# Risk Prediction of Enterprise Credit Financing Using Machine Learning

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*For the credit financing risk of small, medium-sized and micro enterprises, a risk prediction model of enterprise credit financing management based on antagonistic neural network and least squares support vector machine is proposed. The data samples are processed combined with antagonistic neural network, and the risk prediction of enterprise credit financing is realized by using least squares support vector machine model. Compared with many classification models, the effectiveness of the least squares support vector machine model is verified. The results show that the accuracy rate of the least squares support vector machine model is 90.15%, the recall rate is 85.63%, and the prediction error rates of the model in default and non-default are 6.48% and 3.09% respectively, which is better than BP neural network, random forest algorithm and Gaussian naive Bayesian algorithm. The least squares support vector machine model can effectively and accurately predict the enterprise credit financing risk, provide scientific and efficient risk early warning for the enterprise credit financing control, and provide technical support for preventing and reducing the occurrence of loan default.*

*Povzetek: Narejena je metoda strojnega učenja za ugotavljanje tveganj za mala in mikro podjetja.*

## 1 Introduction

At present, China is in the social background of economic transformation and upgrading. The country has put forward the development strategy of innovation and entrepreneurship for all, encouraged and supported entrepreneurs to actively explore the market, boosted the development speed of the national economy and consumption, and solved important livelihood issues such as employment [1]. With the emergence of startups, how to promote the sound development of small, medium-sized and micro enterprises has become a key issue in the national economic development. It is required to increase support for enterprises and help enterprises solve important financing problems in the early development of entrepreneurship [2-3]. The traditional enterprise bank loans have complex procedures, long review process, and high borrowing threshold, which are difficult to meet the borrowing needs of enterprises. The development of Internet finance has proposed new solutions to the financing problems of small, medium-sized and micro enterprises. The operation process of Internet financial lending is simple, and it has the advantages of low entry threshold and low difficulty in lending. It greatly makes up for the lack of micro lending for enterprises in the traditional financial industry, provides new financial channels for enterprise financing, and solves the problems of small, medium-sized and micro enterprises with difficult and slow loans [4-5]. However, the entry threshold of Internet finance micro lending is low. While increasing the possibility of enterprise financing, it also increases the default risk of enterprise credit financing [6]. In addition, the development of the Internet finance micro lending platform is relatively short, and there are still problems such as lack of management experience and imperfect operation structure, which are prone to the situation that the loan funds cannot be recovered. It is required to do a good job in loan risk management, provide early warning for enterprise credit financing risk control while reducing the operating risk of the lending platform, and promote the common healthy development of the Internet finance micro lending platform and small, medium-sized and micro enterprises. Therefore, aiming at the problem of credit financing risk management of small and medium-sized micro enterprises, this paper proposes a prediction model of enterprise credit financing risk based on confrontation neural network and least squares support vector machine model, expecting to predict and warn the default risk of enterprise credit financing.

## 2 Related works

Facing the problems of unbalanced data samples and small amount of data, many scholars use various means such as anti-neural network to process data samples. Xu y and other scholars proposed a feature data processing system suitable for neural network calculation for the processing of medical feature data, and took the network traffic data of medical Internet of things as the object to verify the effectiveness of the data processing system in convolution neural network and recursive neural network [7].

H Li and his team build a face anti-deception recognition system. When the sample size of training data is small, they use the deep learning advantage of neural network to extract the characteristic information of the original sample, so as to increase the richness of attack samples [8]. When solving the problem of medical image diagnosis, scholars such as junior F, aiming at the imbalance of medical data and few data points, proposed a generation anti-neural network pruning algorithm based on evolutionary strategy and multi criteria decision-making, which uses the anti-neural network to obtain information features from the original data distribution and synthesize more data for problem-solving training [9]. Aiming at the problem of synthetic computed tomography, scholars such as green a j use the anti-neural network to process and analyze the virus data, convert the three-dimensional structure information of the virus into weighted points, and train the neural network to realize the effective prediction of the toxicity of untested chemicals [10].

