J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 7425--7440

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

# Risk Early Warning of Enterprise Financial Management Risk Based on CNN and BiLSTM under Accounting Informatization

Haoliang Chen[1,2], Ruiying Guo[3,✉], Yunyun Jin[2]

[1] *School of Accounting, Dalian University of Finance and Economics, Dalian, Liaoning, 116622, China*

[2] *School of Accounting, Dongbei University of Finance and Economics, Dalian, Liaoning, 116025, China*

[3] *School of Accounting, Guangzhou Xinhua University, Dongguan, Guangdong, 523000, China*

ABSTRACT

Based on accounting informatization, this paper constructs a financial risk prediction system by applying the CNNs (Convolutional Neural Networks)- BiLSTM (Bi-directional Long Short-Term Memory)-Attention model to accurately identify and classify various risk types in enterprise FM (financial management), and improve the accuracy and efficiency of financial risk prediction. CNN was used to extract local features in financial data, BiLSTM was used to capture time dependencies, and finally the importance of financial indicators was weighted and fused through the Attention mechanism. During the training process, the Adam optimizer and cross entropy loss function are used for optimization, and appropriate learning rates and training rounds are set to ensure the stability and performance of the model. The experimental results show that when the epochs is 50, the accuracy of risk classification is 98.9% and the loss value is 0.012. In the analysis of each data level, the average response time of the proposed system and the traditional system is 1.80s and 7.17s respectively. The system in this paper shows obvious advantages in response time and prediction accuracy. The response time is greatly shortened, and it can provide effective support in real-time decision-making. This paper model has significant application prospects in financial risk prediction, and can provide enterprises with efficient and accurate risk warnings, which has important theoretical significance and practical value.

*Keywords:* Enterprise Financial Management, Risk Classification, Financial Data, Accounting Informationization, Convolutional Neural Networks

✉ Corresponding author.
*E-mail address:* guoruiyingxh@gmail.com (R. Guo).
Received 25 February 2024; Revised 10 May 2024; Accepted 15 December 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-405

## 1. Introduction

At present, in the context of the era of global information explosion, the rapid development of network big data technology, so that enterprises in the financial management work inevitably to data information as a management medium [1-2]. Enterprises want to improve their own management level, it is necessary to give full play to the technical advantages of information technology management, to promote their own financial management concepts, management models and organizational transformation of information technology, so as to fit the current era of development background and trends, and establish a competitive advantage for the future development of enterprises [3].

Financial management belongs to the important content of enterprise management, enterprises must focus on financial risk management, through the identification, assessment, response to effectively control financial risk, in order to achieve prevention [4]. Effective control of financial risk is an important means for enterprises to achieve financial management objectives, if the enterprise financial risk is high, will lead to the enterprise financial management objectives are difficult to achieve, and to a certain extent, weaken the enterprise's internal control ability [5-8]. Lagging enterprise financial management system construction will lead to risk, specifically manifested in the financial information reporting is not timely, information reporting form is not standardized, the information content is not comprehensive, which will lead to financial information system analysis and research results are difficult to reflect the actual operation of the enterprise, thus affecting the realization of financial management objectives [9-13]. The enterprise financial risk early warning analysis and control belongs to one of the important contents of enterprise financial management, which not only directly affects the level of enterprise financial risk management, but also affects the internal control of the enterprise as well as the production and operation situation [14-16]. Therefore, enterprises need to pay full attention to financial risk early warning analysis and control work, and effectively improve its level and ability. In the context of informationization, the design of a set of perfect enterprise financial management risk early warning system, the enterprise financial management risk control within a certain range, can effectively reduce its financial risk, improve the company's financial management level [17-19].

The data of corporate financial statements can be collected and standardized to ensure the consistency and comparability of data during model training. CNN deeply mines local features in financial data, captures nonlinear relationships between different financial indicators, and enhances the model's ability to identify potential financial risk signals. This paper innovatively combines CNN and BiLSTM, making full use of the strengths of both, and further improves the model's ability to focus on key financial features through the Attention mechanism, so that the model can still achieve accurate classification in complex financial data. The deep learning model realizes the automatic classification of FM risks, reduces the need for manual intervention, and has strong adaptability and high accuracy under different financial data conditions. This method provides an effective decision support tool for corporate financial risk management and has broad practical application prospects.

### *1.1. Financial Data Acquisition*

Data collection is an important step in financial risk prediction. The data in this paper were collected from January 2018 to January 2023, involving financial data of multiple companies. In order to ensure the reliability and generalization of the data, the collected data should cover multiple companies, covering companies of different types and sizes, to ensure that the model can adapt to various financial environments.

Financial historical data includes revenue, costs, profits, current assets, fixed assets, etc. These data help reveal the financial trends of the company and provide historical data support for the model. External data includes market data, industry data, macroeconomic data, etc.

The labeled data includes different types of financial risks, a total of 10 categories. This provides labeled samples for supervised learning algorithms, which helps in model training.

Some of the collected financial data are shown in Table 1.

