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Predicting Credit Bond Default with Deep Learning: Evidence from China

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Abstract: China's credit bond market has rapidly expanded in recent years. However, since 2014, the number of credit bond defaults has been increasing rapidly, posing enormous potential risks to the stability of the financial market. This study proposed a deep learning approach to predict credit bond defaults in the Chinese market. A convolutional neural network (CNN) was selected as the classification model and to reduce the extreme imbalance between defaulted and non-defaulted bonds, and a generative adversarial network (GAN) was used as the oversampling model. Based on 31 financial and 20 non-financial indicators, we collected Wind data on all credit bonds issued and matured or defaulted from 2014 to 2021. The experimental results showed that our GAN+CNN approach had superior predictive performance with an area under the curve (AUC) of 0.9157 and precision of 0.8871 compared to previous research and other commonly used classification models—including the logistic regression, support vector machine, and fully connected neural network models—and oversampling techniques—including the synthetic minority oversampling technique (SMOTE) and Borderline SMOTE model. For one-year predictions, indicators of solvency, capital structure, and fundamental properties of bonds are proved to be the most important indicators.

Key words: credit bond default; prediction; convolutional neural network; imbalanced data processing; generative adversarial network

1 Introduction

China's credit bond market has rapidly expanded in recent years. According to data from the Wind economic database, the circulation of credit bonds reached 11.89 trillion RMB (1.68 trillion US dollars) in 2022. Historical rigid payment regulations ensured the stable development of the credit bond market in China until 2014. However, on 7 March 2014, the default of "11 Chaori bond" signaled the end of the era of rigid payment regulations[1]. Since then, the number of credit bond defaults has increased rapidly, the risk of credit bond default being the economic impact caused by the debtor's failure to repay the principal and interest of the debt on time[2]. This, in turn, can have a negative impact on the sustainability of enterprises and creditors[3], leading to increased bankruptcy risks. These risks pose dangers to the banking system and potentially the entire financial market, placing enormous pressure on its stable development[4]. Consequently, predicting the risk of credit bond defaults is critical for creditors, debtors, and the market.

A credit bond default is the manifestation of financial distress[5]. Early models for predicting financial distress in enterprises included univariate statistical regressions[6] and structural models[7]. Altman[8], one of the earliest first scholars to study the problem of financial distress warnings, used five financial indicators to construct the Z-score financial distress prediction model. Over time, an increasing number of financial indicators have been added to the pool of predictive factors, resulting in improved predictive abilities. However, some recent studies have

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emphasized the limited explanatory and predictive power of financial indicators and introduced non-financial factors[9, 10]. Wang et al.[11] argued that if an enterprise did not have a good mechanism to adapt to a changing business environment, it could easily encounter problems such as insufficient liquidity and excessive debt. Ma et al.[1] verified that the indicators of bond issuers and the macroeconomic environment had a major impact on bond default predictions; and Huo[12] studied the relationship between credit ratings provided by various rating agencies and default risk using a machine learning algorithm.

With the development of artificial intelligence, an increasing number of scholars have begun to adopt machine learning methods to predict financial distress and credit risk[13, 14]. Specifically, Wang et al.[15] compared machine learning models with traditional econometric models to predict corporate debt default risk, their results showing that the random forest (RF) method was superior to other models. Although machine learning models can adapt to nonlinear causality, their predictive ability depends enormously on the construction of characteristic indicators[16]. Recent studies have found that deep learning methods could compensate for the shortcomings of machine learning in feature screening with high dynamic adaptability[17]. For financial distress predictions, deep learning methods—especially convolutional neural networks (CNNs) and long short-term memory (LSTM) neural networks—have demonstrated excellent performance[18, 19]. Hosaka[20] constructed a CNN by converting numerical financial ratio data into grayscale images as features, outperforming traditional models. Tan et al.[21] also verified that CNNs outperformed the support vector machine (SVM) and k-nearest neighbor (KNN) algorithms.

