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Construction and Evaluation of Credit Risk Early Warning Indicator System of Internet Financial Enterprises Based On AI and Knowledge Graph Theory

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Abstract

Through in-depth analysis of credit risk in the context of the development of Internet finance, the study recognized that its diversification and complexity not only include financial risks, but also involve the impact of non-financial factors. Based on this, combined with ESG factors, principal component analysis and grey correlation method are used to optimize the indicators, ensuring the comprehensiveness and accuracy of the indicator system. Using Convolutional Neural Network (CNN) as the warning model, considering the dynamic and static characteristics of data, a sub convolutional network was designed for training different types of data. At the same time, the credit rating division and warning threshold selection methods were optimized, improving the accuracy and practicality of the model. Through experimental verification, we found that the CNN model has a high accuracy in credit risk warning, and it also shows excellent classification performance and comprehensive effect compared to other models. Through systematic research and application, this paper provides a complete solution for the credit risk management of Internet financial enterprises, and makes positive contributions to the stability of the financial system and risk prevention. At the same time, we also emphasize the important role of technological innovation in financial intelligent management, especially the application of innovation systems centered on AI and knowledge graphs in the field of credit management, which points out the direction for the future development of the financial industry.

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Keywords: Risk control and early warning, Digital financial institutions, AI technology, Data graph theory, Neural network algorithm

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1. Introduction

Relying on digitalization, information technology and the Internet, Internet finance, a new business model based on the network, has developed rapidly. The market size of China's Internet finance industry has shown continuous growth from 2016 to 2022, and the growth rate has declined to rise and then to stabilize, showing that the industry is in a stage of steady development. However, amid fierce competition, Internet financial enterprises face many challenges, such as "routine lending", Ponzi scheme, P2P platform risk and so on. Strengthening norms and governance, anti-monopoly and unified supervision became the key words of the year, and the supervision was constantly increasing, and the industry as a whole underwent major changes. In the future, Internet financial platforms need to re-examine the boundary between finance and technology business, showing a development trend of great differentiation and strong supervision.

Under the current global economic depression and domestic economic transformation, commercial banks are facing profound changes. In the past, the rapid development of relying solely on the expansion of credit scale has passed, and the credit business of commercial banks is facing urgent pressure of transformation. At the same time, with the rapid development of financial technologies such as artificial intelligence, big data and cloud computing, digital transformation has become a key driving force for the development of commercial banks. Agricultural Bank of China fully grasped the opportunity of financial technology development, formulated the "financial technology +" strategy, led the application of knowledge graph and "AI+ Knowledge graph" technology in the field of credit management, and provided strong scientific and technological support for credit product innovation and credit risk control.

This paper aims to build an efficient credit risk early warning model for Internet financial enterprises, realize timely and accurate identification of risks, and propose effective risk control measures, improve the overall risk management level and risk control ability, and promote the industry to a more mature and stable development stage. Current credit risk warning models mainly include statistical model and artificial intelligence model based on machine learning, but each has advantages and disadvantages. In this paper, the convolutional neural network (CNN) technology will be used to build a credit risk early warning method suitable for Chinese Internet financial enterprises, and at the same time, the existing problems will be deeply analyzed and solved, so as to provide more accurate risk assessment and prediction, and provide a reliable basis for risk identification, judgment, early warning and regulation.

2. Related Research

In the field of credit risk assessment, researchers have carried out in-depth research on different aspects. S Chen established a credit risk assessment index system for online supply chain finance, focusing on factors such as financing enterprise qualification, core enterprise qualification, supply chain operation and macro environment[1]. This study provides decision support for credit risk management of small and medium-sized enterprises.

M Mushafiq's research explores the relationship between credit risk and financial performance in non-financial firms, with a particular focus on the effects of Altman Z-scores, leverage, and firm size on financial performance, providing important insights for investors and managers[2]. M Wang constructed a transferable personal credit risk model through transfer learning, which has advantages in application value and robustness, and provides a new method for personal credit evaluation[3].

