Research on the Impact of Green Technology Innovation on Enterprise Financial Information Management Based on Compound Neural Network

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ABSTRACT

To enhance the early warning level of financial risks in enterprises, mitigate the financial risks arising from diverse adversities, and drive green technological innovation and sustainable development, this study proposes a financial risk prediction model (MS-BGRU) that amalgamates multi-scale convolution and two-way GRU. Firstly, a multi-scale feature extraction module is devised that assimilates financial information from various scales by leveraging hole convolution with distinct expansion rates. This assimilated information is then fused to obtain richer context information. Secondly, the BGRU network is employed to discern the sequence characteristics and time information of financial indicators. The empirical results showcase that the model proposed in this paper exhibits a high identification accuracy, surging up to 98.03%, which surpasses other benchmark models. The model can accurately prophesize the financial risk of enterprises and offer guidance to management decision-makers in averting financial risk.

KEYWORDS

BGRU, Financial Risk Prediction, Green Technology Innovation, Neural Network

INTRODUCTION

In recent years, due to the sluggish recovery of the global economy and the enormous financial pressure, along with the need for economic transformation and upgrading faced by various countries, listed companies are encountering amplified operational stress, thereby gradually unveiling delisting risks (Xing et al., 2020). The risk conundrum of listed companies not only engenders significant losses to the enterprises but also critically affects the interests of investors, creditors, and other stakeholders. If enterprises can predict these risks in advance, they can proactively evade such potential hazards (Xing et al., 2020). With the advent of the new generation of information technology, artificial intelligence
(AI) has emerged as a pivotal tool to alleviate the problem of inadequate support from conventional financial management methods for green innovation in enterprises. Hence, it is essential to explore the ways to employ emerging technologies such as AI to extract indicators from the intricate data of the enterprises for risk prediction and prevention, which not only facilitates the enterprises in seizing a larger market share and maneuvering through the intricate economic landscape of dynamic transformations but also propels the circulation of innovation resources and market transformation of green technology innovation products.

Green technological innovation, as a novel form of technological innovation that emphasizes both environmental protection and green economic development, is playing an increasingly pivotal role in enterprise development. However, weak innovation capability has consistently remained the most significant obstacle to the transformation, upgrading, and development of enterprises (Cambria et al., 2018). The level of green technology innovation capability directly affects the degree of pollution generated by the enterprise. As the green technology innovation capability of an enterprise improves, the degree of pollution decreases accordingly. The enhancement of green technology innovation capability is therefore indispensable to the green transformation of the manufacturing industry. Currently, the majority of domestic and foreign scholars’ research on the financial risk prediction mechanism of enterprises is primarily based on financial text data, such as the z-score model. Although these methods have proven to be effective in early warning of financial crisis of listed companies, they have not incorporated risk evaluation indicators related to green finance (Gao et al., 2022). Consequently, they cannot provide a comprehensive measurement of the future overall development of a company. From the perspective of information disclosure, financial data can visually present the company’s present operation status, while the pertinent risk evaluation indicators of green finance can supplement quantitative data, trace indications of changes in the company’s operation, and encourage the company to achieve green technology innovation while maximizing profits. Generally speaking, when a company’s operating conditions change, the financial report disclosure information related to green financial risk assessment indicators will also change correspondingly. We can perceive these signals through text analysis. Meanwhile, the manager will also reveal the company’s outlook for the next one to two years in the financial report information. Hence, incorporating risk evaluation indicators related to green finance would prove beneficial in promoting the sustainable development of the company and predicting financial crises.