In addition to the classification problem, imbalanced data processing is another important problem to address when predicting credit bond defaults. The dataset for default and non-default samples is extremely imbalanced, which can have a major impact on classification effectiveness[22]. Some researchers chose to match default samples with non-default samples at a 1:1 ratio and ignore the problem of imbalanced data processing[15]. Synthetic minority oversampling technique (SMOTE) and its variants (such as Borderline SMOTE) are commonly used oversampling methods. Recent studies have found that using deep learning methods for oversampling—particularly generative adversarial networks (GANs)—can solve problems such as marginal distribution, which exist in SMOTE and its variants[23]. Although GANs and their derivative models are frequently used for image generation, studies have shown that they can be effectively applied to other types of data-generation scenarios—such as credit fraud detection—which also involve imbalanced datasets[24]. Specifically, Yao et al.[5] applied Wasserstein generative adversarial networks (WGANs) to an imbalanced sample of bond defaults and achieved good results when combined with machine learning algorithms for classification.

Overall, although deep learning has already showed superior performance in financial distress prediction in recent years, its application to credit bond defaults is only beginning to receive attention. In addition to the classification model, the oversampling model is of great importance because of the extreme imbalance between defaulted and non-defaulted bonds. However, very few studies focus on the application of deep learning to either of them. Yao et al.[5] took the first step in exploring the effect of deep generative oversampling techniques on machine learning classification models with eight predictive indicators. In this study, we took it a step further by using a GAN as the oversampling model and a CNN as the classification model with fifty-one predictive indicators. Other commonly used classification models—including the logistic regression, support vector machine, and fully connected neural network models—and oversampling models—such as the SMOTE and Borderline SMOTE models—were compared with the proposed GAN+CNN approach. Experimental results showed that the proposed method achieved the best predictive performance in the Chinese bond market.

2 Predictive Indicator and Data

Based on previous studies, we selected 31 financial and 20 non-financial factors to predict credit bond defaults in the Chinese market, with a total of 51 indicators (Table 1). As shown, the financial factors are classified as capital structure, profitability, solvency, growth capacity, or operating capacity, with nonfinancial

Table 1 Predictive indicators.

Type		Indicator name	Reference
Financial	Capital structure	Human capital investment rate of return	[25]
		Asset liability ratio	[26]
		Shareholder equity ratio	[27]
		Ratio of current assets Current debt ratio	[28]
	Profitability	Return on equity Net sales rate Ratio of sales to cost Net operating profit margin Main business profit margin	[19]
		Operating net cash flow ratio	−
		All the assets of the cash recovery rate	−
		Earnings before interest, taxes, depreciation, and amortization (EBITDA) rate	[22]
		Income tax rate	−
	Solvency	Current ratio Quick ratio Proportion of long-term liabilities	[28]
		Net debt ratio	[29]
		Equity ratio	[19]
		EBITDA/interest expenses	[22]
	Growth capacity	Total profit growth rate Main profit growth rate	[19]
		Business income growth rate Owner’s equity growth rate	[28]
		Fixed asset proportion	[22]
	Operating capacity	Inventory turnover rate	[21]
		Accounts receivable turnover rate Current asset turnover rate Total asset turnover rate Fixed asset turnover rate	[28]
		Cash turnover rate	[26]
Non-financial	Fundamental properties of bonds or debtors	Coupon rate at issue Amount of bond issuance/RMB Issuing period/Year	[28]
		Corporate credit rating at issue Bond rating at issue Listed company or not	[30]
		Interest payment method Bond type Industry Whether special terms are included	[19]
		Interest-bearing interest rate varieties	−
		Interest rate on new issues	−
	Macroeconomic environment	Macroeconomic prosperity index Manufacturing purchasing managers’ index (PMI) (year on year (YoY))	[19]

(To be continued)

Table 1 Predictive indicators. (Continued)

Type		Indicator name	Reference
Non-financial	Macroeconomic environment	GDP (YoY)	[19]
		Consumer price index (CPI) (YoY)	
		Social financing stock (YoY)	
		RMB/USD exchange rate	
		Local fiscal revenue/debt stock	[31]
		10-year treasury rate	−

factors including fundamental properties of bonds or debtors, and the macroeconomic environment. The classification of indicators at the third level follows the same way as Wind economic database.

Data on all credit bonds issued and matured or defaulted between 2014 and 2021 were collected using the Wind economic database, totaling 26 561 bonds. After removing those with missing values, 25 290 bonds remained, of which 416 were defaulted bonds and 24 874 were non-defaulted bonds. The dataset was then divided into a test dataset and a training dataset in the ratio of 3:7. Consequently, 17 703 bonds were included in the training dataset, of which 284 were defaulted and 17 419 were non-defaulted. We used the bond data for year $t-1$ to predict whether a default would occur in year t. During the period from issuance to maturity, if no default occurred in year t, the bond data for year $t-1$ were labeled 0; otherwise, they were labeled 1.