The least squares support vector machine model can effectively deal with nonlinear prediction problems. Tian C and other scholars introduced the least squares support vector machine model into the ship collision conflict prediction problem and proposed a least squares support vector machine model based on empirical mode decomposition and quantum behavior particle swarm optimization, combined with the time series of ship collision, the effective prediction of ship collision is realized [11]. Zhang X and Ge Z applied the least squares support vector machine model to optimize the local target set parameters in the field of industrial soft sensing, combined with the distribution estimation algorithm to reduce the prediction error of the target set, and carried out the prediction and estimation experiment of CO2 content on the cloud computing platform. The results show that the improved least squares support vector machine model is optimized and feasible [12]. Ge Q and his team proposed a combined power load forecasting method based on particle swarm optimization algorithm and least squares support vector machine for high-performance industrial power load forecasting, and combined with K-means clustering algorithm for data classification to realize high-precision prediction of industrial power load [13]. Facing the prediction problem of boiler NOx emission, Chengang team proposed an emission prediction model based on least squares support vector machine, which was improved combined with whale optimization algorithm to optimize the kernel function width and penalty factor of the model. The experimental results show that the integrated model has high stability and prediction accuracy [14]. Zhao Z and other scholars introduced the least squares support vector machine model into the ultrafast photovoltaic power prediction problem, combined with the single iterative gray wolf optimization algorithm for photovoltaic power prediction, and optimized the super parameters by combining iterative local search and adaptive differential evolution to improve the prediction accuracy of the model [15].

To sum up, the antagonistic neural network can effectively deal with the imbalance of data samples, enrich the sample data volume, and the least squares support vector machine model has significant advantages in nonlinear prediction. Therefore, it is studied to build an enterprise credit financing risk prediction model based on the antagonistic neural network and least squares support vector mechanism, it is expected to provide technical support for enterprise credit risk control.

# 3 Construction of risk prediction model for enterprise credit financing management

## 3.1 Data extraction and structured processing

Extract the enterprise's loan application information data from the loan institution database, and obtain the basic information of the legal person, loan qualification examination data, enterprise operation data and loan application product information of the loan enterprise, including the credit record of the loan enterprise, enterprise capital flow, enterprise operation years and other relevant information. The obtained enterprise loan information is structured, the keywords in the data information are extracted, and the data variables are classified and filled in combination with the data dictionary. The data structured processing flow is shown in Figure 1.

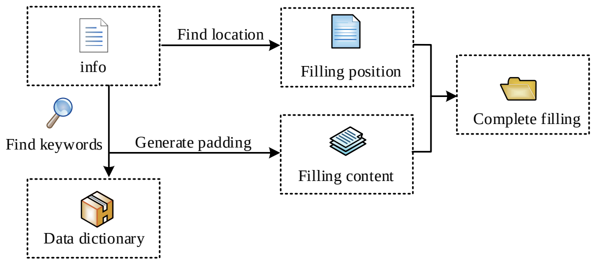



Figure 1: Data structure processing flow

In the process of model prediction, the original data has certain characteristic differences. If the original data is directly used for calculation, the size difference of the data value will affect the final operation result. Therefore, it is necessary to standardize the original data and control the variable value within a certain range through the normalization of the sample data, so as to make the data samples comparable and facilitate the subsequent operation and prediction. The maximum and minimum method is used to normalize the data. The formula of the maximum and minimum method is as follows:

$$x_k = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}}. \quad (1)$$

In formula (1), $x_k$ is sample data, and $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values in the data sequence respectively. There are many variable indicators in the sample data, and redundant irrelevant information will affect the operation efficiency and prediction effect of the model. Therefore, it is necessary to reduce the dimension of the variable indicators, process the data variables with the principal component analysis method, and screen the indicators in combination with the variance contribution rate and cumulative square difference contribution rate of the variable indicators, Eliminate the variable indicators with low correlation with enterprise loan risk.

## 3.2 Sample processing based on Countermeasure neural network

Structured processing has preliminarily sorted out the information data of loan enterprises, but the positive and negative proportion of loan data samples is seriously unbalanced, which is not conducive to subsequent risk prediction. Therefore, the data samples need to be further processed. The research uses the antagonistic neural network to generate and reconstruct the data samples, uses the construction of the neural network model to learn the distribution characteristics of the data samples, and combines the generated neural network to generate, reconstruct and update the original data samples. This paper studies the learning and generation of original data samples by using the structure network of automatic denoising coder. In the coding process, the automatic coder first carries out the spatial mapping of information, mapping the input vector $x \in [1,1]^d$ into hidden $y \in [1,1]^d$, and $d$ is the spatial dimension. The mapping formula is shown as follows:

$$y = s(wx + b). \quad (2)$$

In equation (2), $s(.)$ is a nonlinear function, tanh function and sigmoid function can be used, $w$ is the weight and $b$ is the mapping angle. Then map $y$ to reconstruction vector $z$ and decode the data information. The mapping formula is shown as follows:

$$y = s(w'x + b'). \quad (3)$$

In equation (3), $w'$ is the weight and $b'$ is the mapping angle. The loss function of vector reconstruction is the cross entropy function, which is expressed as follows:

$$L_H(x,z) = -\sum_{k=1}^{d}\left[x_k \log z_k + (1-x_k)\log(1-x_k)\right]. \quad (4)$$