With the emergence of natural language processing (NLP) technology, there has been a gradual shift towards utilizing machine learning and deep learning methodologies for processing financial text data. From the initial word vectorization to the current Word2Vec model, NLP and deep learning have become fully integrated (Wasserbacher & Spindler, 2021). Recurrent neural networks (RNN), bidirectional gate recurrent units (BGRU), and long short-term memory (LSTM) are commonly employed models in natural language processing for the analysis and prediction of financial text data, with promising predictive results (Ling & Yinying, 2022). For example, in literature (Maltritz, 2010), a composite NLP model and daily trading market data were employed to calculate the probability of financial crisis within the US banking industry during the 2007–2009 financial crisis, utilizing maximum likelihood estimation methodology. Kumar et al. (2019) used machine learning algorithms such as logistic regression, random forest, and support vector machines to correct unbalanced early warning financial text data and predict the financial situation of listed companies. Yan et al. (2020) employed unconstrained distributed lag models and support vector machines to introduce financial ratios and macroeconomic factors with 3–5 cycle lags in order to detect the impact of early internal and external changes on the financial status of a company. Niu et al. (2020) proposed a deep learning model based on two-stage feature selection, effectively capturing the nonlinearity of multiple financial time series. Moreover, an error correction model was employed to improve the generalization and accuracy of the predictions. Dixon et al. (2015) predicted the futures prices of the Chicago Board of Trade by employing deep neural networks (DNN), and the experimental results showed good potential for financial time series prediction with a DNN.
Marso and Merouani (2020) used the SA algorithm to optimize the weights of the feedforward neural network, significantly improving the prediction effect on financial text data. Furthermore, Anwar et al. (2018) proposed the use of financial ratios and macroeconomic indicators, utilizing artificial neural network (ANN) technology to establish a financial performance early warning system model for Islamic banks. Fatima and Said (2018) used an ANN to establish a financial early warning system, screening key indicators according to the company’s financial status to assess the risk of the company. Sezer et al. (2018) proposed a robust model to predict the trend of a company’s stock market, based on a two-dimensional convolutional neural network, and analyzed the possibility of a financial crisis. Moews et al. (2018) employed the deep learning model to predict the trend of financial time series, and Jeong and Kim (2018) added regression to the DNN to improve the accuracy of the financial situation forecast. Xie et al. (2020) explored the ability of deep learning models to predict stock index and company financial crises, while Duan (2019) proposed a deep neural network composed of a multi-layer perceptron with three hidden layers to model a company’s financial data systematically. Notwithstanding the triumph of these approaches in the processing and analysis of financial textual data, their proficiency in extracting profound semantic characteristics from extensive financial text data remains a formidable challenge. Consequently, this drawback hampers efficiency and undermines the precision of financial risk prediction, particularly in light of the ongoing expansion of financial text data.

To enhance the precision of financial risk prediction for enterprises and advance sustainable development, this manuscript introduces the MS-BGRU financial risk prediction model, which is further substantiated through experimental validation in predicting extensive financial text data. The following steps were undertaken:

1. A substantial financial text database was established by incorporating diverse indicators, and through rule-based filtering and data normalization operations, anomalous data were identified and eliminated.
2. A multi-scale feature extraction module (MS-FEM) was integrated with BGRU to extract features from financial text data comprehensively. The integration of risk assessment indicators pertaining to green finance facilitated accurate financial risk prediction within the realm of green technological innovation.
3. The incorporation of the max pooling operation enhanced the model’s capacity for generalization and stability.

The structure of this manuscript is organized as follows: the next section expounds on the construction of the financial text database employed in this study. The following sections delineate the proposed financial risk prediction model, MS-BGRU, and present the experimental outcomes, validating the model’s effectiveness. The conclusion summarizes the findings and outlines avenues for future research.

CONSTRUCTION OF FINANCIAL TEXT DATABASE

Data and Index Selection

Acquiring and gathering data is an indispensable foundation for this research. To obtain the necessary data, the SMAR database was utilized, whereby financial indicators from 16,595 A-share listed companies between 2015 and 2020 were retrieved, including 335 ST companies. The financial index data of each listed company on the day when the annual report was released were collected, which resulted in 283 financial index data points, sourced exclusively from the balance sheet, profit and loss statement, and cash flow statement as publicly disclosed by the company.
In consideration of industry and financial risk characteristics, this study selected 66 financial indicators, including return on assets, net profit rate of total assets, and net profit rate of current assets, alongside 12 green financial risk indicators to establish a financial risk prediction indicator system by drawing on relevant literature and combining the expertise of relevant enterprises in achieving green technology innovation (Niu et al., 2020). Table 1 presents some turnover data in certain financial indicators, whereas Table 2 expounds on the specific contents of green financial risk indicators.