H Peng proposed a new method of credit risk identification for Internet financial enterprises based on big data, and adopted improved analytic Hierarchy Process (AHP) and linear weighted comprehensive method, which can accurately assess the credit risk of Internet financial enterprises[4]. FBaser proposed a clustering based fuzzy classification (CBFC) method for credit risk assessment[5]. By using the fuzzy theory to calculate default risk and better select contributing factors, the prediction ability of machine learning method has been improved, which has guiding significance for credit assessment practitioners and decision makers.

J Lu established a bank credit decision-making system for small and medium-sized enterprises, quantified risks through credit records and reputation ratings, and established an enterprise default screening model and a risk level refinement model, which provided an effective tool for credit decision-making in banking business[6]. H Zhang studied the impact of credit rating migration risk on the market in the pricing of Chinese convertible bonds. Through the analysis of Tsiveriotis and Fernandes (1998) model, the results showed that this model had a good fit to the market price and could provide guidance for participants in the convertible bond market[7].

The study explores the impact of economic policy uncertainty (EPU) in listed Tunisian banks on credit risk, lending decisions and bank performance during the period 1999-2019, and recommends that Tunisian banks should establish credit risk monitoring and early warning systems to ensure sustainable development[8]. GAFE Shen's research has developed a new deep learning integrated credit risk assessment model for credit data imbalance, which has a competitive advantage by combining the improved SMOTE method and LSTM with AdaBoost algorithm[9].

KS Naik aims to use machine learning to predict credit defaults on unsecured credit card loans, and the results show that the LGBM classifier model is better suited to improve learning speed, efficiency, and processing larger volumes of data, helping bank decision makers to better predict credit defaults[10]. MSS Danish is dedicated to developing mathematical methods for dealing with time-varying parameters in rolling window Logit models for credit risk assessment[11]. The prediction coefficient can improve the accuracy of the model more than simply using the past statistical parameters. A new method is proposed, which combines a variety of models to calculate the default probability of borrowers more accurately. The empirical results show that the method is effective.

These studies not only provide new ideas and methods for credit risk management in the financial industry, but also promote the integration of financial technology and risk management, laying a solid foundation for future financial innovation and risk prevention.

3. Method

3.1 System support of "AI+ Knowledge Graph

Agricultural Bank of China actively promotes financial technology innovation, laying the foundation of the "financial technology +" strategy, and takes the construction of financial brain and the construction of knowledge graph as an important measure, providing core scientific and technological support for digital operation and intelligent transformation. Among them, the financial brain, as the core system of artificial intelligence, realizes the intelligent concentration of the whole bank and empowers AI technology for various business fields. Through GPU/CPU high-performance AI computing architecture and virtualization technology, Financial Brain provides high-precision intellisense services and whole-lifecycle machine learning and model management to provide more intelligent real-time support for business decisions.

In terms of knowledge graph, based on the DIKW system, Agricultural Bank of China extracts information from massive data through knowledge identification, fusion, storage and other links to build a complete knowledge graph, and converts knowledge into wisdom through semantic analysis, search, graph mining and other knowledge services to endow financial brains with higher intelligence capabilities. It adopts a four-layer architecture model, including knowledge identification, fusion, storage, calculation and knowledge service, and realizes the extraction and application from data to information and then to knowledge, forming the first knowledge graph system of the whole life cycle management in the whole bank.

The breakthrough and innovation of the knowledge graph of Agricultural Bank is reflected in many aspects: the comprehensive life cycle management covers the whole process from data acquisition to application, and realizes knowledge extraction from structured, semi-structured and unstructured data; Ontology modeling adopts the combination of top-down and bottom-up mode, which is easy for business personnel to understand and manage. It adopts hybrid architecture, which has the characteristics of high availability, high performance and scalability, and supports the construction and calculation of large-scale knowledge graph. The computing engine based on the knowledge graph realizes the full coverage of intelligent services, avoids the "island" phenomenon, and provides strong scientific and technological support for financial product innovation and risk prevention and control.

