

Retraction

Retracted: Security Warning Model of Chinese Corporate Bond Defaults Based on Deep Neural Networks

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.




The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Bo, W. Zhang, C. Chen, and M. Ji, "Security Warning Model of Chinese Corporate Bond Defaults Based on Deep Neural Networks," *Security and Communication Networks*, vol. 2022, Article ID 8152073, 16 pages, 2022.

Research Article

Security Warning Model of Chinese Corporate Bond Defaults Based on Deep Neural Networks

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The Chinese bond market has achieved rapid development over the years. However, since the “rigid payment” in China was broken in 2014, the number and size of bond defaults have climbed up promptly and caused huge volatility in bond and even stock markets. To better manage and control the risk of the Chinese corporate bonds market, deep learning can be used as a helpful tool to predict the corporate default risk. This paper constructs a security warning model based on deep neural networks after a reasonable selection of characteristic indicators. By comparing Multi-Layer Perceptron (MLP) with the logistic regression method, it is found that MLP is more suitable in the security warning model to predict the default risk. And, hyper-parameter analyses and ablation study are conducted to explore the performance and accuracy of the best MLP settings. The experimental results show that the deep learning method accommodating the widely chosen factors in the security warning model is effective in predicting corporate bond defaults in China.

1. Introduction

In recent years, China's bond markets have developed vigorously, and the types of bonds issued have become increasingly diversified. According to the Bank of China, a total of 61.9 trillion yuan of different types of bonds were issued in China in 2021, ranking China as the second-largest bond market in the world. The growth of the Chinese bond market, to a large extent, meets the financing needs of the society and promotes economic development. However, as China's economy is facing new downward pressure, bond defaults inevitably appeared following the expansion of the bond markets. Ever since Shanghai Chaori became the first public company to default in the bond markets in 2014, a total of 846 bonds from 236 companies amounting 584.996 billion yuan are reported to default by the end of 2021 in China. The types of defaulted bonds include Corporate Bonds (issued by corporations and traded solely on the exchange market), Medium-term Notes, Short-term Financing Bonds, Enterprise Bonds (issued by large state-owned enterprises and traded on both the exchange and the

inter-bank market), Exchangeable Bonds, Asset-backed Notes or Securities, Convertible Bonds, etc. Meanwhile, the default cases of state-owned enterprises are climbing up as well. The frequent occurrence of default events in the bond markets may create and aggravate the spread of panic from investors, even cause systemic financial risks and harm the development of the real economy. Therefore, the identification and control of default risk is one of the important issues faced by China. This paper conducts research on the security warning of corporate bond default risk by comparing traditional machine learning—logistic regression with deep learning—Multi-Layer Perceptron, which further enriches the extant study of corporate bonds risk and provides enlightenment to the risk management of the Chinese bond market.

Corporate bond (Unless specified otherwise, corporate bonds mentioned in this paper is a general term for various bonds issued by companies.) defaults are not merely the problem of enterprises themselves. Within the unique institutional background of China, implicit guarantee or intervention from local governments and the failure of the

financial intermediaries to execute their due care and diligence may all play a role in corporate bond defaults. Therefore, this paper broadly incorporates the factors reflecting the influence from individual companies, industries, local governments, financial institutions, etc., into the deep learning model.

The following sections are arranged as follows: Section 2 is the literature review on prediction methods of corporate default risk; Section 3 elaborates the background of China's bond market and the corporate bond default risk; Section 4 presents the theoretical models of both the traditional machine learning and the deep learning methods; Section 5 is the experimental evaluation of the security warning model applying the deep learning method; and the last part is the conclusion.

2. Literature Review

Generally, the security warning prediction methods for default risk involve statistics-based and model-based approaches. The traditional statistical forecasting technique originates from Altman's [1] innovative contribution to the prediction of corporate bankruptcy, which applies discriminant analysis by using accounting data. Other quantitative methods to predict the default probability of entities include logistic regression analysis [2], logit model [3], mixed logit model [4], or an integrated analysis by combining principal component analysis with logistic and probit regressions [5]. The most widely used model-based approaches to the security warning of bond defaults could be grouped into two categories. One is the structural models, represented by the Merton model [6] and the KMV model [7] which derive the credit risk from the company's assets and liabilities. The other category is reduced-form models [8, 9], which consider default as exogeneous and release the symmetric information assumptions underlying the structural models.

Although the traditional models are easy to use, their limitations are obvious, such as they must follow certain assumptions. Scholars and practitioners then resort to computational techniques to predict default events in different countries. Barboza et al. [10] use support vector machine models to forecast bankruptcy for North American companies and argue that the computational methods are more accurate than statistical techniques. Mai et al. [11] use data mining techniques to extract textual disclosure information such as qualitative discussion, managerial discussion, and analysis to predict financial distress for public companies in the US. Bragoli et al. [12] study the Italian firms with XGBoost techniques and find that industrial variables correctly matter in classifying insolvent companies. Zhao et al. [13] and Zhang et al. [14] both propose the warning tools based on kernel extreme learning machine for financial decision-making. Tang et al. [15] propose an evolutionary pruning neural network model to conduct financial bankruptcy analysis, which provides satisfactory classification accuracy. Siswoyo et al. [16] apply a hybrid machine learning model by combining a two-class boosted decision tree and multi-class decision forest to predict

financial failure for the Indonesian banking industry. Jang et al. [17] identify the impact of input variables by using the long short-term memory recurrent neural network to predict the probability of bankruptcy for the US construction market. Wang [18] uses the combination of an ant colony algorithm and a neural network algorithm to build an early warning system for financial management. Park and Shin [19] employ a combination of random forest algorithms and the Bayesian regulatory neural network to monitor the financial solvency of companies for Korean insurers.

Academic research concentrating on the Chinese corporate bond defaults shows a preferential use of the KMV model. Chen et al. [20] develop an improved model based on the original KMV with tunable parameters to measure the credit risk of the Chinese small-medium listed enterprises. Chen and Chu [21] examine the default risk of Chinese real estate companies with the KMV model and time-varying copula. Cheng et al. [22] introduce a genetic algorithm into the KMV model to analyze the credit risk of the real estate industry in China and prove that the augmented KMV model has good applicability. However, other scholars also deduce different conclusions on the use of the KMV. Li et al. [23] evaluate the credit risk of Chinese listed companies by comparing the zero-price probability model and the KMV model and demonstrate that the former is superior in terms of discriminatory power. Peng et al. [24] investigate Chinese corporate bond defaults by a comparative study between accounting-based models and Merton market-based models and find KMV's distance to default exhibit languid discriminating power than hazard models. Some scholars employ computational techniques to study the default risk in the Chinese capital market. Jiang and Jones [25] adopt TreeNet Gradient Boosting Machine, a powerful commercial machine learning model, to forecast corporate financial distress in China and produce very accurate out-of-sample predictions. Lu and Zhuo [26] use both the linear support vector machine and kernel support vector machine models in the corporate bond default prediction, which perform better than traditional default risk models.

The extant studies on the Chinese corporate bond defaults mainly focused on the listed companies. The input variables used in prediction generally involve quantitative factors, such as bonds/issuer specific attributes and macroeconomics indicators, without adequate consideration of the impact of the local government and the service quality of the financial institution. This paper enlarges the research samples to include the nonlisted companies and also incorporates the qualitative variables representing the local governments and the intermediary agencies, aiming to improve the performance of the security warning tool and extend the application of the deep learning method.

3. China's Bond Market and Corporate Bond Default Risk

Before 2014, China's bond market has been maintaining "rigid payment," so there is a lack of security warning mechanism and disposal measures to deal with risk events. As the downward pressure of macro-economy continues to

increase, the default events in China's bond market emerged one after another. With the increasing financial liberalization and globalization, losses among different companies and industries will spread rapidly, and individual risks gradually become systemic risks. Risk events such as the credit crunch and the European debt crisis have had a major impact on the global economy, and also threatened the economic and financial stability of China. In this context, it is of great significance to study the security warning mechanism to prevent and control corporate bond default risk in China.

3.1. Bond Market in China. China's bond market is unique in that it reflects the ongoing wave of development and liberalization of the finance sector. Currently, companies can issue bonds with similar characteristics and maturities in different ways, managed by different regulators, with different rules, and traded on different platforms in different market segments.

