2014/6/1	0001	I	Safety
2013/7/1	2014/7/1	0001	I	Safety
2013/8/1	2014/8/1	0001	I	Safety
2013/9/1	2014/9/1	0001	I	Safety
2013/10/1	2014/10/1	0001	I	Safety
2013/11/1	2014/11/1	0001	I	Safety
2013/12/1	2014/12/1	0010	II	Slight risk
2014/1/1	2015/1/1	0010	II	Slight risk
2014/2/1	2015/2/1	0100	III	Heavy risk
2014/3/1	2015/3/1	0100	III	Heavy risk
2014/4/1	2015/4/1	0100	III	Heavy risk
2014/5/1	2015/5/1	0100	III	Heavy risk
2014/6/1	2015/6/1	0010	II	Slight risk
2014/7/1	2015/7/1	0001	I	Safety
2014/8/1	2015/8/1	0001	I	Safety
2014/9/1	2015/9/1	0001	I	Safety
2014/10/1	2015/10/1	0001	I	Safety
2014/11/1	2015/11/1	0001	I	Safety
2014/12/1	2015/12/1	0001	I	Safety
2015/1/1	2016/1/1	0001	I	Safety

2015/2/1	2016/2/1	0001	I	Safety
2015/3/1	2016/3/1	0001	I	Safety
2015/4/1	2016/4/1	0001	I	Safety
2015/5/1	2016/5/1	0001	I	Safety
2015/6/1	2016/6/1	0001	I	Safety
2015/7/1	2016/7/1	0001	I	Safety
2015/8/1	2016/8/1	0001	I	Safety
2015/9/1	2016/9/1	0001	I	Safety
2015/10/1	2016/10/1	0001	I	Safety
2015/11/1	2016/11/1	0001	I	Safety
2015/12/1	2016/12/1	0001	I	Safety
2016/1/1	2017/1/1	0001	I	Safety
2016/2/1	2017/2/1	0001	I	Safety
2016/3/1	2017/3/1	0001	I	Safety
2016/4/1	2017/4/1	0001	I	Safety
2016/5/1	2017/5/1	0001	I	Safety
2016/6/1	2017/6/1	0001	I	Safety
2016/7/1	2017/7/1	0001	I	Safety
2016/8/1	2017/8/1	0001	I	Safety
2016/9/1	2017/9/1	0001	I	Safety
2016/10/1	2017/10/1	0001	I	Safety
2016/11/1	2017/11/1	0001	I	Safety
2016/12/1	2017/12/1	0001	I	Safety
2017/1/1	2018/1/1	0001	I	Safety
2017/2/1	2018/2/1	0001	I	Safety
2017/3/1	2018/3/1	0001	I	Safety
2017/4/1	2018/4/1	0001	I	Safety
2017/5/1	2018/5/1	0001	I	Safety
2017/6/1	2018/6/1	0001	I	Safety

2017/7/1	2018/7/1	0001	I	Safety
2017/8/1	2018/8/1	0001	I	Safety
2017/9/1	2018/9/1	0001	I	Safety
2017/10/1	2018/10/1	0001	I	Safety
2017/11/1	2018/11/1	0001	I	Safety
2017/12/1	2018/12/1	0001	I	Safety
2018/1/1	2019/1/1	0001	I	Safety
2018/2/1	2019/2/1	0001	I	Safety
2018/3/1	2019/3/1	0001	I	Safety
2018/4/1	2019/4/1	0001	I	Safety
2018/5/1	2019/5/1	0001	I	Safety
2018/6/1	2019/6/1	0001	I	Safety
2018/7/1	2019/7/1	0001	I	Safety
2018/8/1	2019/8/1	0001	I	Safety
2018/9/1	2019/9/1	0001	I	Safety
2018/10/1	2019/10/1	0001	I	Safety
2018/11/1	2019/11/1	0001	I	Safety
2018/12/1	2019/12/1	0001	I	Safety
2019/1/1	2020/1/1	0001	I	Safety
2019/2/1	2020/2/1	0001	I	Safety
2019/3/1	2020/3/1	0001	I	Safety
2019/4/1	2020/4/1	0001	I	Safety
2019/5/1	2020/5/1	0001	I	Safety
2019/6/1	2020/6/1	0001	I	Safety
2019/7/1	2020/7/1	0001	I	Safety
2019/8/1	2020/8/1	0001	I	Safety
2019/9/1	2020/9/1	0001	I	Safety
2019/10/1	2020/10/1	0001	I	Safety
2019/11/1	2020/11/1	0001	I	Safety

2019/12/1	2020/12/1	0001	I	Safety
2020/1/1	2021/1/1	0001	I	Safety
2020/2/1	2021/2/1	0001	I	Safety
2020/3/1	2021/3/1	0001	I	Safety
2020/4/1	2021/4/1	0001	I	Safety
2020/5/1	2021/5/1	0001	I	Safety
2020/6/1	2021/6/1	0001	I	Safety
2020/7/1	2021/7/1	0001	I	Safety
2020/8/1	2021/8/1	0001	I	Safety
2020/9/1	2021/9/1	0001	I	Safety
2020/10/1	2021/10/1	0001	I	Safety
2020/11/1	2021/11/1	0001	I	Safety
2020/12/1	2021/12/1	0001	I	Safety
2021/1/1	2022/1/1	0001	I	Safety
2021/2/1	2022/2/1	0001	I	Safety
2021/3/1	2022/3/1	0001	I	Safety
2021/4/1	2022/4/1	0001	I	Safety
2021/5/1	2022/5/1	0001	I	Safety
2021/6/1	2022/6/1	0001	I	Safety
2021/7/1	2022/7/1	0001	I	Safety
2021/8/1	2022/8/1	0001	I	Safety
2021/9/1	2022/9/1	0001	I	Safety
2021/10/1	2022/10/1	0001	I	Safety
2021/11/1	2022/11/1	0001	I	Safety
2021/12/1	2022/12/1	0001	I	Safety
2022/1/1	2023/1/1	0001	I	Safety
2022/2/1	2023/2/1	0001	I	Safety
2022/3/1	2023/3/1	0001	I	Safety
2022/4/1	2023/4/1	0001	I	Safety

2022/5/1	2023/5/1	0001	I	Safety
2022/6/1	2023/6/1	0001	I	Safety
2022/7/1	2023/7/1	0001	I	Safety
2022/8/1	2023/8/1	0001	I	Safety
2022/9/1	2023/9/1	0001	I	Safety
2022/10/1	2023/10/1	0001	I	Safety
2022/11/1	2023/11/1	0001	I	Safety
2022/12/1	2023/12/1	0001	I	Safety
2023/1/1	2024/1/1	0001	I	Safety
2023/2/1	2024/2/1	0001	I	Safety
2023/3/1	2024/3/1	0001	I	Safety
2023/4/1	2024/4/1	0001	I	Safety
2023/5/1	2024/5/1	0001	I	Safety
2023/6/1	2024/6/1	0001	I	Safety
2023/7/1	2024/7/1	0001	I	Safety
2023/8/1	2024/8/1	0001	I	Safety
2023/9/1	2024/9/1	0001	I	Safety
2023/10/1	2024/10/1	0001	I	Safety
2023/11/1	2024/11/1	0001	I	Safety
2023/12/1	2024/12/1	0001	I	Safety