### Table 1. Partial turnover data of financial indicators

<table>
<thead>
<tr>
<th>Turnover Rate of Accounts Receivable</th>
<th>Total Asset Turnover</th>
<th>Fixed Assets Turnover</th>
<th>Turnover Rate of Working Capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.6144</td>
<td>0.4871</td>
<td>4.5514</td>
<td>0.5803</td>
</tr>
<tr>
<td>2.1081</td>
<td>0.3042</td>
<td>6.6901</td>
<td>1.2964</td>
</tr>
<tr>
<td>14.2777</td>
<td>0.0306</td>
<td>1.0731</td>
<td>1.3901</td>
</tr>
<tr>
<td>6.7014</td>
<td>0.4632</td>
<td>0.4151</td>
<td>0.1045</td>
</tr>
<tr>
<td>58.7999</td>
<td>1.2578</td>
<td>1.3074</td>
<td>1.4192</td>
</tr>
<tr>
<td>8.7731</td>
<td>0.8475</td>
<td>5.4526</td>
<td>2.1585</td>
</tr>
<tr>
<td>5.4197</td>
<td>0.5617</td>
<td>4.3546</td>
<td>1.6427</td>
</tr>
<tr>
<td>2.913</td>
<td>0.4151</td>
<td>107.1148</td>
<td>0.8399</td>
</tr>
<tr>
<td>2.1833</td>
<td>0.6277</td>
<td>8.1515</td>
<td>0.6496</td>
</tr>
<tr>
<td>4.8782</td>
<td>0.5616</td>
<td>4.2472</td>
<td>0.7851</td>
</tr>
</tbody>
</table>

### Table 2. Contents of green financial risk indicators

<table>
<thead>
<tr>
<th>Index Name</th>
<th>Content Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy risk</td>
<td>Risks of inappropriate, unstable, and ineffective policies</td>
</tr>
<tr>
<td>Legal risk</td>
<td>Risk of incomplete and inappropriate laws and regulations</td>
</tr>
<tr>
<td>Financial support risk</td>
<td>Risks of insufficient or inappropriate financial support for green finance, green projects, and green technological innovation at all levels</td>
</tr>
<tr>
<td>Green credit risk</td>
<td></td>
</tr>
<tr>
<td>Green bond risk</td>
<td>Risk of improper design, standard and use of green financial products</td>
</tr>
<tr>
<td>Green fund risk</td>
<td></td>
</tr>
<tr>
<td>Green securities risk</td>
<td></td>
</tr>
<tr>
<td>Green insurance risk</td>
<td></td>
</tr>
<tr>
<td>Carbon finance risk</td>
<td></td>
</tr>
<tr>
<td>Green investment risk</td>
<td>The risk of insufficient social green investment scale and green investment awareness</td>
</tr>
<tr>
<td>Green industry risk</td>
<td>Risk of insufficient scale and slow development of green industry</td>
</tr>
<tr>
<td>Green technology risk</td>
<td>Risk of insufficient green technology innovation and insufficient conversion rate from green technology innovation to practical application</td>
</tr>
</tbody>
</table>
Data Pre-Processing

Data Leaning

Selection of Indicators. We will eliminate indicators from the dataset that have a missing value percentage of more than 30%. Among the profit index data of the listed companies obtained, many reference indicators of enterprises are missing, such as the series data of the net profit rate of current assets, which exhibit a significant gap in the datasheet. Therefore, these indicators need to be eliminated during data processing.

Supplementing Missing Values. We have adopted the method of value supplementation to address the issue of missing values. The value supplementation methods that we employed include mean value supplementation, minimum value supplementation, and so forth. It is worth noting that the supplemented value is not the mean value of supplementation. After examining the distribution of each financial indicator, we observed that the majority of financial indicator values fluctuate within 30% of the mean value, and we do not consider a small proportion of unique financial values that deviate from the mean value. In this paper, we supplemented the missing values in accordance with the distribution of financial indicators, as follows:

\[
\text{missing value} = \text{mean value} + \text{random number} \times \text{mean value}
\]  

Supplementing Missing Values

Some companies’ sales rates, asset impairment losses, and other data are not available in the obtained data, resulting in corresponding data loss. Therefore, we have filled the corresponding parts with relevant data.