3.1.1. Bond Market Development. The development of China's bond market truly took off following the open door policy. Over the years, the size of the bond market continues to expand and the bond varieties have been gradually enriched. The bond market has become an important part of China's capital market. The history of China's bond market can be roughly divided into the following four stages:

The first stage of the budding period (1981–1986). In 1981, the issuance of treasury bonds was resumed, followed by corporate bonds and financial bonds. The bond market at this stage is still in a spontaneous state: without a well-established bond trading mechanism or trading place, the transfer and trading of bonds are restricted.

The second stage of starting period (1987–1996). In March 1987, the State Council implemented the Interim Regulations on the Administration of Corporate Bonds, which laid the institutional foundation for the development of China's bond market. In 1990, the establishment of the exchange bond market was officially established which became a milestone in the development of China's bond market. In 1995, the pilot project of national bond issuance by tender was successful. This indicates that China's bond issuance has gradually shifted from administrative apportionment to market-oriented methods such as underwriting and bidding.

The third stage is the standardized rectification and standardization stage (1997–2005). In 1997, the People's Bank of China established the national inter-bank bond market and prohibited commercial banks from participating in the trading. After that, the inter-bank bond market gradually grew and became the most important trading venue in the bond market. Together with the exchange bond market and the commercial bank over-the-counter market, it constitutes the Chinese bond market system.

The fourth stage is the accelerated development period (2005–2019). With the advancement of interest rate marketization, various types of bonds emerged, such as short-term financing bills, medium-term notes, corporate bonds,

enterprise bonds, and so on, followed by the development of derivatives, such as bond forwards and interest rate swaps, etc. The continuous emergence of these products has greatly enriched the Chinese bond market. At the same time, it highlights the status and role of China's bond credit rating gradually.

The fifth stage is the era of the comprehensive registration system (2020–present). Starting from March 2020, China's new securities law permits corporate bond and enterprise bond issuance to shift from approval-based system to registration-based system, which relaxes the conditions for issuance but strengthens the information disclosure requirements for bonds issuers, underwriting and securities service institutions. The new system respects the market's decisive role in security sales and would substantially enhance the liquidity of the bond market.

3.1.2. Bond Market Structure. China's bond market consists of a primary bond market and a secondary bond market. Its specific structure is shown in Figure 1:

The primary market, that is, the issuance market participants are mainly the People's Bank of China, policy banks such as the China Development Bank, the Export-Import Bank, the Agricultural Development Bank, other commercial banks, enterprises, and the governments. Financing demanders in the primary market issue bonds to raise funds through bidding or underwriters.

The secondary market is the circulation market, which consists of three parts: the inter-bank market, the exchange market, and the commercial bank over-the-counter (OTC) market. Participants in the OTC bond market are mainly individual and corporate investors of commercial banks. Investors can buy and sell bonds through bank outlets, and handle bond custody and settlement business. At present, the products traded in China's OTC bond market are limited to treasury bonds and some financial bonds. Although the transaction size is small, it has added new investment channels for small and medium enterprises and individual investors. It also promotes the liquidity of the bond market to a certain extent.

3.1.3. Bond Credit Rating. Bond credit rating means that an independent professional rating agency evaluates the bond issuer's ability and willingness to repay the principal and interest in full and on schedule, so as to indicate the default risk of the assessed bond and the likely severity of the damage to investors. Credit ratings help market participants understand the credit risk level and default probability of the evaluated objects through rating symbols. It solves the problem of information asymmetry between buyers and sellers and reduces the negative impact due to missing or nondisclosure of information.

According to the 2006 Credit Rating Management Guidance of the People's Bank of China, credit rating for the financial product issuers mainly inspects the macroeconomic, industry, and regional economic environment and the quality of the company, e.g., property rights, corporate governance, operating management, financial quality, and

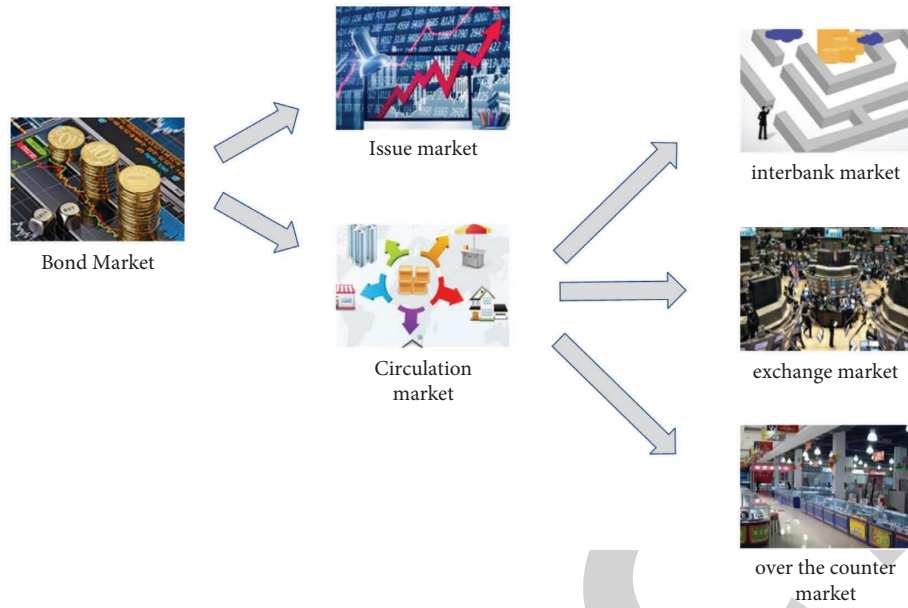


FIGURE 1: Structure of the Chinese domestic bond market.

ability to resist risk, etc. The rating of financial products shall consider the feasibility, risks, profitability, and cash flows of the project to be invested, and the measures to guarantee debt repayment. Usually, the highest rating AAA represents a strong ability to service the debt, and a rating below BBB indicates weak debt solvency. The credit rating distribution of Corporate Bonds in 2021 is presented in Figure 2:

It can be seen that low ratings such as BBB+, BBB, and C-rated bonds together account for only 1% of total bonds issued in 2021 but more than 94% of bonds are rated AA- or above, with the largest proportion (47.63%) of bonds rated AAA. However, such a high credit rating market has seen a series of defaults of AAA bonds, which indicates that credit ratings in the Chinese bond market are falsely high. When poor-quality bonds are mixed with good ones, it will be very hard for investors to differentiate the credit risk of various bonds. The credit rating system cannot alleviate information asymmetry between issuers and investors; therefore, it is difficult to establish a substantial relationship between bond credit rating and the actual default rate.

3.2. Corporate Bond Default Risk. The modern economic society has been closely related to “credit.” Various credit behaviors have been used throughout the businesses. Credit activities have become an important part of economic life. It is no exaggeration to say that a market economy is a credit economy, which brings prosperity and convenience at the same time. With the frequent conduct of credit behaviors and the continuous expansion of credit transactions, the emergence and expansion of default risks will inevitably follow.

In the early days, the default risk in the traditional sense refers to the behavior that the two parties involved in the credit activity fail to implement the contract terms and cause economic losses to the participants in the credit activity.

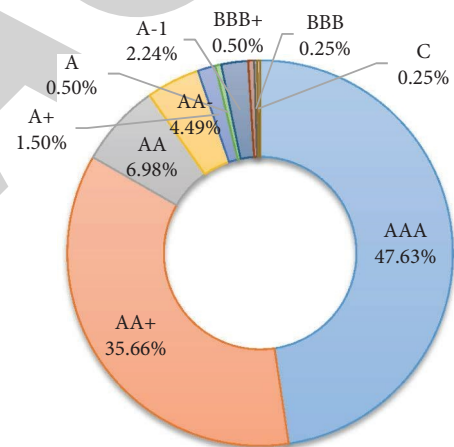


FIGURE 2: Credit rating distribution of corporate bonds in 2021. Data source: wind statistics.