Next, we used GANs as an oversampling technique to increase the number and proportion of defaulted records to reduce the extreme imbalance between defaulted and non-defaulted bonds.

3 Methodology and Model

3.1 Oversampling method using GANs

Owing to the highly imbalanced distribution between the default and non-default samples in the dataset, an oversampling technique was required to increase the size of the default sample. The traditional SMOTE algorithm and its variants ignore the distributive characteristics of adjacent samples, which can lead to overgeneralization, a problem which can be solved using GANs.

A GAN comprises a generative network (generator) and a discriminative network (discriminator). The generator generates simulated data and continuously adjusts the parameters to improve the generation of data that the discriminator cannot accurately distinguish. The discriminator continuously adjusts the parameters to distinguish real data from simulated data as far as is possible. The two networks are trained against one another until the discriminator is unable to determine whether the data are simulated or real, and the training converges. Consequently, a GAN can generate new data very similar to the original data, making it a highly effective oversampling method[32] for generating new data to augment the size of the original sample[33].

In this study, we used the generative network component of a GAN to generate novel synthetic data that were indistinguishable from real data by the discriminative network. The network was constructed using a series of dense and leaky rectified linear unit (ReLU) layers. Additionally, a batch-normalization layer was incorporated after each combination of the dense and leaky ReLU layers, the output of the generative network being presented via a dense layer. The training and oversampling processes of the GAN are shown in Fig. 1.

3.2 Predictive model using a CNN

Given the complexity of our experimental dataset—which involved 51 indicators—an effective high-dimensional classification model was required to accurately predict credit bond defaults. The CNN has already been proven highly effective in processing high-dimensional data[34], as it can automatically extract relevant features from high-dimensional datasets and generalize these features to other datasets of a similar nature.

A typical CNN comprises a combination of convolution, pooling, and fully connected layers. In the convolution layer, a few convolution kernels of equal size are applied, each convolution kernel being used to recognize a specific pattern from the input data (convolution being the extraction of features or the