At present, Agricultural Bank of China has a huge scale of knowledge graph, including 100 billion level of raw data, tens of millions of nodes and about 200 million relationships, which can support real-time online and batch access for various business applications. By constructing this knowledge graph, Agricultural Bank of China successfully transformed data into entity representation, established a knowledge association system based on entity relationship network graph, realized the semantic based accurate retrieval function, and used ontology for knowledge reasoning, providing strong technical support and guarantee for the intelligent development of financial business.

3.2 Construction of credit risk early warning index system for Internet financial enterprises

In the process of selecting indicators, we consider comprehensiveness, comparability, combination of qualitative and quantitative, scientificity and economy based on literature analysis and scientific principles. After preliminary design, we determined a credit risk early warning system with 33 financial indicators and 13 non-financial indicators, covering finance, market and operation, aiming to improve the accuracy and effectiveness of early warning.

The composition of the sample set and the selected sample companies are clearly defined. According to the close relationship between credit risk and bond default, whether the sample companies have bond default is taken as the standard for judging credit risk. 81 companies were selected as samples, 12 of which had a record of default. We classified these enterprises and set different observation days.

Data preprocessing plays a key role in data mining, including the processing of outliers and missing values and the standardization of data. Outlier processing is usually done using the interquartile (IQR) method, where points greater than 1.5 times the IQR are treated as outliers and rows containing outliers are removed accordingly. For missing data values, the processing methods include deletion, interpolation and filling, etc. Considering the data characteristics of Internet financial enterprises, this paper selects the same kind of mean to interpolate missing values. Finally, data standardization is an important step to ensure that different indicators have comparability and unified scale. Min-max method is a commonly used standardization method, mapping data between 0 and 1 to avoid affecting model training and prediction accuracy due to different index dimensions.

Before the significance test, the samples need to be tested for normality to determine whether they are suitable for parametric test or non-parametric test. For the sample size less than 5000, Shapiro-Wilk test was used in this paper for normality test, where a P-value less than 0.05 indicates that the data conforms to normal distribution. By further testing the significance of each index, it is found that the asset-liability ratio, return on assets, sustainable growth rate and other indicators have a significant impact on the credit risk of Internet financial enterprises. Then, the influence factors were further screened by using Manwhitney U test for comparison. Subsequently, KMO test and Bartlett spherical test were conducted, and the results were shown in Table 1, confirming that the samples were suitable for principal component analysis. The number of principal components is determined by the cumulative variance contribution rate, and the load coefficient of each factor is analyzed, which reveals the degree of influence of factors such as profitability, solvency and cash acquisition ability of Internet financial enterprises on credit risk.

Table 1. KMO and Bartlett sphericity tests

Test	Value
KMO value	0.745
Approximate chi-square	1789.450
Degree of freedom	102
p-value	0.000

In the field of Internet finance, non-financial indicators play an important role, they are closely related to financial data, directly or indirectly reflect the company's business conditions. Changes in non-financial data such as user numbers and activity often directly affect the performance of financial data such as revenue and profit. In addition, some non-financial factors such as brand image and employee satisfaction will also indirectly affect the company's business development and management efficiency, which will have an impact on financial data. Therefore, in the selection of non-financial indicators, we must consider the relationship between them and financial indicators, combined with the actual situation of the market for a comprehensive analysis. In this study, grey correlation analysis was used to screen out non-financial indicators closely related to financial performance.

According to the results of principal component analysis, profitability is recognized as one of the most influential financial indicators for credit risk. In grey correlation analysis, we choose non-financial indicators as reference objects, profitability as comparison objects, and measure the relationship between them through the evaluation of correlation degree. The results show that market risk assessment and the type of audit opinion are the non-financial indicators most closely related to profitability, while the correlation degree of other indicators is low, so these indicators are excluded when the correlation degree is comprehensively considered.

After correlation degree analysis, we obtained a set of preferred non-financial indicators, combined with financial indicators to construct a complete sample data set, including financial principal component factors and non-financial indicators. This process contributes to a more accurate assessment of a company's credit risk and improves the reliability of early warning results.