With the continuous development and deepening of the credit economy, especially the birth of the stock market, bond market, financial derivatives, and the vigorous development of various investment and financing tools, default risk in the traditional sense can no longer meet the needs of participants in credit activities, and the connotation of default risk is enriched and expanded. For example, a bondholder holds an outstanding bond. He can judge whether the principal and interest of the debtor can be repaid timely when the bond becomes due by knowing whether the asset status, operating ability, and other factors of the issuer of the bond have changed or not. In this process, the default risk in the traditional sense has not occurred yet, but the credit quality of the issuer is actually a process of continuous change. Bondholders can judge the possibility of bond default at various points in time and decide whether to continue to hold essential bonds, thereby reducing losses.

Default risk not only means the potential loss for bondholders as stated above but could also be transferred between companies. With the extension and expansion of economic transactions across time and space, the participants in various credit activities are closely related and linked to one another, like a chain. When any economic subject has a financial problem, it will cause the break of the credit chain, thus disturbing the stability of the entire credit chain. If the default risk is not dealt with in a timely manner and spreads to the relevant economic entities, it will disturb the stability of the entire credit market.

3.3. The Factors Influencing Corporate Bond Default Risk. The default risk of a corporate bond is mainly affected by macroeconomic, industrial, and the company's own operating conditions.

At the macro-level, the economic cycle has a great impact on the solvency of enterprises. As the downward pressure on the economy increases, the business situation of enterprises deteriorates and the risk of default increases.

At the meso-level, the characteristics of the industry in which an enterprise is located, such as the degree of competition, development stage, and industrial policies, will affect the viability of enterprises as well. Debt defaults can easily occur in industries with strong cycles, excess capacity, or excessive competition.

At the micro-level, companies are the basic units of the microeconomy. Endogenous characteristics are the most direct and effective indicators to reflect default risk, for example, the financial status, willingness to repay, credit quality, etc.

Under the combined effect of different factors, some companies diversify their operations without careful consideration or implement aggressive investment strategies, resulting in higher liquidity risk. If there is no funding support at this point, there will eventually become a default event. The factors that will influence a company's default behavior are shown in Figure 3:

As shown in Figure 3, the synergies of macro, meso, and micro factors together could cause a liquidity risk, and the lack of financial support in this process may trigger the default behavior of a company ultimately.

4. Security Warning Methods of Corporate Bond Default Risk

As mentioned in the literature review, traditional default risk models mainly use corporate financial information, which is extracted from the existing data. While simple and easy to implement, it also has flaws. Companies generally release corporate accounting information on an annual or quarterly basis with a time lag. This makes it difficult for information users to track changes in corporate credit quality in a timely manner. On the other side, some multi-dimensional non-financial information is hard to incorporate into the traditional methods; however, models applying computational techniques could be a good complement.

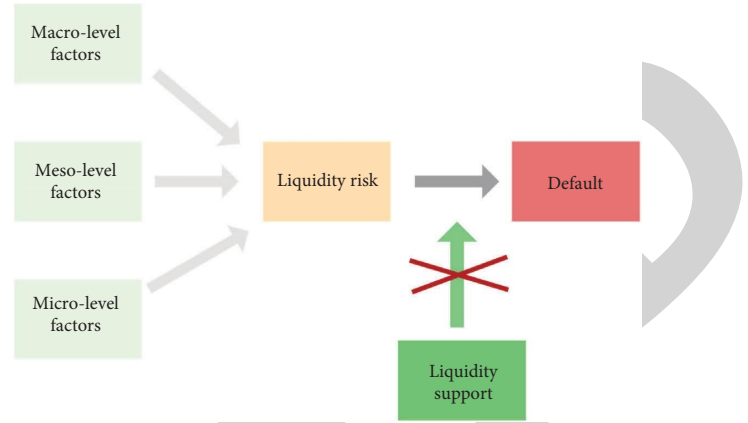


FIGURE 3: The factors influencing a company's default behavior.

The corporate bond default problem can be viewed as a binary classification problem, which could complete the classification by training a prediction model on the training set after data cleaning and feature engineering. This section introduces predictive models from both traditional and deep learning perspectives and expounds on the mathematical theoretical meaning of them.

4.1. Traditional Machine Learning—Logistic Regression. Logistic regression is one of the most common and widely studied machine learning methods. When a categorical or numerical feature set is required to predict the probability of an event, logistic regression is usually an effective method. Logistic regression can be presented in Figure 4, as a generalized linear regression model where the function f transform is added, and the linear combination of data features is used as the input of the model. It takes binary variables 0 and 1 as output and finds the functional relationship between input and output through a lot of learning and training.

Assuming the input is x

$$x = x_1, x_1, \dots, x_n, \quad (1)$$

and output is y

$$y = \{0, 1\}. \quad (2)$$

The conditional probability of an event can be expressed as:

$$p(y = 1|x) = \frac{1}{1 + e^{-(wx+b)}} = h_w(x), \quad (3)$$

$$p(y = 0|x) = 1 - \frac{1}{1 + e^{-(wx+b)}} = 1 - h_w(x),$$

where $w \in R$ indicate that the model is the proportion of input variables, that is, the parameters that need to be learned, and $b \in R$ is the bias of x . By combining the above two equations, the following equation is obtained:

$$p(y|x) = (h_w(x))^y (1 - h_w(x))^{(1-y)}. \quad (4)$$

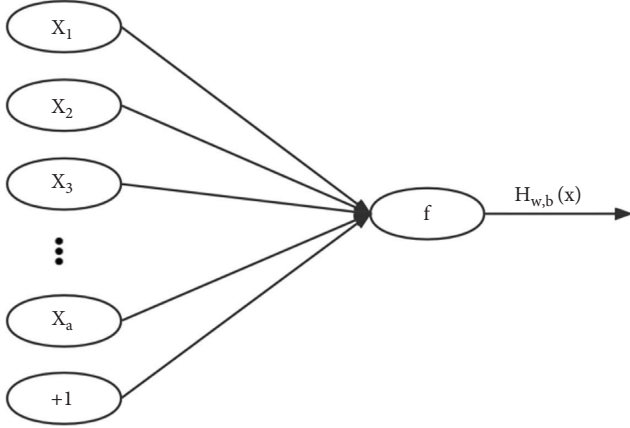


FIGURE 4: Graphical representation of logistic regression.

Logistic regression uses maximum likelihood estimation to learn update weights. So the loss function is:

$$J(w) = -\frac{1}{m} \left[\sum_{i=1}^n y_i \log h_w(x_i) + (1 - y_i) \log(1 - h_w(x_i)) \right]. \quad (5)$$

Logistic regression is a generalized linear regression analysis model, which is often used in data mining, automatic disease diagnosis, economic forecasting, and other fields. The advantages of logistic regression may include the following: the predicted outcomes are probabilities between 0 and 1; it can be applied to both continuous and categorical independent variables; and it is easy to use and interpret.

The disadvantage of logistic regression is that the input of the model is required to be independent of each other. In fact, the real features in the model may have complex nonlinear relationships with each other, which is difficult to simulate in a logistic regression. Therefore, it is usually necessary to do feature engineering manually before building a predictive model for logistic regression.

4.2. Deep Learning Method—Multi-Layer Perceptron (MLP). Most of the current shallow structure models have limitations to express more complex functions, but the generalization ability for complex classification and regression problems could be solved by deep learning.

Deep learning is a new research direction in the field of machine learning, which was introduced into machine learning to bring it closer to its original goal—artificial intelligence. Deep learning is to learn the inherent laws and representation levels of sample data, and the information obtained during these learning processes is of great help to the interpretation of data such as text, images, and sounds. Its ultimate goal is to enable machines to have the ability to analyze and learn like humans, and to recognize data such as words, images, and sounds.

Neural Network is a model that simulates the basic characteristics of neurons in the human brain and has been theoretically proven. The three-layer neural network can

abstractly simulate any function mapping relationship. Logistic regression above can be regarded as a special form of the neural network, which is a linear representation of the neural network.

Multi-Layer Perceptron is a class of forward propagation neural networks. An MLP contains at least three node layers. Except for the input node, each node is a neuron using a nonlinear activation function. The MLP learns back propagation using a method called supervised learning. Its multi-layered structure and nonlinear activation capabilities differentiate MLP from linear perceptron. MLP can identify data that are not linearly separable.