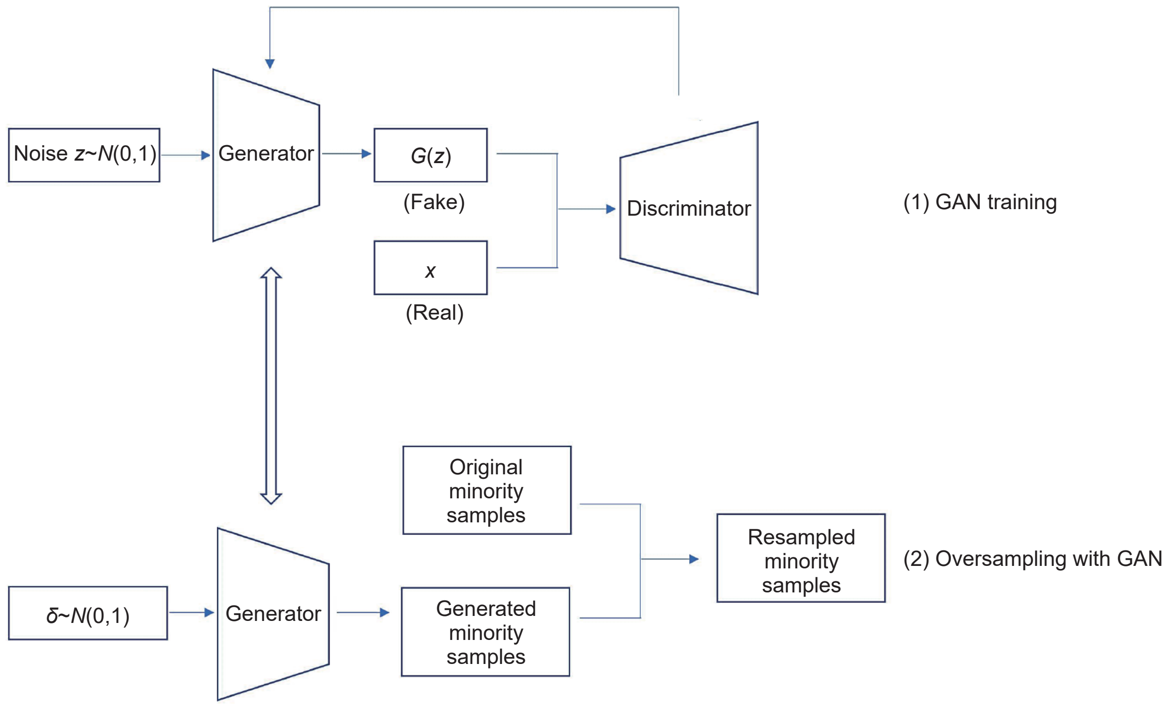

Fig. 1 Oversampling process using a GAN.

matching of information[35]).

In this study, a one-dimensional CNN was used to construct a predictive model for credit bond defaults. By changing the model structure, activation function, optimizer, and learning rate, we continuously improved the model training effect. After multiple rounds of 3-fold cross validation, an optimal model was obtained. The final architecture is shown in Fig. 2 and includes an input layer, an output layer, four convolution layers, two pooling layers, a flattened layer, and a fully connected layer.

The first two convolution layers each contain 16 convolution kernels, each with a size of three. This is followed by a pooling layer with a kernel size of three. The next two convolution layers have 64 convolution kernels of the same size as the first two layers. This is followed by another pooling layer with a kernel size of three. A flattened layer is used to connect the convolution layers to a fully connected network. The SoftMax function is used as the activation function for the fully connected layer, which conveniently compresses the final output results within the range of [0, 1]. Finally, a fully connected neural network is used as the binary output classifier to establish the mapping relationship between the indicators and the predictive results of credit bond defaults.

4 Experimental Design and Result

4.1 Training process and predictive results

The GAN was implemented using TensorFlow and Keras. The loss values of the generator and discriminator in each epoch during the training are shown in Fig. 3. The loss value of the generator reaches its maximum at 200 epochs and then decreases rapidly, indicating that the generator starts generating data similar to the original data after 200 epochs. After 2000 epochs, the loss values of the discriminator and generator are very similar, indicating that the generator can generate defaulted bonds very similar to the original defaulted ones—that is, for the discriminator, the correct rate and error rate of distinguishing defaulted bonds generated by the generator are nearly 50% each.

Current research showed that when using GANs or other oversampling algorithms, the diversity of the generated samples is better when its size is 2 to 4 times that of the original minority samples[36]. Therefore, we conducted pre-experiments to determine the size of the generated samples, and the result showed that the classifier has the best performance when the size is 2.5 times the original one. Thus, using the generative network of the GAN, 710 (284×2.5) new defaulted

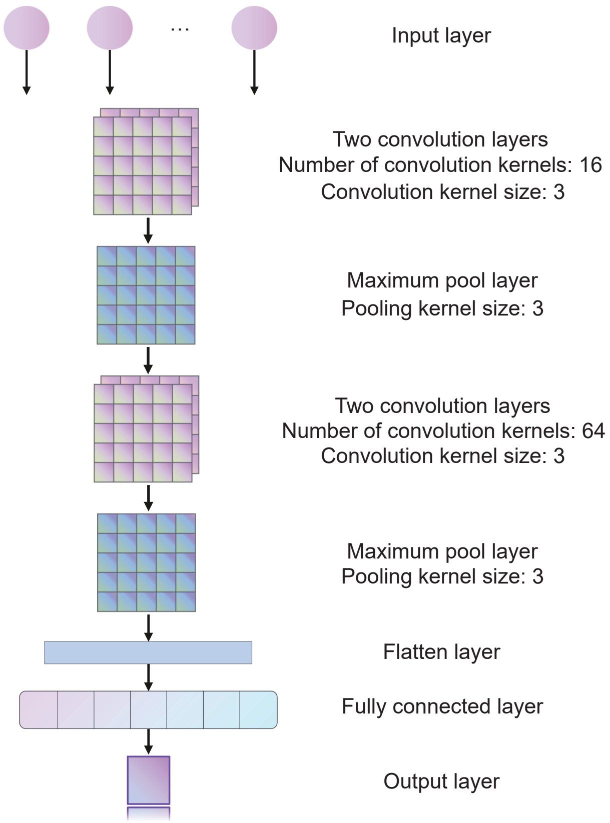

Fig. 2 Architecture of predictive model using a CNN.