In formula (4), $k$ is the sample number. The $Min-Max$ standardization method is used to standardize the original data samples. Set the maximum and minimum values of attribute $A$ as $MaxA$ and $MinA$ respectively, and map the original value $x$ of $A$ to $x'$ and $x' \in [0,1]$. The standardization processing formula is shown as follows:

$$x' = \frac{data - MinA}{MaxA - MinA}. \quad (5)$$

In equation (5), $data$ is the sample data. The standardized original data samples are simulated and reconstructed by using the generated neural network, and the false samples with similar characteristics are generated by using the mapping processing of input layer, hidden layer and output layer, combined with the input original samples. The judgment neural network is constructed to distinguish the real original data samples and the generated false samples. The BP neural network is used to distinguish the samples. The input information is processed through the forward transmission and back propagation of the signal. Combined with the adjustment of the network weight and threshold, the error between the output of the neural network and the expected value is reduced. Let the input vector and output vector of the neural network be $\bar{x} = [x_1, x_2, \cdots, x_i], i = 1, 2, \cdots, m$ and $\bar{y} = [y_1, y_2, \cdots, y_k], k = 1, 2, \cdots, m$ respectively, and the output of hidden layer neurons is $h^{(l)} = \left[h^{(l)}{}_1, h^{(l)}{}_2, \cdots, h^{(l)}{}_s\right], s = 1, 2, \cdots, p$, of which $p$ is the number of hidden layer neurons in layer $l$, then the input of the $i$ neuron in layer $l$ is expressed as follows:

$$\begin{cases} net_i^{(l)} = \sum_{j=1}^{p} w_{ij}^{(l)} h_j^{l-1} + b_i^j \\ h_j^l = f\left(net_i^{(l)}\right) \end{cases}. \quad (6)$$

In equation (6), $w_{ij}^{(l)}$ is the connection weight of the $i$ neuron in layer $l$ and the $j$ neuron in layer $l-1$, $b_i^{(l)}$ is the bias of the $i$ neuron in layer $l$, and $f(.)$ is the activation function of neurons, which is usually a nonlinear activation function. The false samples generated by the model are marked as 0 and the true samples are marked as 1 to form the sample training set of BP neural network to judge and distinguish the generated samples from the original samples.

The counter neural network is used to deal with the imbalance of the original data samples. Firstly, the generated neural network is used to simulate and reconstruct the original data samples to generate false samples that can confuse the false with the true. Combined with the training optimization of the judgment neural network, the true and false samples are identified and judged, and then the connection weight of the model is updated to update the generation and judgment series model, The schematic diagram of model update is shown in Figure 2.

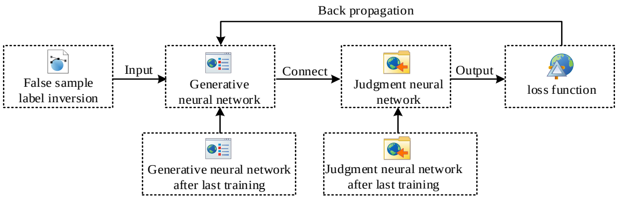



Figure 2: Schematic diagram of model update.

While updating the generated neural network, the training of the judgment neural network is also updated, and the new false samples generated by the updated generated neural network are trained again to form the confrontation competition under the confrontation neural network. In order to avoid the homogenization of samples after competition due to the randomness of the generation of the original sample matrix, it is studied that after a random sample competition, only one sample is randomly selected as the generated sample, and the sample set is formed through multiple generation and extraction.