3.3 Construction of early warning model based on neural network

The convolutional neural network constructed in this article consists of two sub convolutional networks, which are used to process dynamic data (financial indicators) and static data (non-financial indicators), respectively. These two sub networks extract features separately and generate their feature representations. The feature representations will be merged and input into a fully connected layer, which comprehensively processes the feature representations of two sub networks and performs classification tasks, ultimately outputting the probability distribution results transformed by the Softmax function.

The convolutional layer contains multiple feature maps, each of which is composed of multiple neurons. Each neuron is connected to the local region of the previous layer's feature map through a convolutional kernel. The convolutional layer reduces the number of free parameters in the network and reduces the complexity of the network through local connections and weight sharing mechanisms. Assuming that the j input feature vector of the convolutional layer is X_j^l, its calculation is shown in formula (1).

$$X_j^l = f(\sum_{i \in M_j} \mathrm{X}_\mathrm{j}^{\mathrm{l}-1} \otimes K_{ij}^l + b_j^l) \tag{1}$$

Among them, X_j^l is the nth input feature vector, K_{ij}^lrepresents the nth convolution kernel of the nth input feature vector in the nth layer, and b_j^l is the corresponding bias parameter.

The pooling layer connected to the convolutional layer downsamples the input vector. Each convolutional layer is connected to the next pooling layer to simplify the calculation of feature vectors. The calculation formula for the pooling layer is shown in (2):

$$X_j^l = f(\beta_j^l \cdot d(\mathrm{X}_\mathrm{j}^{\mathrm{l}-1}) + b_j^l) \tag{2}$$

The first sub convolutional network consists of 2 convolutional layers, 2 pooling layers, and 1 residual structure. This network is used to process financial data, and the first convolutional layer uses a 1x3 kernel to extract features of sample companies at different time points. After the convolutional layer, a 2x2 pooling layer is connected to further extract features, and the maximum value in the local area is selected through the max pooling operation. The second convolutional layer uses a 3x3 convolutional kernel to further extract features of different indicators and time series. After the second convolutional layer, connect three residual units to solve the problem of data explosion. Finally, add a 2x2 pooling layer. The second sub convolutional network consists of one convolutional layer and one pooling layer, which are used to process non-financial data. The convolutional layer uses a 1x3 kernel.

The outputs of two sub convolutional networks are fused in a fully connected layer. The dimensions of the first fully connected layer and the second fully connected layer are 64 and 32, respectively. The calculation formula for the fully connected layer is (3):

$$X_j^l = f(\sum_{i \in (l-1)} \ \mathrm{X}_\mathrm{j}^{\mathrm{l}-1} \otimes W_{ij} + b_j^l) \tag{3}$$

Finally, we choose the Softmax function as the output classifier to estimate the probability that the output x x belongs to a specific category $j \in k$， j ∈ k, which can be calculated using formula (4):

$$P(y = j \mid x) = \frac{e^{x^T W j}}{\sum_{k=1}^{K} e^{x^T W k}} \tag{4}$$

The activation function selects the commonly used correction linear unit (ReLU), which is defined as formula (5):

$$f_{ReLU}(x) = max(0, x) \tag{5}$$

To prevent overfitting, BN normalization, L2 regularization, and Dropout functions were used. Dropout is an effective method in convolutional neural networks to prevent overfitting by randomly discarding neurons during the training process. This article performs a Dropout operation after the last pooling layer of each sub convolutional network, with an inactivation rate generally set to 0.5.

The convolutional layer calculates residuals through the backpropagation process, which can be calculated using formulas (6) and (7):

$$\delta_{l-1} = upsample(\delta_l) \odot \delta'(z_{l-1}) \tag{6}$$

$$\delta_{l-1} = \delta_l \odot rot180(W_l) \odot \delta'(z_{l-1}) \tag{7}$$

The weight update formulas are (8) and (9):

$$\frac{\partial J}{\partial W_l} = \delta_l \odot rot180(a_{l-1}) \tag{8}$$

$$bl = \sum(\delta l) \tag{9}$$

The weight update formula is (10):

$$\theta_{i+1} := \theta_i - \alpha \nabla J(\theta_i) \tag{10}$$

Among them, $\theta_{i+1}$is the optimized weight, θ_i is the initial weight, α is the learning rate, $\nabla J(\theta_i)$ It is the gradient of the loss function.