It assumes that the input of the neural network is x , and the activation function f is assumed. Through the transformation of the activation function of the hidden layer, multiple neurons form a layer. The output of the previous layer is used as the input of the hidden layer, and the output of the hidden layer is used as the upper input of the final output layer. The formed network structure model is called a neural network, as shown in Figure 5:

The input to the hidden layer is:

$$y_j = f \left(\sum_{i=1}^m w_{ij} x_i + b_j \right). \quad (6)$$

The output of the output layer n is:

$$y_j^{[n]} = f \left(\sum_{i=1}^m w_{ij}^{[n]} x_i + b_j^{[n]} \right). \quad (7)$$

The choice of activation function is usually the Sigmoid function. When the input value x is any, the output value is limited to (0, 1); when the input value is 0, the output value is 0.5. The sigmoid function can be expressed as follows:

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}}. \quad (8)$$

Another more common activation function is the ReLU (Rectified Linear Unit) function, which can be expressed as the following formula:

$$\text{ReLU}(x) = \max(0, x). \quad (9)$$

From the (9), the derivative of ReLU(x) can be obtained, which can be expressed as:

$$\text{ReLU}(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases} \quad (10)$$

According to the structure shown in Figure 5, the training samples calculate the activation values in turn and output them. This process is a forward propagation algorithm. Then, use the gradient descent method to update the weights, so that the following loss function $\text{loss} = J(W, b)$ is the smallest. This process is called the backpropagation algorithm.

$$J(W, b) = \left[\frac{1}{m} \sum_{i=1}^m \left(\frac{1}{2} |h(x) - y|^2 \right) \right] + \frac{\lambda}{2} \sum_l \sum_i \sum_j (w_{ij}^l)^2. \quad (11)$$

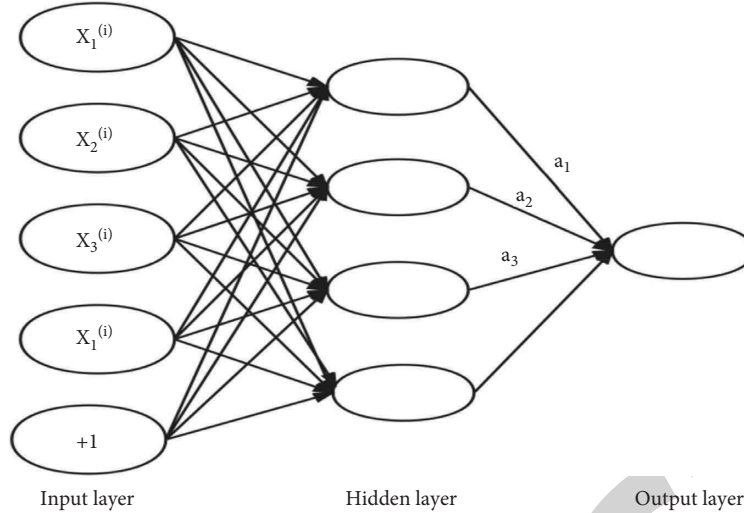


FIGURE 5: Neural network model structure diagram.

The limited number of trainable layers of the traditional neural network leads to limited feature learning and extraction ability, which ultimately affects the effect of pattern recognition. Inspired by the hierarchical processing of information by the structure of the human brain, neural network researchers have been working on deep neural networks.

A Deep Neural Network (DNN) is a relatively advanced type of deep learning, which is a nonlinear combination of multi-layer representation learning methods. Representation learning is a method of learning features from data to extract useful information from data in classification prediction. Compared with shallow learning, DNN has better feature learning and prediction ability, especially in complex classification and regression problems.

Input layer:

$$X = \{X_1, X_2, X_3, \dots, X_n\}. \quad (12)$$

Hidden layer:

$$h^{(l)} = f(W^{(l)}h^{(l-1)} + b^{(l)}) (\forall l \in 1, 2, 3, \dots, L-1). \quad (13)$$

Output layer:

$$y_{\text{pre}} = \arg \max_c P(y = C, X, w, b). \quad (14)$$

The DNN model can tap the potential latent features in the data through multiple nonlinear fittings to the training data. This has a strong learning effect in complex big data environments.

In most classification problems, prediction accuracy can be used as an evaluation index. But for the problem of class imbalance, the classification accuracy is not comprehensive enough as the evaluation index of the method. Thereby, Precision and Recall can be used as the evaluation index:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad (15)$$

$$\text{Recall} = \frac{TP}{TP + FN}.$$

Furthermore, *F1*-score which combines the Precision and Recall evaluation metrics is calculated as:

$$F1 - \text{score} = \frac{2}{1/\text{Precision} + 1/\text{Recall}}. \quad (16)$$

5. Evaluation of the Security Warning Models

5.1. Data Description and Evaluation Setup

5.1.1. Data Description. Based upon the factors influencing corporate default risk, this paper selects 37 variables in the security warning model of corporate bond default risk, covering the macro, meso, and micro-levels, and the financial and nonfinancial characteristics of the company, the bond, the corresponding underwriting and securities service institutions, the local government, and the macro-economy. Bond-year observations are collected for the period from 2014 to 2021, including various bonds issued by listed, nonlisted, state-owned, and private companies. As some of the issuers did not release complete financial information, only 317 observations are satisfied for testing purposes. And, 11,661 nondefaulted bond-year observations are chosen as well. The input variables used in the experiments are shown in Table 1.

5.1.2. Evaluation Setup. The whole data set 11,978 is firstly randomly split into the training and validation sets by a proportion of 80%: 20%, i.e., 9,582 observations in the

TABLE 1: Input variables.

Characteristics	Variable
Bond issuer	Monetary assets
	Net assets
	Total debt
	Interest-bearing debt
	Net operating cash flows
	Operating income
	Operating profit/loss
	Net profit/loss
	Operating profit margin
	Sales growth rate
	Current ratio
	Quick ratio
	Inventory turnover ratio
	Debt ratio
	Cash ratio
	Interest cover ratio
	Is it being audited?
Is it an SOE?	
Is it a listed company?	
Industry	
Company rating before default	
Bond	Trading place
	Issue size
	Outstanding balance
	Interest rate at issuance
	Is it a guaranteed bond?
Intermediary agencies	Bond rating before default
	Is the underwriter a top 10?
	Is the auditor a top 10?
Local government	Audit opinion
	Provincial government GDP
	Provincial government revenue
	Provincial government expenditure
Macro-economy	Provincial marketization index
	The relationship between provincial government and the market
Macro-economy	Total social financing
	Broad money M2

training set and the remaining 2,396 ones in the validation set. In this way, all versions of model architectures could be trained on the training set, so as to select the best ones based on their performance in predicting the target variable of the validation set.

$F1$ -score is used as the evaluation criteria for this binary classification task. This is motivated by the fact that the data set is imbalanced in terms of the labels. Among all observations, only 317 observations (2.65%) are labeled as “default,” while the remaining 11,661 (97.35%) are all “legitimate.” As a side note, while splitting the training and validation sets, it is ensured that the proportion of “default” is 2.65% in both training and validation sets. In this highly imbalanced data scenario, classification accuracy would no longer be appropriate as the evaluation metric since it can simply predict every new observation as the majority class of “legitimate” and still get an accuracy score of 97.35%. In

other words, the metric can be tricked. Thus, Precision and Recall numbers are used to avoid this from happening. In addition, $F1$ -score as the harmonic mean of Precision and Recall could further prevent our method from focusing on one indicator only. Therefore, in the following sections, $F1$ -score would be the main criteria to present, while the Precision and Recall numbers are provided as supplements. The evaluation is conducted on Label 1 (default), Label 0 (legitimate), and their average performance is weighted by their corresponding number of observations.

5.2. Comparing the Best MLP Method with Logistic Regression.

In this part, the experiments are conducted on both the traditional logistic regression method and the deep learning method for model comparisons. Regularization is used for logistic regression to boost its performance and the

TABLE 2: Comparing logistic regression with MLP.

Models	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
Logistic regression	0.97	1.00	0.98	1.00	0.03	0.97	0.99	0.06	0.96
MLP	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

regularization hyper-parameter is fine-tuned. Table 2 provides a summary of the performance of logistic regression and Multi-Layer Perceptron (MLP) using the corresponding best hyper-parameter settings, in terms of $F1$ -score along with auxiliary Precision and Recall information. The selection of the settings for MLP is explained in Section 5.3.