Data Selection. In data acquisition, it is common for financial indicator samples to be absent. In this study, we have set the sample missing threshold accurately at 20%. Whenever a sample missing value data alarm is detected, it will be removed. Even after filtering the data layer by layer, some companies still obtain less experimental data. For example, a company in Guangdong has only collected 42 out of 69 indicators, and such data samples will be excluded from the experiment.

Removal of Outliers. We have used the 36 principles to eliminate industries with missing values. This principle is applied because the data exhibit a normal distribution after undergoing normal distribution testing. We have removed outliers based on the upper and lower quantiles of different years since the years differ.

Data Normalization

Data normalization is conducted because the dimensions of each indicator are inconsistent. To enable a fair comparison of each indicator, we need to eliminate the inconsistency between indicators. The primary objective of data normalization is to convert the sample vector into a unit vector, typically by using methods such as minmax and z-score. In this study of financial text data, we have selected the minmax method and utilized its specific conversion function, which is illustrated in the following formula.

\[
x' = \frac{x - \min(x)}{\max(x) - \min(x)}
\]  

where \( \min(x) \) and \( \max(x) \) respectively represent the minimum and maximum values of financial indexes in all samples, \( x \) represents the normalized financial index value and maps the data to the closed interval \([0, 1]\) through the minmax method.
FINANCIAL RISK PREDICTION MODEL

MS-BGRU Model Structure

A typical deep learning model extracts multi-layer representations of data features by adding hidden layers, forming hierarchical transformation labels of features. This learning method is very suitable for understanding large and complex nonlinear models in data. Convolutional neural networks (CNNs) are one of the most commonly used algorithms in deep learning. These networks use a convolutional filter to extract local translation invariant features from sequence data and then combine these locally optimal results to find the global optimal, saving financial data training costs. A single multi-scale convolution can effectively extract the spatial local relationships of inputs, but it ignores temporal information. Therefore, to address this limitation, we propose a hybrid model called MS-BGRU that combines a multi-scale feature extraction module and BGRU. The BGRU model is selected because it has a superior sequence learning ability in the time domain and is simpler than LSTM. The MS-BGRU model is designed to enhance the accuracy of financial risk prediction and provide a theoretical foundation for financial decision-making in enterprises. The model considers multi-scale feature extraction, pooling, and BGRU and is mainly divided into two parts: the feature extractor and the classifier. The composition of the network structure is depicted in Figure 1.

The convolution kernels utilized in our proposed MS-BGRU model have sizes of $3 \times 3$ and $5 \times 5$, with 4 and 8 corresponding numbers, respectively. The ReLU activation function is employed, and the padding method is set the same. To extract multi-scale features from financial data comprehensively, we stack two multi-scale feature extraction modules consecutively to form a multi-scale feature extractor. To illustrate, if we input data of size $66 \times 1$, with each financial indicator value represented by an element, the first layer of multi-scale convolution will generate two groups of feature maps, each containing four feature maps with a size of $66 \times 1$. By concatenating these two groups, we obtain eight $66 \times 1$ feature maps. Subsequently, the second layer of multi-scale convolution produces 16 feature maps of size $66 \times 1$. The feature maps are then subjected to a pooling layer operation, with the pooling mode set to max pooling and the size to $2 \times 1$. This process results in a feature map size of $33 \times 1$. After flattening and concatenating all feature maps, a $528 \times 1$ feature vector is generated. The extracted features are pooled to reduce the dimension of features and remove redundant information and then fed into the BGRU network. The BGRU network consists of forward and backward GRU

![Figure 1. MS-BGRU model network structure](image-url)
networks, which learn the forward and backward features of financial data, respectively. The output $Y$ is generated to predict whether the company is ST. The network structure and parameter information are detailed in Table 3.

**Multi-Scale Feature Extraction Module**

The MS-FEM (multi-size feature extraction module) is designed to consider the different combinations of financial indicators and their importance in reflecting the status of financial risk and profit. The module uses hole convolution with different expansion rates to obtain financial information of different scales and fuses the information to obtain richer contextual information. This helps in adapting to the importance of learning each channel.

The structure of MS-FEM involves first taking the input as the feature map obtained after four iterations of residual block extraction. Then, different expansion factors are used for convolution operation with a $3 \times 3$ convolution kernel. After extensive experimental verification, the expansion factor $r$ was set to 1, 3, 5, and 7. Adaptive average pooling operation is used to obtain the context feature information of the same resolution, the same number of channels, and different scales. The feature information of each scale is cascaded to obtain the final fused feature map. The overall structure of MS-FEM is shown in Figure 2.