The convolutional neural network constructed in this paper consists of two sub-convolutional networks for processing dynamic data (financial indicators) and static data (non-financial indicators) respectively. These two subnetworks extract features separately and generate their feature representations. The feature representation is merged into the full connection layer, which synthesizes the feature representation of the two subnetworks, performs the classification task, and finally outputs the probability distribution result transformed by the Softmax function.

The CNN structure is shown as follows: The convolutional layer is composed of multiple feature surfaces, each feature surface contains multiple neurons, and each neuron is connected to the local area of the feature surface of the previous layer. Local connections and weight sharing are used to reduce the number and complexity of network parameters. Pooling layer is a subsampling operation of input vectors. Each convolution layer is connected to a pooling layer for feature reduction calculation.

Subconvolutional network 1 consists of 2 convolutional layers, 2 pooling layers, and 1 residual structure, and is specifically designed to process financial data. The first convolutional layer uses 1×3 convolution kernel to extract features at different time points, then goes through 2×2 pooling layer for further feature extraction, and then joins the second convolutional layer for further feature extraction. Finally, three layers of residual units are introduced to solve data problems, and a 2×2 pooling layer is connected. Subconvolutional network 2 consists of one convolutional layer and one pooled layer, specially for processing non-financial data, and uses 1×3 convolutional kernel to extract features. The output of these two sub-convolutional networks is merged into the fully connected layer, and the classification results are output through Softmax function.

4. Experimental Test

4.1 Application of credit risk early warning model based on neural network

Optimization of model parameters is a key step in machine learning. Parameters such as learning rate and number of iterations are adjusted to improve the performance of the model, and ADASYN adaptive sampling is used to solve the problem of sample imbalance. The proportion of default samples in this article is 14.81%, resulting in uneven distribution of positive and negative samples. To solve this problem, this article uses the ADASYN method for adaptive synthetic sampling, generates new training samples, and divides them into training and testing sets in an 8:2

ratio. Next, it is necessary to determine the impact of the following hyperparameters on network performance: activation function, learning rate, convolution kernel size, number of convolution kernels, padding method, and Dropout.

The alternative options for the activation function include [Relu, Tanh, Sigmoid, Softplus, Logistic], as shown in Figure 1; The candidate items for learning rate are [0.5, 0.3, 0.2, 0.1, 0.01, 0.001, 0.0001, 0.00001], as shown in Figure 2; The alternative options for the size of convolutional kernels are [1, 2, 3, 5, 7], as shown in Figure 3; The alternative terms for the number of convolutional kernels are [4, 8, 16, 64, 128], as shown in Figure 4; The alternative options for filling method are [0, 1, 2, 3, 5], as shown in Figure 5; The alternative options for Dropout are [0.1, 0.2, 0.3, 0.4, 0.5]. hrough experimental analysis, the final hyperparameter combination is shown in Table 2: the activation function is selected Relu, the learning rate is set to 0.0001, the convolution kernel size is 3, the number of convolution kernels is 64, the filling method is 1, and the Dropout is set to 0.5.