It can be observed that the MLP is superior to logistic regression in all aspects. The MLP has been consistent in terms of performance since it not only achieves 1.00 in Precision, Recall, and $F1$ -score for the easier-to-predict legitimate class (Label 0) but also attains the same performance for the default class (Label 1) that accounts for only 2.65% of the entire data set (317 observations only).

The logistic regression achieves decent performance in predicting Label 0 (Precision 0.97, Recall 1.00, and $F1$ -score 0.99) due to a large amount of Label 0 data but is very conservative in predicting Label 1. It classifies only a few observations as Label 1 when it is confident and obtains a Precision of 1.00. Nevertheless, lots of default observations are incorrectly categorized as Label 0 which makes the Recall as small as 0.03. After taking the harmonic mean, $F1$ -score is only 0.06 for Label 1. This is the main reason why the MLP method is superior to the classical logistic regression method.

5.3. Hyper-Parameter Analyses for MLP. The comprehensive hyper-parameter analyses and ablation study are carried out to validate the best MLP settings for the corporate default prediction model.

5.3.1. Optimizer. Table 3 provides a summary of the performance of the MLP using different optimizers.

Figures 6–8 show the learning curves for using different optimizers: Adam, RMSprop, and SGD. For each of the optimizers, 2 learning curves are plotted: the loss function value and the $F1$ -score with respect to the different numbers of training epochs, respectively.

As shown in Table 3 and Figures 6–8, Adam achieves 1.00 for all metrics regarding all prediction tasks and thus is the best optimizer in the experiments. In addition, the learning curves using Adam are the most stable and the ones that converge the fastest. RMSprop shows close performance compared to Adam; however, the performance of using SGD as an optimizer would result in a performance that is even worse than using logistic regression, which converges very slowly and finally to a higher loss. It proves the importance of selecting the appropriate optimizer for the prediction task. This also aligns with the theory that Adam improves upon the other optimizers since it combines the Momentum method that updates the gradient direction in a more

efficient way and the RMSprop method that changes the learning rate during optimizations adaptively.

5.3.2. Learning Rate. Table 4 provides a summary of the performance of the MLP using different learning rates for the Adam optimizer.

Figures 9 and 10 show the learning curves for using learning rates of extremely small (0.0001) and extremely large (0.1).

According to Table 4 and Figures 9 and 10, it can be observed that using an intermediate learning rate helps. A learning rate that is too small would make it converge very slowly and may take a long time to get a result that approaches the optimal one, thus rendering it less efficient. At the other extreme, using a learning rate that is too large would make the optimization process highly fluctuate and unstable that fails to find the optimal solution. Therefore, a learning rate of 0.001 is chosen since it yields the best validation set performance.

5.3.3. Activation Function. Table 5 provides a summary of the performance of the MLP using different activation functions.

Figure 11 shows the learning curves for using the Sigmoid activation function. Learning curves for using the ReLU activation function are shown in Figure 6.

Comparing Figure 11 with Figure 6, it can be seen that using the ReLU would converge much faster than using Sigmoid. Besides, using the ReLU yields the best validation set performance among ReLU, TanH, and Sigmoid activation functions, as shown in Table 5.

5.3.4. Initialization. Table 6 provides a summary of the performance of the MLP using different initialization methods: random initialization and initializing all weights as zeros.

Figure 12 shows the learning curves for using zeros initialization. Learning curves for using random initialization are shown in Figure 6.

According to Figure 12, zero initialization fails to break the asymmetry during the weight updates. $F1$ -score for both training and validation set stuck at zero during all epochs. It achieves 0.00 for both Precision and Recall for predicting Label 1. This is because the resulting method predicts everything as the majority Label 0 and fails to learn anything beyond that.

5.3.5. Batch Size. Table 7 provides a summary of the performance of the MLP using different batch sizes.

TABLE 3: Comparing the MLP using different optimizers.

Optimizer	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
Adam	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RMSprop	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00
SGD	0.97	0.00	0.95	1.00	0.00	0.97	0.99	0.00	0.96

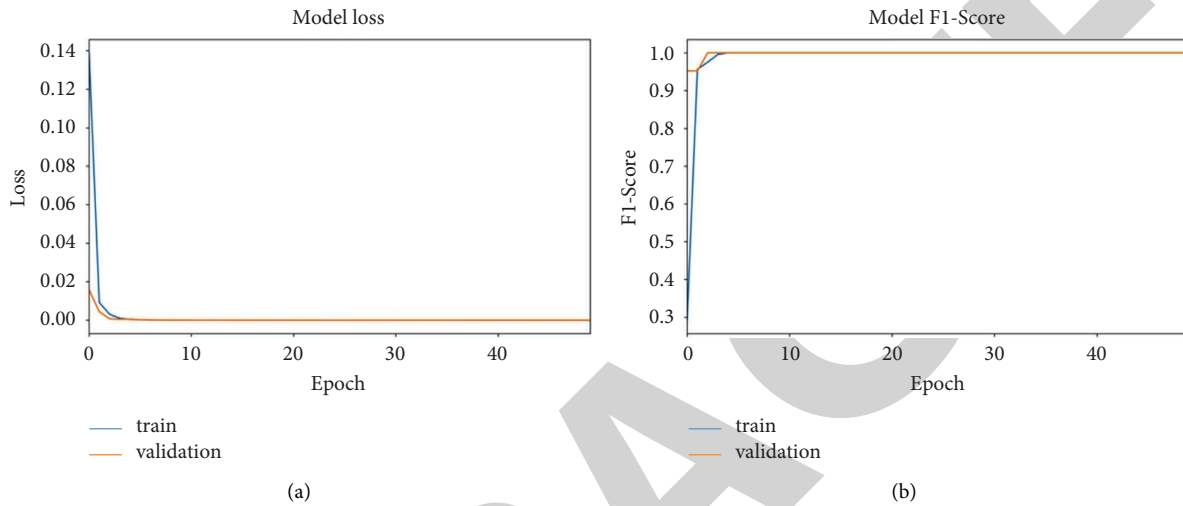


FIGURE 6: (a)–(b) Learning curves for using Adam as optimizer.

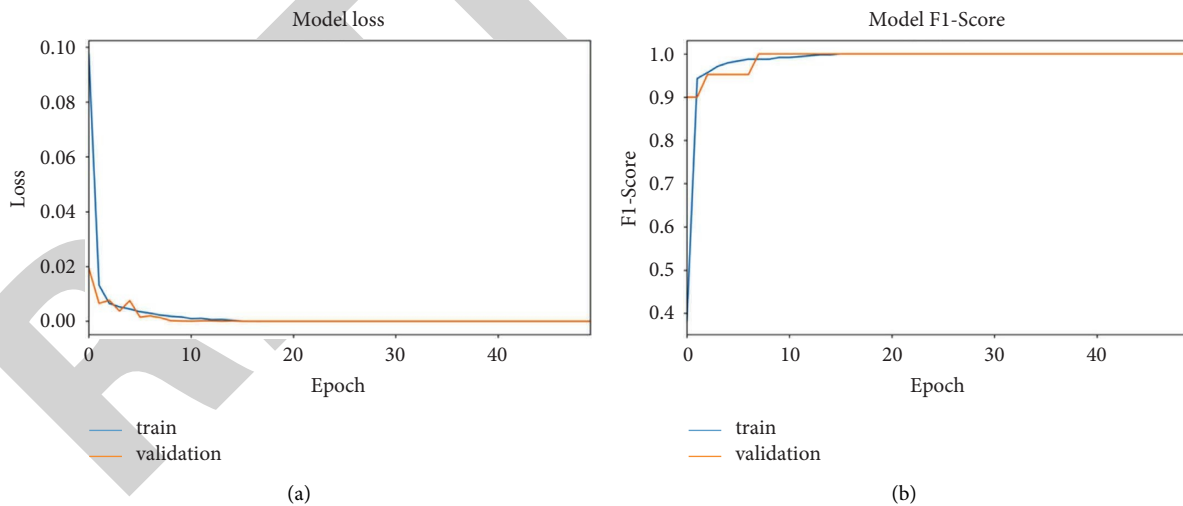


FIGURE 7: (a)–(b) Learning curves for using RMSprop as optimizer.