**Table 3. MS-BGRU network structure parameters**

<table>
<thead>
<tr>
<th>Number of Layers</th>
<th>Layer Name</th>
<th>Nuclear Size</th>
<th>Output Size</th>
<th>Parameter Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Input layer</td>
<td>—</td>
<td>(38, 1)</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Conv1d_1–4</td>
<td>$5 \times 5$, $3 \times 3$</td>
<td>(38, 4), (38, 8)</td>
<td>24, 16, 168, 104</td>
</tr>
<tr>
<td>3</td>
<td>Concatenate</td>
<td>—</td>
<td>(38, 16)</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>Bidrectional_gru_1</td>
<td>64 GRU units</td>
<td>(16, 128)</td>
<td>39552</td>
</tr>
<tr>
<td>5</td>
<td>Bidrectional_gru_2</td>
<td>64 GRU units</td>
<td>(16, 128)</td>
<td>74112</td>
</tr>
<tr>
<td>6</td>
<td>Dropout</td>
<td>—</td>
<td>(16, 128)</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>Flatten</td>
<td>—</td>
<td>(1, 2048)</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>Dense</td>
<td>—</td>
<td>(1, 2)</td>
<td>4098</td>
</tr>
</tbody>
</table>

**Figure 2. MS-FEM structure diagram**
The specific calculation formula of MS-FEM is shown in the following equations:

\[ M_t = \text{Conv}(M_m, r), r \in \{1, 3, 5, 7\} \]  

(3)

\[ M_{ag} = \text{Averagepool}(M_m) \]  

(4)

\[ M_c = C(M_1, M_3, M_5, M_7, M_{ag}) \]  

(5)

where \( \text{Conv}(M_m, r) \) is a feature map \( M_m \) conduct cavity convolution with expansion rate \( r \), \( \text{Averagepool}(\cdot) \) represents average pooling operation for the characteristic diagram \( M_m \), \( C(\cdot) \) cascade all feature maps, \( M_t \) is the characteristic graph after convolution of different expansion factors, \( M_{ag} \) is the characteristic diagram after average pooling, and \( M_c \) is the characteristic diagram after cascade.

**BGRU**

BGRU can operate the sequence in both directions at the same time, improving that RNN does not consider the interaction between the word order before and after the text. In order to better learn the sequence characteristics of financial indicators and consider their time information, this paper introduces the BGRU model to carry out sequence learning.

The GRU (gated recurrent unit) network is a type of recurrent neural network that selectively inputs information by controlling the door structure. The combination of memory unit and hidden layer status is achieved by updating the door and resetting the door. The value range of the door is \((0–1)\), and this value represents the proportion of current information allowed to pass.

The detailed structure of the GRU is shown in Figure 3, where the input vector \( x \) and the previous hidden state \( h(t-1) \) are used to calculate the update gate \( z(t) \) and the reset gate \( r(t) \). The current memory state \( c(t) \) is then calculated based on the update gate \( z(t) \), the reset gate \( r(t) \), and the current input vector \( x(t) \). Finally, the current hidden state \( h(t) \) is obtained by applying the activation function tanh to the current memory state \( c(t) \) and the update gate \( z(t) \).

**Figure 3. Structure of GRU**
\[ r_t = \sigma(W_r [h_{t-1}, x_t] + b_r) \]  (6)

\[ \tilde{h}_t = \tanh(W * [r_t * h_{t-1}, x_t] + b) \]  (7)

\[ z_t = \sigma(W_z [h_{t-1}, x_t] + b_z) \]  (8)

\[ h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \]  (9)

where \( W_r, W, W_z \) constitute the weight matrix, learned from the model in the training process, \( \tilde{h}_t \) is the state function of the candidate memory unit, \( z_t \) is an update gate whose value represents the passing rate of the current candidate memory unit, and \( \sigma \) is the sigmoid activation function.