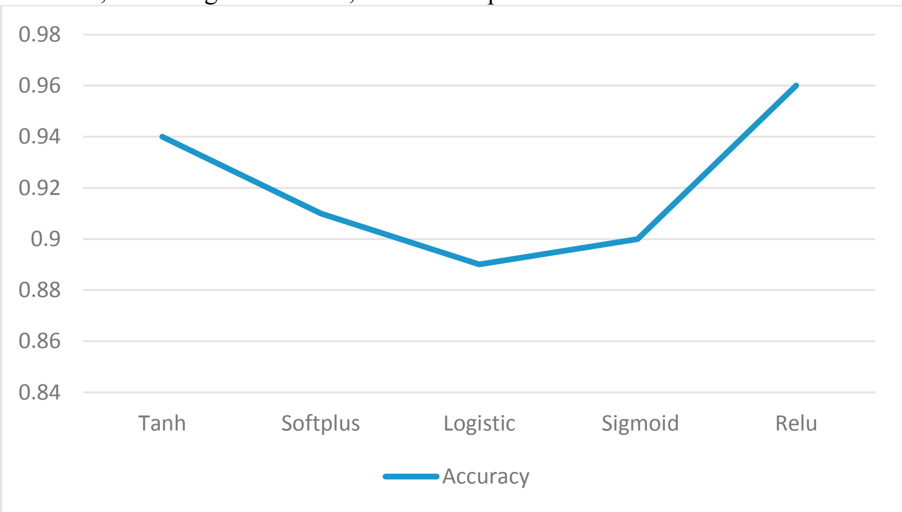

Figure 1. Activation Function Accuracy

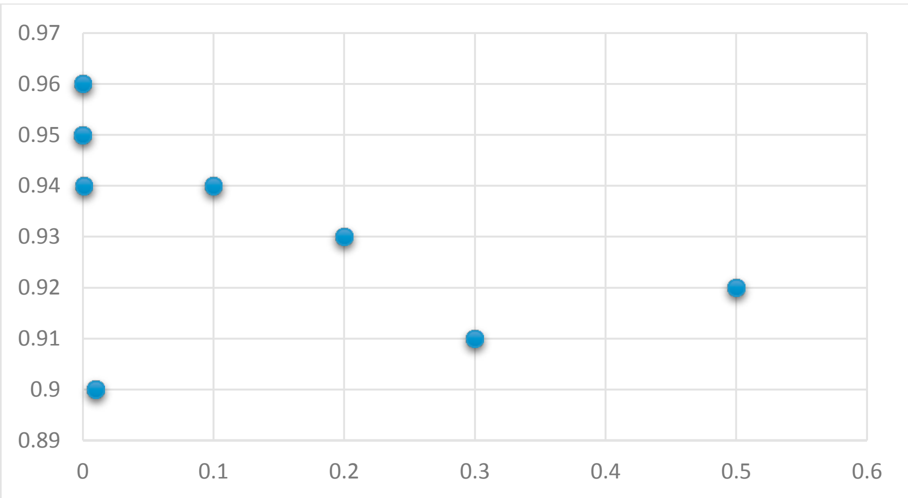

Figure 2. Learning rate

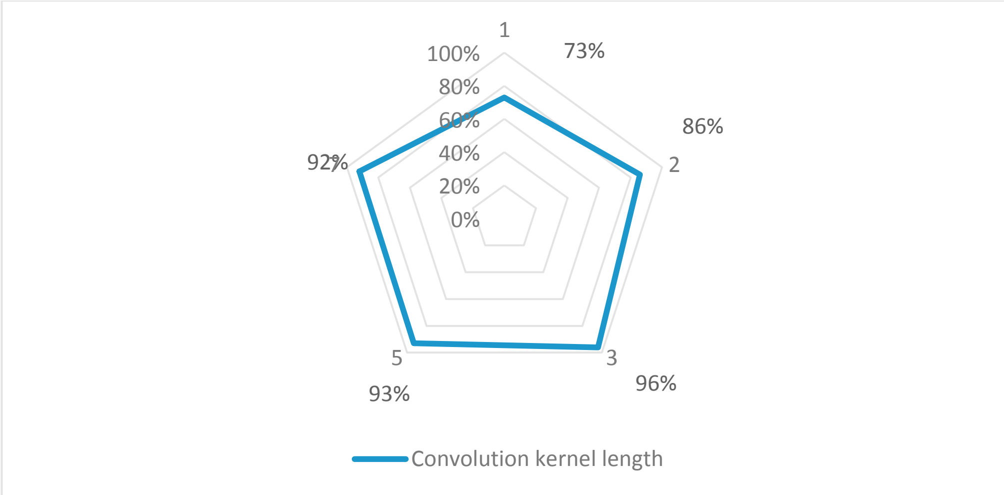

Figure 3. Convolutional Kernel Length

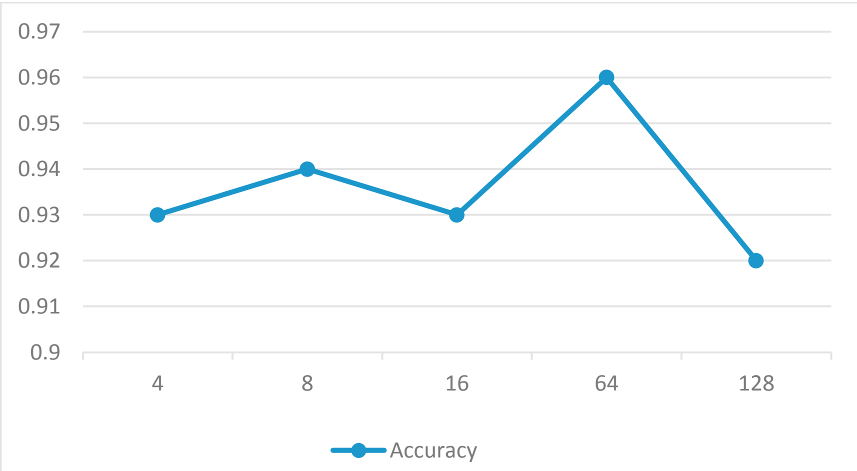

Figure 4. Training accuracy of different numbers of convolutional kernels

The CNN model uses the Softmax layer to convert the default probability *PP* 'into the actual probability *PP* to reflect the real situation. Calculate your credit score in the order of *PP Pi*. For every time you increase the default probability, your score will decrease by 10 points. If not, the probability of default is halved, and the score is increased by 10 points. The score is divided into 9 groups of equal frequency, and the enterprise credit rating is divided according to the most recent principle. For example, the AAA rating ranges [88.7,98.1], representing excellent credit risk, and the C rating ranges [40.1,63.2], representing no credit. Each group accounts for about 11.11% of the sample. After classifying 81 companies, 86.67% of the defaulting samples were in file C (score <63.2), indicating no credit. 75.36% of the non-defaulting samples had a score >72.1, indicating good credit status.

It is very important for binary classification model to choose proper warning limit. The optimal warning limit was determined by ROC curve. This threshold corresponds to a default risk of 2.8% and a credit rating of 68.7. In short, when the default risk of an enterprise is higher than 2.8% and the credit assessment is lower than 68.7, we consider it as a high-risk enterprise, and the model will issue timely and accurate risk warnings and carry out necessary credit risk monitoring.