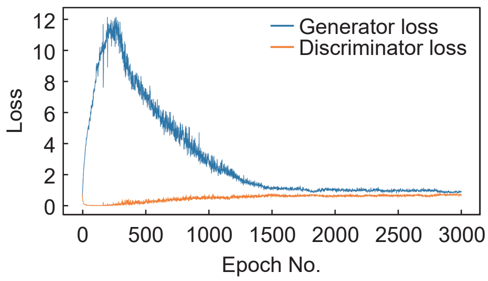

Fig. 3 Loss of generator and discriminator in each epoch.

bonds were generated, i.e., altogether 994 defaulted bonds were included in the final training dataset.

In order to further increase the imbalance ratio between defaulted samples and non-defaulted samples to 1:10[5], we randomly undersampled non-defaulted bonds to 9940, which made up the final training dataset. The predictive model using the CNN was then trained using the final dataset. The training process is illustrated in Fig. 4. The batch size of the training was 30 and the number of epochs was 100. The loss value decreases rapidly in the first 20 rounds before reaching a steady state (approximately 0.01) after approximately 80 to 100 rounds.

Subsequently, the proposed GAN + CNN method

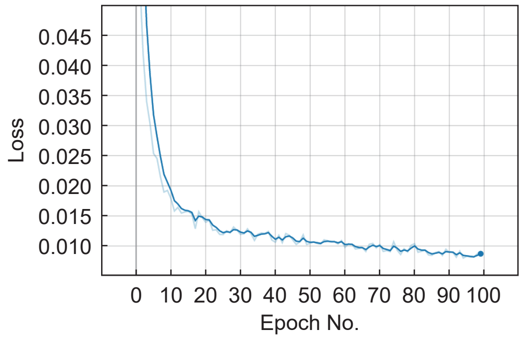

Fig. 4 Loss for each epoch.

was used on the test dataset to predict whether credit bonds would default. A confusion matrix is commonly used to evaluate the classification effects. In this study, the defaulted sample was set as P and the non-defaulted sample as N. Using the true positive (TP), false positive (FP), false negative (FN), and true negative (TN) values in the confusion matrix, the evaluation metrics of precision, recall, accuracy, and area under the curve (AUC) could be calculated. Owing to the imbalanced characteristics of the dataset used in this study, the AUC is the most critical metric for evaluating performance. The precision is another important one for evaluating the performance of predicting defaulted bonds, which is calculated by TP/(TP+FP).

Figure 5 shows the confusion matrix of the predicted results. Among the 7587 bonds in the test dataset, 7463 are predicted as non-defaulted bonds, of which 7441 are predicted correctly. By contrast, 124 bonds are predicted as defaulted bonds, of which 110 are predicted correctly. The accuracy, precision, recall, and area under the curve are 0.9953 ((7441+110)/7587), 0.8871 (110/(110+14)), 0.8333 (110/(110+22)), and 0.9157, respectively. It is evident that the experimental results demonstrate superior performance compared to

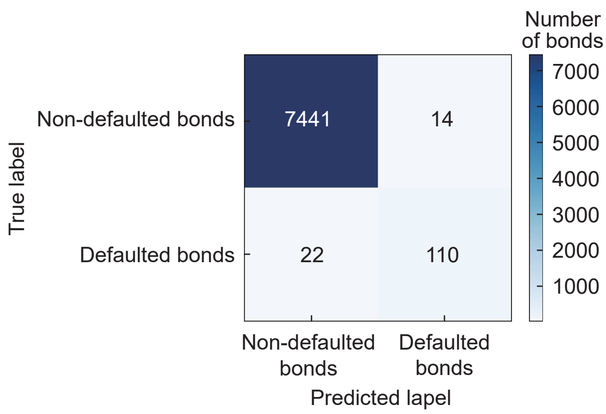

Fig. 5 Confusion matrix of predictive results.

those of previous research.