## 3.3 Enterprise credit risk prediction model based on LSSVM

Support vector machine (SVM) is a commonly used supervised learning algorithm. It analyzes the potential laws of data samples on the basis of known data to realize data prediction and pattern recognition. Support vector machine model has advantages in small sample data and nonlinear problems. Therefore, the research introduces the support vector machine model into the enterprise credit risk problem, and constructs the enterprise credit financing risk prediction model based on the least squares support vector mechanism to predict and analyze the enterprise credit financing risk. Least square support vector machine (LSSVM) inherits the structural risk minimization strategy and the basic idea of kernel function of traditional SVM model, simplifies the calculation process of quadratic programming problem, transforms it into the solution of linear equations, and improves the operation efficiency of the model. The support vector machine model is based on the structural risk minimization strategy. Its optimization objective function is composed of empirical risk and model complexity parameters. Select the function subset in the function set structure of the model to minimize the confidence interval of the function, and further select the function that can minimize the empirical risk in the function subset, so as to minimize the upper bound of the actual risk. The support vector machine model takes the limited sample data information as the starting point to find the balance between the model learning ability and the complexity of the model, so as to improve the generalization ability and comprehensive performance of the model.

LSSVM model adopts the least square method, constructs the square loss function of the model through the selection of the optimal hyperplane and the square of the error, and converts the inequality constraint of SVM into linear equation to realize the linear solution of the problem. Let the data sample set be $D=\{(x_1,y_1),\cdots,(x_i,y_i),\cdots,(x_n,y_n)\}$, $n$ represent the number of samples, the $i$ input sample is $x_i$, and $y_i$ represent the label of the input sample. The relaxation variable $\xi_i \geq 0$ is introduced into the model, and the constraints of the model are expressed as follows:

$$y_i\left(\omega^T x_i+e\right)\geq 1-\xi_i, i=1,2,\cdots,n. \quad (7)$$

In equation (7), $\omega$ is the normal vector of the hyperplane, $T$ is the transpose, and $e$ is the intercept term. The constrained optimization problem of the model is expressed as follows:

$$\begin{cases} \min\limits_{\omega,b} \ \ \dfrac{1}{2}\|\omega\|^2+C\sum\limits_{i=1}^{n}\xi \\ s.t. \ \ y_i\left(\omega^T x_i+e\right)\geq 1-\xi_i, \xi\geq 0, i=1,2,\cdots,n \end{cases}. \quad (8)$$

In equation (8), $C$ is the penalty parameter, and the values of $C>0$ and $C$ are positively correlated with the penalty of misclassification. The constrained optimization problem is transformed by Lagrange method, and the model constrained optimization problem is expressed as follows:

$$\begin{cases} \min\limits_{\alpha} \ \ \sum\limits_{i=1}^{n}\alpha_i-\dfrac{1}{2}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n}\alpha_i\alpha_j y_i y_j x_i^T x_j \\ s.t. \ \ \sum\limits_{i=1}^{n}\alpha_i y_i=0, 0\leq\alpha_i\leq C, i=1,2,\cdots,n \end{cases}. \quad (9)$$

Since it is difficult for linear functions to correctly distinguish data samples, nonlinear mapping is introduced into the model to realize the mapping transformation from low-dimensional space information to high-dimensional space, making it linearly separable. The schematic diagram of nonlinear mapping is shown in Figure 3.

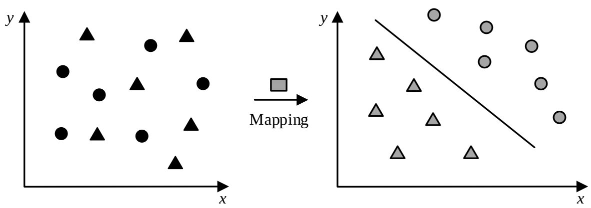



Figure 3: Nonlinear mapping diagram.

After introducing nonlinear mapping $x\rightarrow\phi(x)$ into the model, the nonlinear mapping is expressed in the form of inner product in the model, so it is not necessary to obtain the specific expression of $\phi(x)$, but the corresponding model decision function is obtained from the inner product form of $\phi(x)$. The kernel function is used to complete the inner product operation in the low dimensional space. The kernel function is expressed as follows:

$$K\left(x_i, x_j\right) = \phi\left(x_i\right)^T \phi\left(x_j\right). \quad (10)$$

The choice of kernel function is directly related to the performance of the whole LSSVM model. Linear kernel function, polynomial kernel function, sigmoid kernel function and radial basis function kernel function are commonly used. Among them, RBF kernel function has the advantages of strong locality and less parameters, and has good applicability in large sample data and small sample data. Therefore, RBF kernel function is selected as the kernel function of the model. The radial basis kernel function formula is expressed as follows:

$$K\left(x_i, x\right) = \exp\left(-\frac{\left\|x_i - x\right\|^2}{2\sigma^2}\right). \quad (11)$$