According to our research, we used the binary classification prediction algorithm to predict default and non-default of the sample, and conducted comparative and statistical analysis of the prediction results to evaluate the training effect of the model. After training, as shown in Table 2. After the early warning of 81 listed Internet finance companies as of December 31, 2022, we found 12 high-risk enterprises, 10 of which were accurately identified as high-risk, and the model has a good monitoring and early warning effect.

Table 2. Evaluates the training effect of the model

Index	Accuracy rate	Precision rate	Recall rate	F1 score	AUC value	KS value
Numerical value	97.64%	98.35%	98.76%	98.55%	0.97	0.63

4.2 Evaluation and analysis of credit risk early warning model based on neural network

Current research is to evaluate the performance of CNN model and other traditional early warning models, and evaluate their performance in early warning. Four kinds of multi-classification classifiers, including random forest, Adaboost, SVM and BP neural network model, are introduced, and their performance is compared with CNN model. Through comparative analysis, it is found that CNN model has better performance in accuracy rate, accuracy rate, recall rate, F1 score, AUC value and KS value, and has higher warning accuracy and better classification effect, especially in identifying positive and negative samples and improving warning performance. For example, the early warning accuracy of the CNN model reaches 96.30%, the F1 score is 0.9696, the AUC value is close to 1, and the KS value is 0.64, which is much higher than the general standard. At the same time, other models also show good accuracy and classification performance, such as the early warning accuracy of the random forest model is 87.92%, the F1 score is 0.8982, and the AUC value is 0.91. As shown in Figure 5, these data results indicate that the CNN early warning model constructed in this paper has higher early warning accuracy and good classification performance in the credit risk early warning of Internet financial enterprises.