The input sequence is respectively operated from front to back and from back to front. The output of the hidden layer state function of the forward GRU is \( \tilde{h}_t \), and the output of the hidden layer state function of the backward GRU is \( \tilde{h}_t \). By connecting the output of the two to the same output layer, the final feature vector of BGRU \( Q \) can be obtained. The output calculation formula of BGRU at time \( t \) is shown as follows.

\[ \tilde{h}_t = \sigma(W_{xh} x_t + W_{hh} \tilde{h}_{t-1} + b_h) \]  (10)

\[ \tilde{h}_t = \sigma(W_{xh} x_t + W_{hh} \tilde{h}_{t-1} + b_h) \]  (11)

\[ Q = W_{by} [\tilde{h}_t; \tilde{h}_{n}] + b_y \]  (12)

**Loss Function**

This paper trains the model by minimizing the cross-entropy loss function to achieve better training results. The specific formula is as follows.

\[
\text{Loss}(W) = -\sum_{i \in J} \sum_k y_{i,k} \ln \left( p(y_{i,k} | v_i; W) \right)
\]  (13)

where \( W \) represents the weight of the network model, \( k \) represents the number of categories, \( v_i (i \in 1, \ldots, n) \) represents the text embedding of \( i \)-th financial data, \( n \) represents the maximum number of text, \( J \) represents a set of training samples, and \( y_{i,k} \) represents the corresponding binary representation of financial data.
EXPERIMENT

The experimental environment included a 3.70 GHz Intel Core i7-8700K CPU with 32 GB of memory, using the Python programming language and the TensorFlow framework. The experimental data set was the financial text database described in this document.

Analysis of Model Training Effect

The loss curve, generated during the model’s training, serves as a critical indicator for assessing its training efficacy and generalization capability. To evaluate the model’s performance on the financial text database, we conducted 60 epochs of training and recorded the loss curve in real time, as depicted in Figure 4. The findings demonstrate that the loss function value in the database decreases as the number of iterations increases, indicating the model’s remarkable resilience and accurate financial risk prediction capability.

Impact of Different Dropout Values on Model Performance

To ascertain the effect of the model’s dropout value on the experimental results, this paper conducted multiple experiments within the same environment, each employing a distinct dropout value in the range of [0, 0.9]. The classification accuracy results for each experiment are depicted in Figure 5. Evidently, the dropout value has a noticeable impact on the results, with the highest classification accuracy rate of 98.03% achieved at a dropout value of 0.3. Accordingly, this paper selects the aforementioned value as the optimal dropout value for the model.

Performance Comparison

To further corroborate the model’s effectiveness in financial risk prediction, this paper conducted a series of comparative experiments, employing SVM, RNN, GRU, BGRU, MS-GRU, and MS-BGRU models (Ling et al., 2022) in an identical experimental environment. To ensure the integrity and fairness of the results, the study utilized the control variable method to maintain uniformity among certain hyperparameters, including the number of iterations, batch size, dropout value, network depth, convolution core size, and number. The outcomes of the experiment are presented in Figure 6.

As depicted in the figure, the proposed model outperforms SVM, RNN, GRU, BGRU, and MS-GRU models, achieving the highest accuracy of approximately 98%. At the same time, the accuracy of the model in this paper is higher than other models at any stage of training. Therefore, it can be considered that the model in this paper has high robustness and generalization ability and can complete
accurate and stable financial risk prediction. The superiority of the proposed model can be attributed to the use of a multi-scale convolution feature extractor and BGRU, which enables the extraction of various features of financial indicator data using multi-level convolution cores of varying sizes, thus acquiring the deep semantic data of financial indicators. The feature information acquired using this approach is considerably more discriminative.

CONCLUSION
To elevate the level of enterprise financial risk prediction and promote green technology innovation, this paper proposes a financial risk prediction model that integrates multi-scale convolution and two-way GRU, which is validated using a self-built large-scale financial text database. The experimental outcomes reveal that the proposed model attains a recognition accuracy of 98.03% on the financial text database, outperforming the BGRU model lacking a multi-scale feature extraction framework,
thereby enabling accurate financial risk prediction for enterprises. Since the work done in this paper has not been verified in practical applications, we will consider expanding the green finance risk assessment indicators in the database and reducing model parameters to achieve more efficient financial risk prediction in practical applications.

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**CONFLICTS OF INTEREST**

The authors declare that they have no competing interests.

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