In equation (11), $\sigma$ is the kernel function parameter. Then the constrained optimization problem of the model is expressed as follows:

$$\begin{cases} \min\limits_{\alpha} \ \sum\limits_{i=1}^{n} \alpha_i - \frac{1}{2}\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n} \alpha_i \alpha_j y_i y_j K\left(x_i, x\right) \\ s.t. \ \sum\limits_{i=1}^{n} \alpha_i y_i = 0, 0 \le \alpha_i \le C, i = 1, 2, \cdots, n \end{cases}. \quad (12)$$

In equation (12), $\alpha_i$ is Lagrange multiplier, $\alpha_i \ge 0$. The model decision function is expressed as follows:

$$f\left(x\right) = \mathrm{sgn}\left[\left(\omega^*\right)^T \phi\left(x\right) + e^*\right] = \mathrm{sgn}\left(\sum_{i=1}^{n} \alpha_i^* y_i K\left(x_i, x\right) + e^*\right) \quad (13)$$

The operation process of enterprise credit financing risk prediction model based on antagonistic neural network and least squares support vector machine is shown in Figure 4. Firstly, the data samples are structured and normalized, and then the generation, judgment and update of antagonistic neural network solve the problem of unbalanced data samples, Finally, the risk prediction model based on least squares support vector machine is used to predict and warn the enterprise credit financing risk.

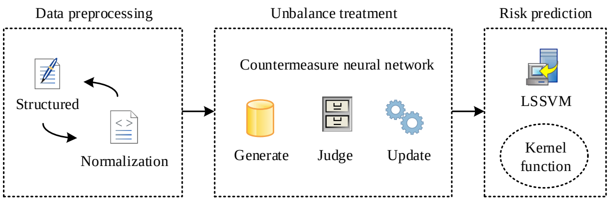



Figure 4: Operation process of enterprise credit financing risk prediction model.

# 4 Verification of risk prediction effect

## 4.1 Model performance analysis

The performance of the enterprise credit financing risk prediction model constructed by the research institute is verified and analyzed. The kernel function parameter $\sigma$ of the model controls the complexity of the model and affects the generalization ability of the model, while the regularization parameter $\gamma$ is related to the trade-off between the empirical risk and confidence range of the model. The parameter settings of the model are shown in Table 1.

| Duration of entrepreneurship | Freshman | Sophomore |
|---|---|---|
| Generative neural network | Number of neurons in hidden layer 1 | 30 |
| | Number of neurons in hidden layer 2 | 25 |
| Judgment neural network | Number of input neurons | 24 |
| | Number of output neurons | 1 |
| | Learning rate | 0.1 |
| LSSVM | $\sigma$ | 0.292 |
| | $\gamma$ | 34.807 |

Table 1: Parameter setting of model.

The average absolute error is used as the fitness function to verify the performance of the risk prediction model based on LSSVM. The fitness curve of the enterprise credit financing risk prediction model is shown in Figure 5.

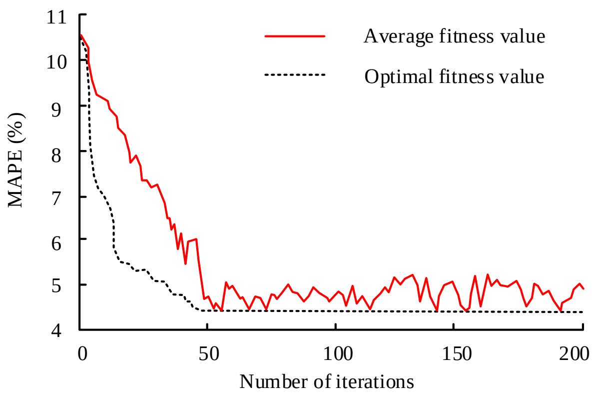



Figure 5: Fitness curve of enterprise credit financing risk prediction model.

As can be seen from Figure 5, the fitness curve of the risk prediction model decreased rapidly in the first 52 iterations, and the average absolute error percentage of the risk prediction model gradually decreased from 15.61% to 4.76%. The model began to converge after the 52nd iteration, and its average absolute error percentage was finally controlled at about 4.83%. In order to verify the effectiveness and optimization of the risk prediction model based on antagonistic neural network and LSSVM, taking the accuracy and recall of the model as the judgment standard, the LSSVM risk prediction model is compared with random forest model, support vector machine model and BP neural network. The accuracy and recall curves of the four models are shown in Figure 6.