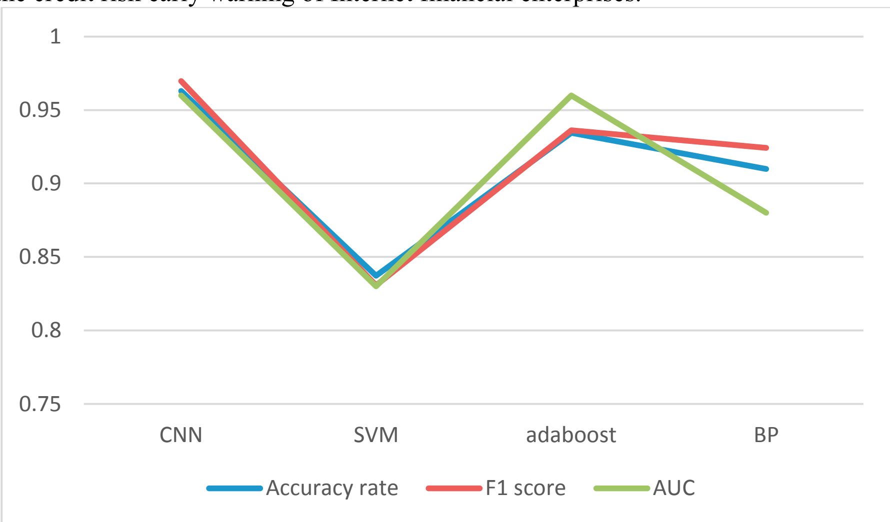

Figure 5. Comparison of test results

The main research objective of this paper is to compare the performance of different early warning models in corporate credit early warning, and explore the relationship between model accuracy and sample size. It is found that the samples of normal companies and credit crisis defaulting companies are different, and the early-warning accuracy of each model is generally higher for normal companies than for credit crisis defaulting companies. This may be because the number of positive samples is larger and the algorithm is more inclined to consider such cases, while the number of negative samples is smaller and less common in practice, causing the algorithm to be less accurate about its learning and predicting results. At the same time, the unbalanced number of samples will also affect the accuracy of the model. Therefore, when using machine learning algorithm for early warning, it is necessary to balance the number of samples, and the experimental results also confirm the necessity of introducing sample balancing method.

In addition, it is found that the training time of CNN model is longer, but its early warning performance is better than other models. The running efficiency is affected by sample size and parameter setting, so it is very important to carry out parameter simulation optimization experiment during training. While HPC platforms can improve operational efficiency, enterprises need to balance high accuracy with low efficiency, while avoiding overfitting problems caused by increasing the number of network layers. The comprehensive research results show that using CNN technology to build a credit risk early warning model suitable for Internet financial enterprises can significantly improve the accuracy rate and reduce the false positive rate, and has high applicability and reference value.

5. Conclusion and Prospect

In the research, it deeply analyzes the construction of credit risk early warning model and its application in Internet financial enterprises, especially the early warning model based on convolutional neural network (CNN). By integrating relevant domestic and foreign literature and existing risk warning indicator systemsAn efficient credit risk warning model based on CNN was proposed to address the challenges and demands of credit risk warning, and empirical research and performance comparison were conducted. The main research conclusions include the construction of a preliminary credit risk early warning indicator system suitable for Internet financial enterprises, the design of an early warning model containing multi-layer convolution and pooling layers, and the performance comparison with other classic models, showing a higher early warning accuracy and differentiation ability. Future research will focus on solving the problem of imbalanced samples, improving indicator systems, and exploring the limitations of CNN models to enhance the applicability and practicality of credit risk warning models, and promote the development and innovation of credit risk management.

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