Figure 13 shows the learning curves for the extreme case of using a batch size of 1. Learning curves for using a batch size of 32 are shown in Figure 6.

In this part, training time is added for comparison to show the efficiency of different modelling choices. It can be found that the larger the batch size, the smaller the amount of time needed for the training. In the extreme case where

the batch size is 1, it would take 394.30 seconds to run 50 epochs, which is much longer than the other choices. In terms of the validation set performance, the experiments have shown that the intermediate value achieves the best outcome as can be seen from Table 7. A batch size that is too small would make the learning process much more unstable, as shown in Figure 13.

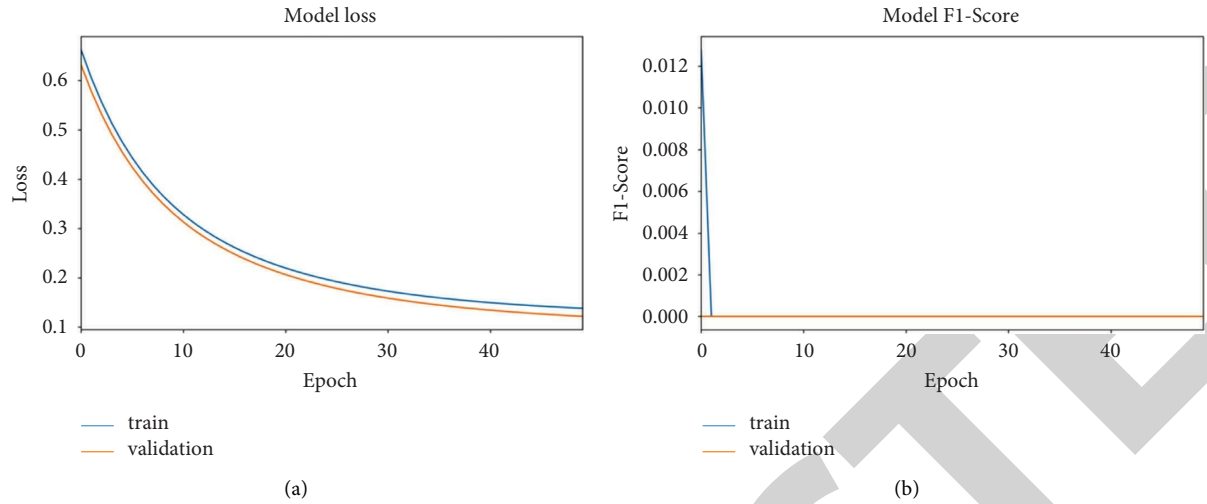


FIGURE 8: (a)–(b) Learning curves for using SGD as optimizer.

TABLE 4: Comparing the MLP using different learning rates.

Learning rate	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
0.0001	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00
0.001	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.01	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00
0.1	1.00	0.90	1.00	1.00	0.98	1.00	1.00	0.94	1.00
0.5	0.97	0.00	0.95	1.00	0.00	0.97	0.99	0.00	0.96

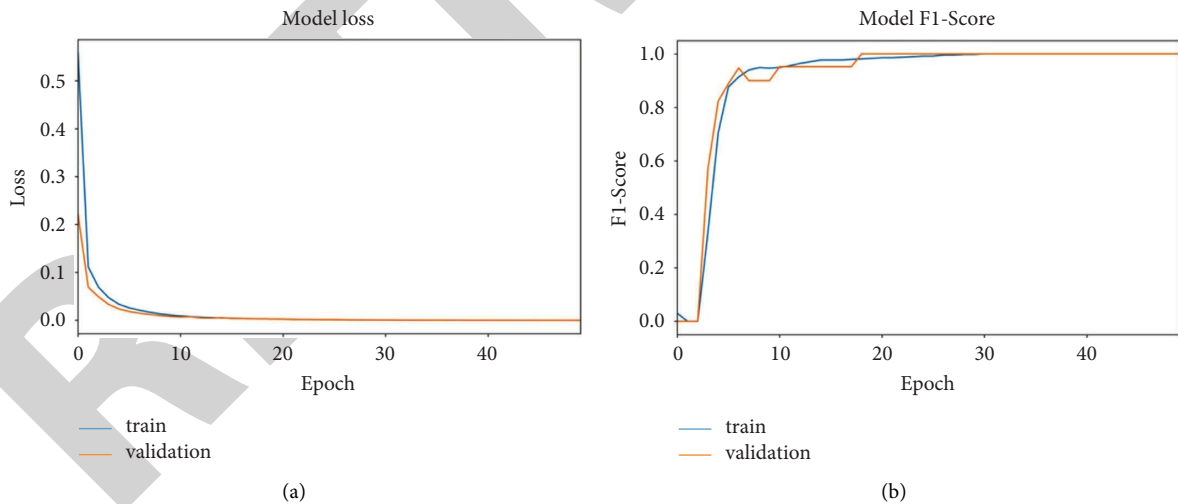


FIGURE 9: (a)–(b) Learning curves for using 0.0001 as the learning rate.

5.3.6. *Depth.* Table 8 provides a summary of the performance of the MLP using different number of hidden layers (i.e., different depth of the network).

Figure 14 shows the learning curves for the case of a shallow network that uses only one hidden layer. Learning curves for using 3 hidden layers are shown in Figure 6.

According to Table 8 and Figure 14, the depth of the network does not have many impacts on performance. The performance drops a little bit if the depth is too large, since in this case the architecture is too complex for our specific problem. Three hidden layers are chosen instead of only 1 hidden layer mainly due to efficiency considerations–it

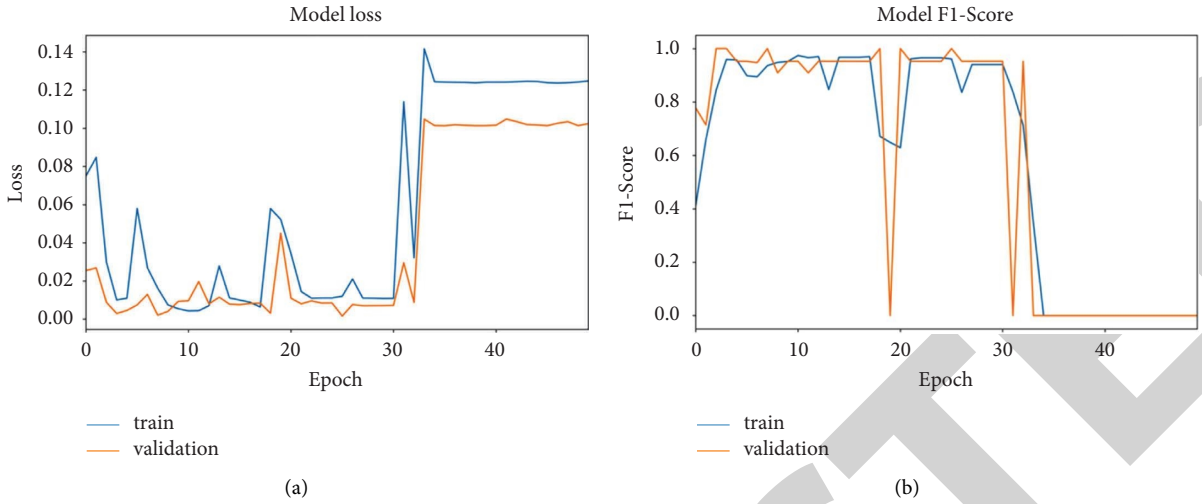


FIGURE 10: (a)–(b) Learning curves for using 0.1 as the learning rate.

TABLE 5: Comparing the MLP using different activation functions.