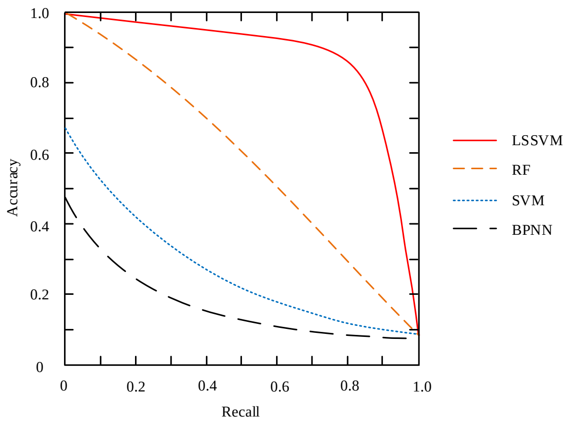



Figure 6: Accuracy and recall curves of four models.

As can be seen from Figure 6, the risk prediction model based on LSSVM has obvious advantages in accuracy and recall rate. The accuracy rate of the model is 90.15% and the recall rate is 85.63%, which is significantly higher than that of random forest model, support vector machine model and BP neural network. LSSVM model has obvious advantages in classification prediction accuracy and recall rate, and the stability of the model is the best, which can effectively predict and analyze enterprise credit financing risk.

## 4.2 Prediction and empirical analysis

In order to verify the practicability and feasibility of the enterprise credit financing risk prediction model based on LSSVM in the prediction of enterprise loan default risk, 5000 loan enterprise user data of an enterprise loan platform are taken as the experimental data set to verify the application effect of the risk prediction model in the actual enterprise credit risk. Comparing the risk prediction model of enterprise credit financing based on LSSVM with random forest model, Gaussian naive Bayesian model and BP neural network, the root mean square error of the four models is shown in Figure 7.

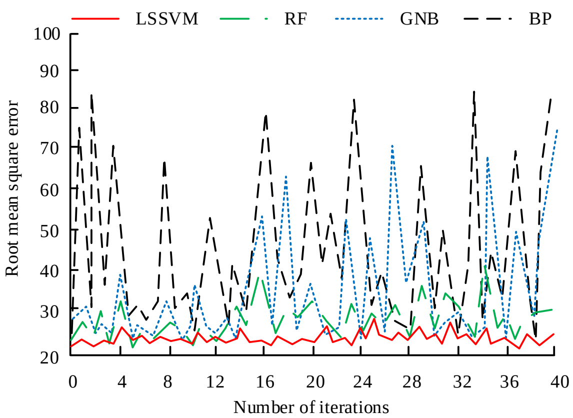



Figure 7: Root mean square error of four models.

As can be seen from Figure 7, the root mean square error of BP neural network is the largest, while the root mean square error of the risk prediction model based on LS VM is the smallest, which can effectively and accurately predict the enterprise credit financing risk. From the change trend of root mean square error curve, it can be seen that the risk prediction model based on LSSVM has the best stability, and random forest model, Gaussian naive Bayes model and BP neural network all have varying degrees of fluctuation. With the increase of iteration times, the root mean square error curve of the three models has poor stability and is prone to large-scale jump. The ROC change curve of the enterprise credit financing risk prediction model based on LSSVM is shown in Figure 8.