4.2 Comparison with other models

To further test the performance of other methods based on our dataset, we conducted experiments using an SVM, logistic regression (LR), and fully connected neural network (FCNN) as classification models, using SMOTE, Borderline SMOTE, or nothing as the oversampling technique. The results are summarized in Table 2. Compared with other baseline classification models and oversampling techniques, the proposed GAN+CNN method provides the most accurate prediction of credit bond defaults in China, with the best performance in all the four metrics. Using a GAN as an oversampling technique greatly improves the predictive performance of all the four classification models. Using SMOTE or its variant as an oversampling technique also improves the predictive performance of the CNN, FCNN, and LR, but is not as good as using the GAN.

The receiver operating characteristic (ROC) curves for different classification models are shown in Fig. 6. When using the GAN as an oversampling technique in the training process, the CNN outperforms the FCNN, SVM, and LR methods, with the largest AUC of 0.9157, followed by the FCNN with an AUC of 0.8835. As to the metric of precision, the CNN also outperforms the other three models, followed by the SVM.

4.3 Importance of indicators

The Shapley value of an indicator can explain its contribution to predicting credit bond defaults. In this study, the total contribution of the indicators with the top 20 Shapley values (shown in Fig. 7) accounts for more than 80% of all indicators. All the six indicators of solvency were ranked in top 20, including proportion of long-term liabilities ranked the 2nd, current ratio ranked the 4th, net debt ratio ranked the 8th, and quick ratio ranked the 9th. Four of the five indicators of capital structure were ranked in top 20, including current debt ratio ranked the 3rd, asset liability ratio ranked the 5th, and shareholder equity ratio ranked the 6th. As a fundamental property of bonds, coupon rate at issue contributes the most to predicting credit bond defaults. Four other fundamental properties of bonds were ranked in top 20 including bond type ranked the 7th. Two of the nine indicators of profitability were ranked in top 20 including ratio of sales to cost ranked the 10th. One indicator of operating capacity was ranked the 12th, and one indicator of growth capacity was ranked the 20th. As to the indicators of macroeconomic environment, only one of them was ranked the 15th.

Consequently, for short-term predictions—that is, one year in this study—the indicators of solvency, capital structure, and fundamental properties of bonds are the most important. It is argued that the indicators of macroeconomic environment are more likely to have an impact on corporate leverage in a long run[37]. They may contribute more for long-term predictions. Only

Table 2 Predictive performance.

Classifier	Oversampling method	Accuracy	Precision	Recall	AUC
CNN	No oversampling	0.9621	0.3438	0.4859	0.6144
	SMOTE	0.9741	0.6704	0.6689	0.7958
	Borderline SMOTE	0.9715	0.6477	0.6901	0.7774
	GAN	**0.9953**	**0.8871**	**0.8333**	**0.9157**
FCNN	No oversampling	0.9616	0.4086	0.4463	0.6245
	SMOTE	0.9762	0.5874	0.5951	0.6709
	Borderline SMOTE	0.9793	0.6211	0.6072	0.6849
	GAN	0.9905	0.7083	0.7727	0.8835
SVM	No oversampling	0.9737	0.4364	0.2352	0.6081
	SMOTE	0.9765	0.5211	0.3622	0.5998
	Borderline SMOTE	0.9822	0.5567	0.3159	0.5994
	GAN	0.9836	8183	0.4015	0.7004
LR	No oversampling	0.9603	0.3068	0.6991	0.7861
	SMOTE	0.9697	0.4182	0.7294	0.8332
	Borderline SMOTE	0.9614	0.4493	0.7725	0.8703
	GAN	0.9685	0.3269	0.7652	0.8686

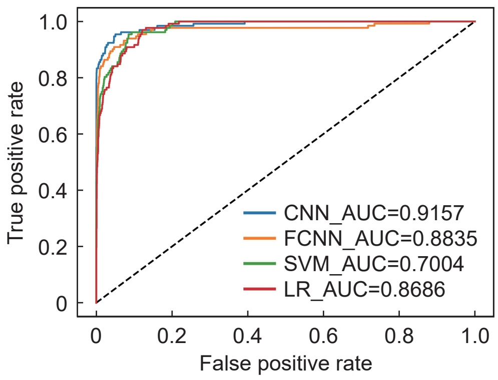

Fig. 6 ROC curves using different classification models.

limited studies have conducted importance analysis of indicators. In Ref. [28], coupon rate at issue, proportion of long-term liabilities, and current ratio also contributed the most.