Activation function	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
ReLU	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TanH	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00
Sigmoid	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00

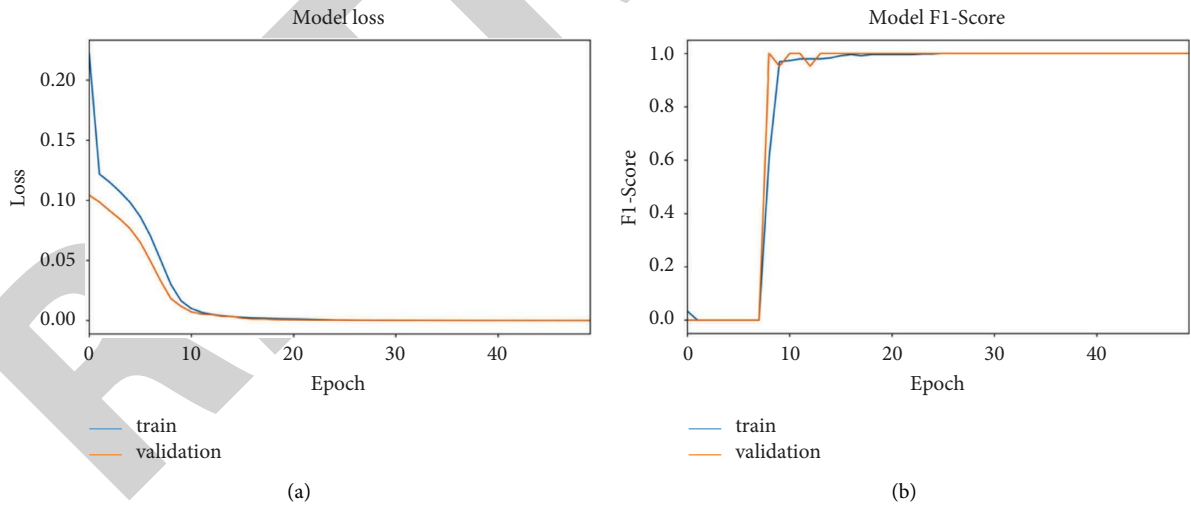


FIGURE 11: (a)–(b) Learning curves for using the sigmoid as activation function.

TABLE 6: Comparing the MLP using different initialization methods.

Initialization method	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
Random	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zero	0.97	0.00	0.95	1.00	0.00	0.97	0.99	0.00	0.96

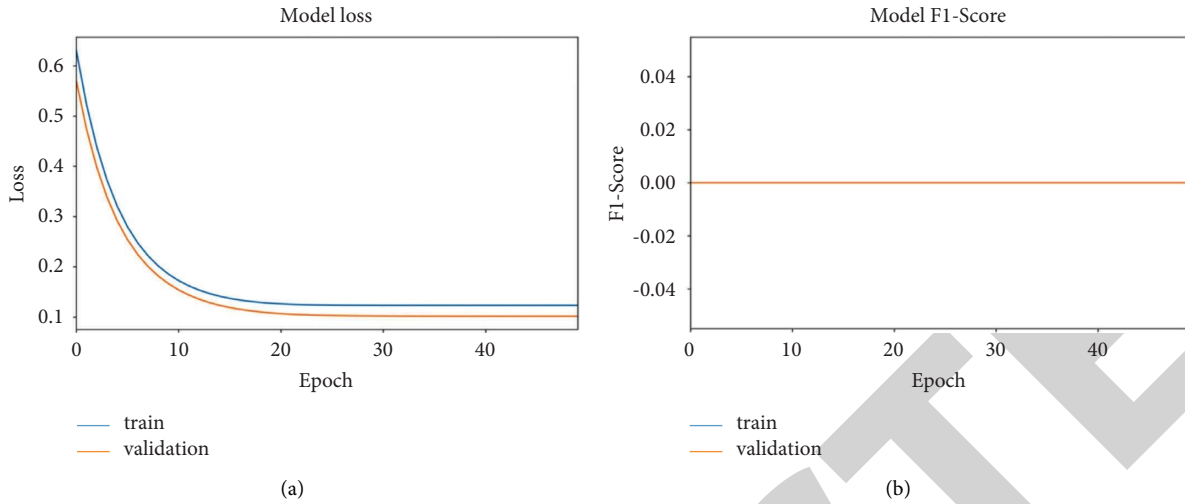


FIGURE 12: (a)–(b) Learning curves for using zero initialization function.

TABLE 7: Comparing the MLP using different batch sizes.

Batch size	Time for 50 epochs (s)	Precision			Recall			F1-score		
		0	1	Avg	0	1	Avg	0	1	Avg
1	394.30	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00
32	15.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
512	2.99	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.98	1.00
1024	2.50	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.98	1.00
2048	2.62	1.00	1.00	1.00	1.00	0.95	1.00	1.00	0.98	1.00

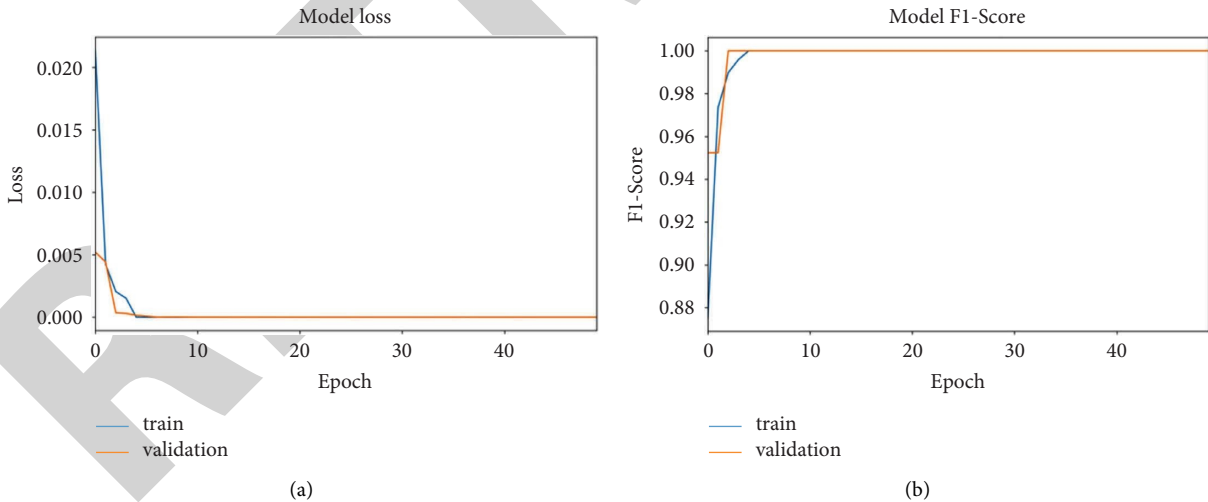


FIGURE 13: (a)–(b) Learning curves for using 1 as batch size (i.e., stochastic gradient descent).

converges in less than 5 epochs for the 3-hidden-layer scenario, whereas about 10 epochs for the 1-hidden-layer case.

5.3.7. *Width.* Table 9 provides a summary of the performance of the MLP using different numbers of hidden

neurons in each of the hidden layers for the 3-hidden-layer case (i.e., different widths of the network), where three scenarios of 4, 32, and 64 neurons are tested.

Figure 15 shows the learning curves for the case of a simpler network that uses only 4 hidden neurons in each hidden layer. Learning curves for using 32 hidden neurons in each hidden layer are shown in Figure 6.

TABLE 8: Comparing the MLP using different number of hidden layers.