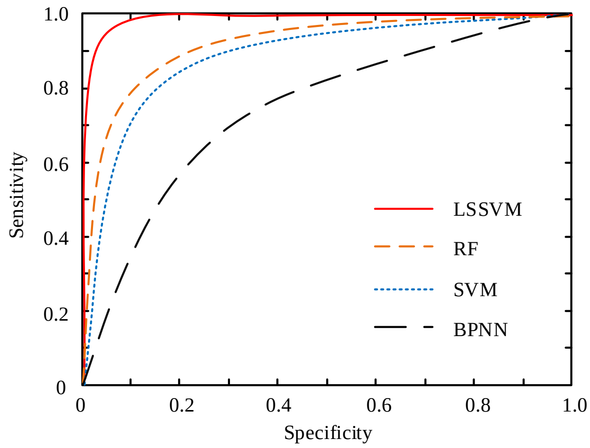
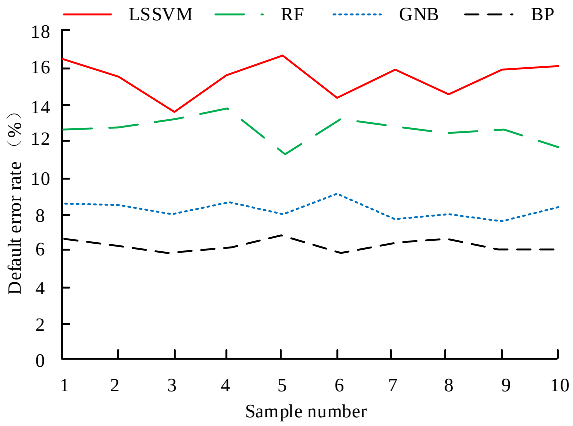
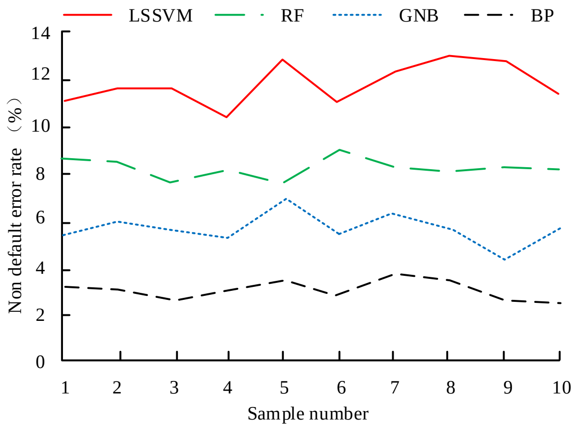



Figure 8: ROC change curve of enterprise credit financing risk prediction model.

As can be seen from figure 8, the area under the ROC curve of the enterprise credit financing risk prediction model based on LSSVM is 0.9677, and its standard deviation is 0.0023, which proves that the risk prediction model has a high accuracy in the classification and prediction of enterprise loan default. Compared with random forest model, Gaussian naive Bayesian model and BP neural network, the area under ROC curve of risk prediction model based on LSSVM is the largest and the area of BP neural network is the smallest, which proves the superiority of risk prediction model based on LSSVM in the four models. The risk prediction model based on LSSVM, random forest model, Gaussian naive Bayesian model and BP neural network are used to conduct 10 random experiments on enterprise loan default prediction. The prediction error rate of the four models in the face of enterprise loan default and non-default is shown in Figure 9.




(a) Forecast results of default




(b) Forecast results of non default

Figure 9: The prediction error rate of the four models in the face of enterprise loan default and non-default.

As can be seen from Figure 9, the average error rate of default prediction of risk prediction model based on LSSVM is 6.48%, while the average error rates of default prediction of random forest model, Gaussian naive Bayesian model and BP neural network are 8.25%, 12.57% and 15.49% respectively, which proves the superiority of risk prediction model based on LSSVM in enterprise loan default prediction, it can effectively and accurately predict the credit financing risk of enterprises. In the prediction of non-default of enterprise loans, the average error rate of non-default prediction of the risk prediction model based on LSSVM is 3.09%, which is significantly lower than 5.66% of the random forest model and 8.24% of the Gaussian naive Bayesian model. The error rate of non-default prediction of BP neural network is the highest, with an error rate of 11.81%, which proves the superiority of the prediction performance of the risk prediction model based on LSSVM.

## 5 Conclusion

Aiming at the credit financing risk control of small, medium-sized and micro enterprises, this paper studies the construction of enterprise credit financing risk prediction model based on antagonistic neural network and least squares support vector machine algorithm, uses antagonistic neural network to solve the problem of data sample imbalance, improves the richness of data samples, and uses least squares support vector machine model to predict enterprise credit financing risk. The experimental results of performance verification show that the accuracy and recall of the risk prediction model based on anti-neural network and branch least squares support vector machine are 90.15% and 85.63% respectively. In the actual risk prediction, the prediction error rates of the model in the case of default and non-default are 6.48% and 3.09% respectively. The prediction accuracy of enterprise credit risk is high, which can effectively predict and warn the enterprise credit default risk and help the enterprise carry out risk management. The research uses the generated neural network to generate false samples, which can further optimize the parameters of the generated anti neural network in the future, improve the learning performance of the model to the original data samples, and enhance the applicability of the generated samples.