5 Conclusion

This study selected 31 financial and 20 non-financial factors to predict credit bond defaults in the Chinese market. Data on all credit bonds issued, matured, or defaulted between 2014 and 2021 were collected from the Wind economic database. We proposed a GAN+CNN deep learning method for the prediction process. Owing to the extremely imbalanced distribution between the defaulted and non-defaulted samples in the experimental dataset, we used the generative network component of the GAN—which is a highly effective oversampling method—to generate more defaulted bonds and augment the size of the defaulted samples. A CNN was used to construct a predictive model and fully explore the information contained in the dataset. The experimental results showed that the proposed approach outperformed previous research and other baseline classification models and oversampling techniques. Specifically, the oversampling method using the GAN could greatly improve predictive performance, with an AUC of 0.9157 and precision of 0.8871 when using the CNN as the classification model. For one-year predictions, indicators of solvency, capital structure, and fundamental properties of bonds are proved to be the most important.

The main contributions of this study are as follows:

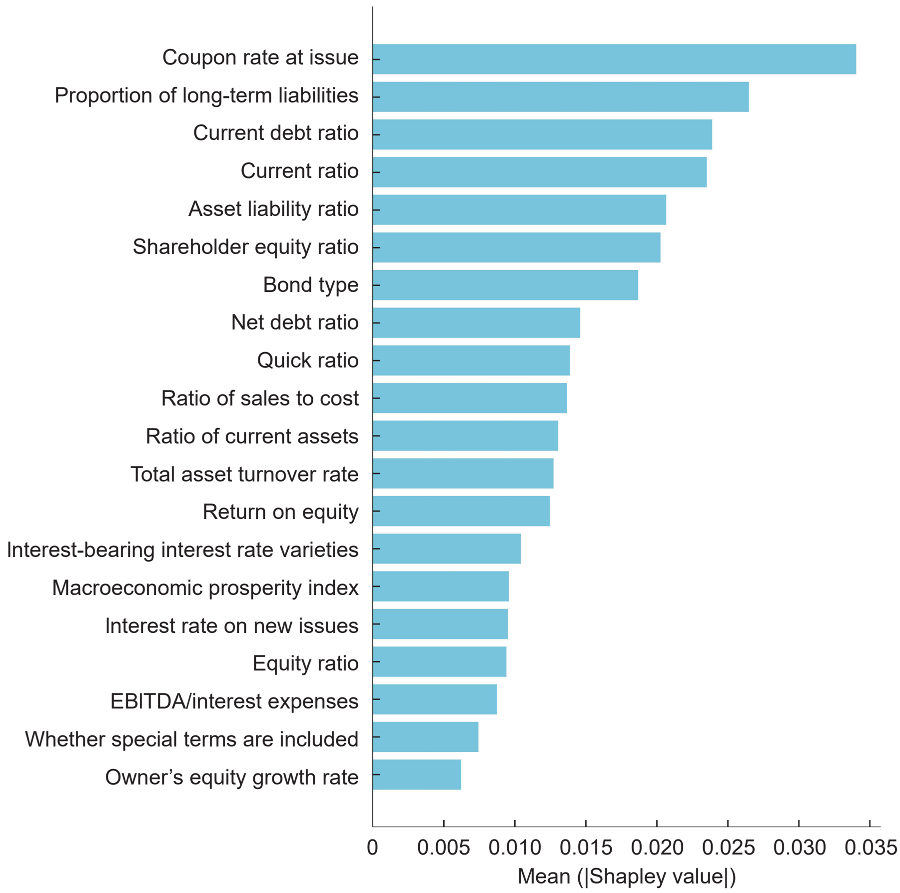

Fig. 7 Indicators with the top 20 Shapley values.

(1) The proposed GAN + CNN method made full use of the advantages of deep learning, not only for classification but also for imbalanced data processing, thereby greatly improving predictive performance.

(2) The large dataset with 51 indicators (financial and non-financial) for each credit bond provided sufficient information to extract, further improving predictive performance, in which indicators of solvency, capital structure, and fundamental properties of bonds are proved to be the most important for one-year predictions.

The major limitation of this study was that we only considered one-year predictions. To extract the features of longer time-series, other deep learning methods—such as the LSTM model—could be combined with the proposed approach in future studies. In addition, more complicated factors—such as investor sentiment[38]—could also be added to our dataset and used for predictions in future work.

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