Number of hidden layers	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00

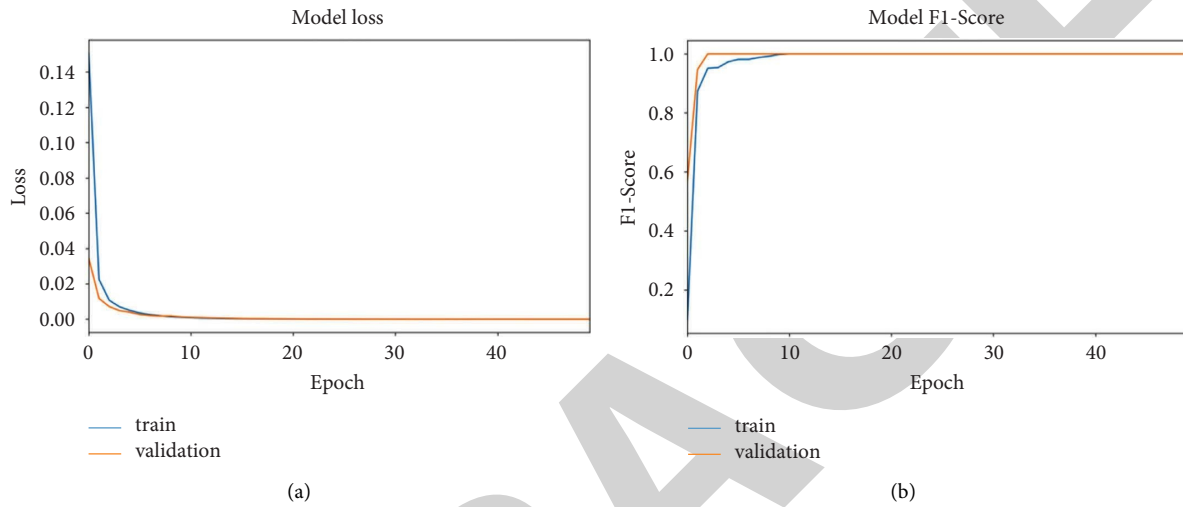


FIGURE 14: (a)–(b) Learning curves for using 1 hidden layer.

TABLE 9: Comparing the MLP using different number of hidden neurons in the hidden layer.

Number of hidden neurons in each layer	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
4	1.00	1.00	1.00	1.00	0.97	1.00	1.00	0.98	1.00
32	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
64	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.99	1.00

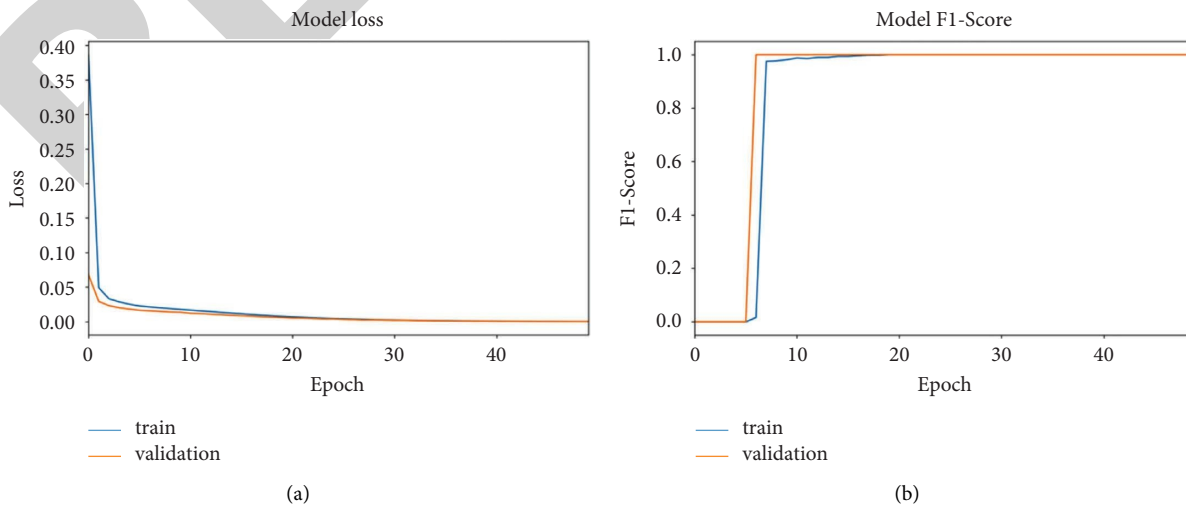


FIGURE 15: (a)–(b) Learning curves for using 4 hidden neurons in each hidden layer.

TABLE 10: Comparing the MLP with and without dropout.

Regulation	Precision			Recall			F1-score		
	0	1	Avg	0	1	Avg	0	1	Avg
Without	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
With	1.00	1.00	1.00	1.00	0.95	1.00	1.00	0.98	1.00

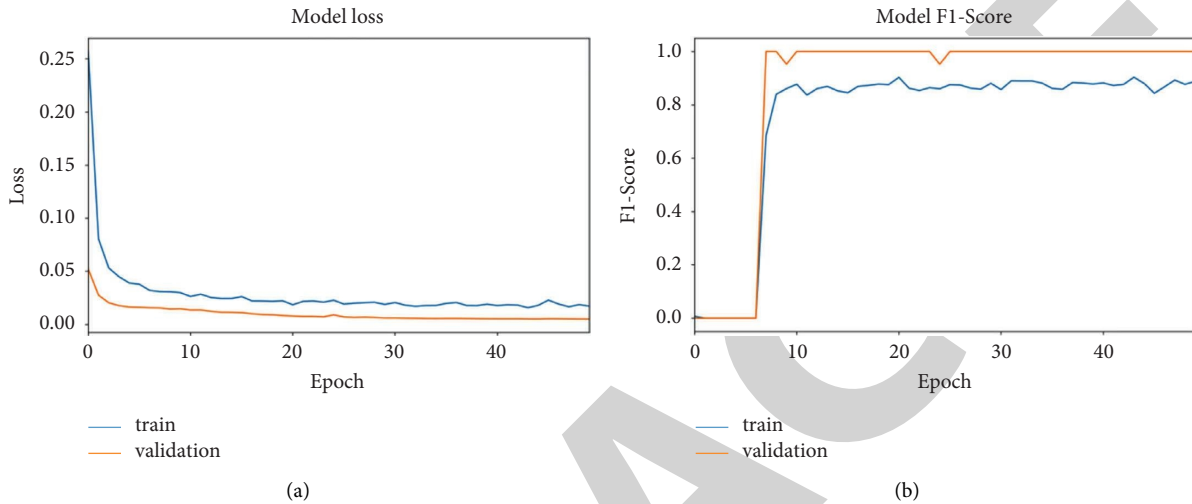


FIGURE 16: (a)–(b) Learning curves for using dropout (80% dropout rate).

As shown in Figure 15, the learning curve converges much slower when using a simpler architecture compared to the best setting. Also, the performance of using a width of 4 is inferior to the choice of 32 according to Table 9. This is mainly because of the decreased model capacity for using a smaller width. The width choice of 64 would make the architecture over-complex for the problem, thus also resulting in a worse performance.

5.4. Ablation Study for MLP-Dropout Regularization. Table 10 provides a summary of the performance of the MLP with and without dropout layers for regularization purposes.

Figure 16 shows the learning curves in the case of a network that uses dropout with a dropout rate of 0.8. Learning curves for a network without dropout layer are shown in Figure 6.

As shown in Figure 6, the selected method (without dropout) does not suffer from the overfitting issue as the learning curves converge smoothly. Thus, any regularization techniques would be unnecessary for the task. This is further proved by the experiment that adding a dropout layer would have a detrimental effect on model performance according to Figure 16 where the learning curves fluctuate a lot and Table 10 where the Recall and F1-score for Label 1’s prediction both have worse performance compared to the “without dropout” counterparts.

6. Conclusions

Taking the corporate bonds issued in China from 2014 to 2021 as the study object, this paper widely chooses 37 qualitative and quantitative variables and constructs a security warning model based on deep neural networks to predict China’s corporate bonds default behavior. By comparing the best Multi-Layer Perceptron with the traditional logistic regression, it finds that the MLP is superior in the performance of default risk prediction. Furthermore, comprehensive hyper-parameter analyses and ablation study are provided to justify the best MLP setting for the prediction model. The experimental results show that the security warning model based on deep neural networks demonstrates the effectiveness in predicting corporate bond defaults.

The major contribution of this paper is the application of the deep learning method in the security warning of corporate default risk which accommodates some special factors in the Chinese context. Existing studies generally look into the quantitative financial and operating aspects of the issuer and the economic conditions. However, factors such as the longstanding support of the local government, the characteristics of the industry, the quality of the bond-service agencies, the relationship of the issuer with the government and the agency, are rarely considered in default risk study. The security warning model constructed in this

paper confirms the usefulness of these nonfinancial qualitative factors and the application of deep neural networks, therefore having some practical implications for the future security warning study on Chinese corporate bond defaults. [27].

Data Availability

The experimental data can be obtained from the corresponding author upon request.

Disclosure

The authors confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

Conflicts of Interest

The authors declare that this research has no conflicts of interest.

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