## References


[1] Stevenson M P, Mues C, Bravo C (2021). The value of text for small business default prediction: A Deep Learning approach.*European Journal of Operational Research*,295, pp. 758-771. https://doi.org/10.1016/j.ejor.2021.03.008

[2] Sariannidis N, Papadakis S, Garefalakis A, Lemonakis C, Kyriaki-Argyro T (2020). Default avoidance on credit card portfolios using accounting, demographical and exploratory factors: decision making based on machine learning (ML) techniques.*Annals of Operations Research*,294, pp. 715-739. https://doi.org/10.1007/s10479-019-03188-0

[3] García V, Marqués AI, Sánchez JS (2019). Exploring the synergetic effects of sample types on the performance of ensembles for credit risk and corporate bankruptcy prediction.*Information Fusion*, 47, pp. 88-101. https://doi.org/10.1016/j.inffus.2018.07.004

[4] Moscato V, Picariello A, Sperlí G (2021). A benchmark of machine learning approaches for credit score prediction.*Expert Systems with Applications*,165, pp. 113986. https://doi.org/10.1016/j.eswa.2020.113986

[5] Niu K, Zhang Z, Liu Y, Li R (2020). Resampling Ensemble Model Based on Data Distribution for Imbalanced Credit Risk Evaluation in P2P Lending.*Information Sciences*,536, pp. 120-134. https://doi.org/10.1016/j.ins.2020.05.040

[6] Li B, Xiao B, Yang Y (2021). Strengthen credit scoring system of small and micro businesses with soft information: Analysis and comparison based on neural network models.*Journal of Intelligent and Fuzzy Systems*, 40, pp. 1-18. https://doi.org/10.3233/JIFS-200866

[7] Xu Y, Liu Z, Li Y, Hou H, Cao Y, Zhao Y, Guo W, Cui L (2020). Feature data processing: Making

medical data fit deep neural networks.*Future Generation Computer Systems*,109, pp. 149-157. https://doi.org/10.1016/j.future.2020.02.034

[8] Li H, Wang S , He P, de Rezende Rocha A (2020). Face Anti-Spoofing with Deep Neural Network Distillation.*IEEE Journal of Selected Topics in Signal Processing*,14, pp. 933-946. https://doi.org/10.1109/JSTSP.2020.3001719

[9] Junior F, Yen G G (2021). Pruning of Generative Adversarial Neural Networks for Medical Imaging Diagnostics with Evolution Strategy.*Information Sciences*,558, pp. 91-102. https://doi.org/10.1016/j.ins.2020.12.086

[10] Green A J, Mohlenkamp M J, Das J, Chaudhari M, Truong L, Tanguay RL, Reif DM (2021). Leveraging high-throughput screening data, deep neural networks, and conditional generative adversarial networks to advance predictive toxicology.*PLOS Computational Biology*,17, pp. 1-16. https://doi.org/10.1371/journal.pcbi.1009135

[11] Tian C, Han X (2021). A study on ship collision conflict prediction in the Taiwan Strait using the EMD-based LSSVM method.*PLOS ONE*,16, pp. 1-16. https://doi.org/10.1371/journal.pone.0250948

[12] Zhang X, Ge Z (2019). Local Parameter Optimization of LSSVM for Industrial Soft Sensing with Big Data and Cloud Implementation.*IEEE Transactions on Industrial Informatics*,16, pp. 2917-2928. https://doi.org/10.1109/TII.2019.2900479

[13] Ge Q, Guo C, Jiang H, Lu Z, Yao G, Zhang J, Hua Q (2020). Industrial Power Load Forecasting Method Based on Reinforcement Learning and PSO-LSSVM.*IEEE Transactions on Cybernetics*,52, pp. 1112-1124. https://doi.org/10.1109/TCYB.2020.2983871

[14] Zhen C, Liu H (2019). Model for Predicting NOx Emission from Boilers Based on MWOA-LSSVM Integration.*Journal of Chemical Engineering of Japan*,52, pp. 702-709. https://doi.org/10.1252/jcej.19we004

[15] Zhao Z, Chen K, Chen Y, Dai Y, Liu Z, Zhao K, Wang H, Peng Z (2021). An Ultra-Fast Power Prediction Method Based on Simplified LSSVM Hyperparameters Optimization for PV Power Smoothing.*Energies*,14, pp. 1-14. https://doi.org/10.3390/en14185752