**Table 1.** Financial data display (ten thousand yuan)

| Time | Income | Cost | Profit | Current assets | Fixed assets |
|---|---|---|---|---|---|
| 2018-1-1 1:00 | 1220 | 810 | 410 | 1520 | 2020 |
| 2018-1-1 2:00 | 1240 | 820 | 420 | 1540 | 2040 |
| 2018-1-1 3:00 | 1250 | 825 | 425 | 1550 | 2050 |
| 2018-1-1 4:00 | 1260 | 830 | 430 | 1560 | 2060 |
| 2018-1-1 5:00 | 1270 | 835 | 435 | 1570 | 2070 |
| 2018-1-1 6:00 | 1280 | 840 | 440 | 1580 | 2080 |
| 2018-1-1 7:00 | 1300 | 850 | 450 | 1600 | 2100 |
| ... | ... | ... | ... | ... | ... |
| 2023-1-1 24:00 | 1320 | 870 | 450 | 1620 | 2120 |

Data cleaning and preprocessing are important steps to prepare for subsequent modeling. Financial data has problems such as missing values, outliers, and different scales. For numerical variables, the mean of the column data is used to fill the missing values. The missing value of a financial indicator $X_i$ is $X_{i,m}$, and the filling process is:

$$X_{i,m} = \frac{1}{n}\sum_{k=1}^{n} X_{i,k} \tag{1}$$

For variables with large outliers, using the median to fill in is better to deal with the impact of extreme values. The method to calculate the median is to arrange the data in ascending order and take the middle value.

The purpose of outlier detection is to find values that appear abnormal in the data. These outliers may be caused by data entry errors or extreme situations. Box plots can be used to identify outliers. Detected outliers can be directly deleted. Since different financial indicators have different dimensions and value ranges, in order to avoid certain features from having too much impact on model training, the data is standardized. The formula is as follows:

$$Z_i = \frac{X_i - \mu_i}{\sigma_i} \tag{2}$$

To scale the data to the specified range, the formula is:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

Financial data often involve time series, which have temporal dependence, so the stationarity of the data needs to be considered when processing. The difference is used to remove the trend and seasonal fluctuations in the time series. The first-order difference is performed on the sequence to obtain a new sequence. The first-order difference can effectively remove the long-term trend component in the time series.

$$Y_t = X_t - X_{t-1} \tag{4}$$

Feature selection and construction are important steps before model training. By selecting features related to financial risk, the training efficiency of the model can be improved. In financial risk prediction, features closely related to risk types are selected. Cash flow from operating activities and free cash flow reveal the company's cash flow status and capital liquidity.

In addition to selecting existing financial indicators, this paper constructs new derivative features to increase the expressive power of the model.

The formula for total asset return is:

$$ROA = \frac{NI}{TA} \tag{5}$$

In formula 5, NI and TA are net profit and total assets respectively.

The formula for return on net assets is:

$$ROE = \frac{NI}{SE} \times 100\% \tag{6}$$

The collected data is divided using 10-fold cross validation, and the data set after division is shown in Table 2.

**Table 2.** Data set display

| Category | Training set | Test set | Total |
|---|---|---|---|
| Financial liquidity risk | 2061 | 229 | 2290 |
| Debt repayment risk | 1701 | 189 | 1890 |
| Profitability risk | 2232 | 248 | 2480 |
| Credit risk | 1926 | 214 | 2140 |
| Market risk | 2007 | 223 | 2230 |
| Operational risk | 1602 | 178 | 1780 |
| Compliance risk | 1701 | 189 | 1890 |
| Tax risk | 1917 | 213 | 2130 |
| Financial fraud risk | 1863 | 207 | 2070 |
| Normal status | 22410 | 2490 | 24900 |

Financial data is divided into 10 categories, 9 of which are risk data and one is normal data. The sample size of normal data is the largest, with a total of 24,900 samples. By classifying financial data risks and analyzing different types of financial risks, it can help companies take effective risk management measures in a timely manner and reduce potential financial crises. Classification can refine risk types and provide enterprises with more specific decision-making basis. Through effective risk classification, enterprises can achieve more accurate FM and resource allocation, thereby improving overall operational efficiency and market competitiveness.

### *1.2. Model Construction*

The features extracted by convolution are input into the BiLSTM layer to capture the temporal dependencies in the financial data. The Attention mechanism is added after the BiLSTM output to automatically assign different weights to different parts of the input data and highlight key features.

Through convolution operations, CNN extracts key nonlinear relationships from financial statement data. Financial data is a sequence of multiple financial indicators, including revenue, cost, profit, etc., for each quarter. For each time step, the input of CNN is a vector containing financial indicators.

The convolution layer uses multiple convolution kernels to extract features at different levels. Each convolution kernel learns how to extract the relationship between local financial indicators. The convolution process is:

$$Feature_t = Conv\left(Input_t, Filter\right) \tag{7}$$

$Filter$ represents the convolution kernel, which performs convolution on the input data through sliding window operation to extract local features.

The pooling layer is mainly used for dimensionality reduction, reducing the dimension and computational complexity of the data while retaining important features in the data. This paper uses maximum pooling to compress the features after convolution to reduce the risk of overfitting. The maximum value in each pooling window is taken to represent the information of the area:

$$PF_t = MaxP\left(Feature_t\right) \tag{8}$$

Through convolution and pooling layers, the network can extract and retain important local features in financial data, reduce data dimensions, and ensure the efficiency of subsequent model processing.

BiLSTM is an important tool for processing time series data.

The formula of LSTM is expressed as:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{9}$$

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{10}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right) \tag{11}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{12}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{13}$$

$$h_t = o_t \cdot \tanh\left(C_t\right) \tag{14}$$

The features extracted by CNN can be used as the input of LSTM and passed to the LSTM layer to capture the temporal dependencies in the data. Unlike unidirectional LSTM, bidirectional LSTM considers both the forward and backward information of the input sequence. Through bidirectional propagation, the model can capture past and future dependencies, thereby enhancing the ability to learn time series patterns. Bidirectional LSTM performs forward and backward propagation through two LSTMs:

$$h_t^{forward} = LSTM\_forward\left(Input_t\right) \tag{15}$$

$$h_t^{backward} = LSTM\_backward\left(Input_t\right) \tag{16}$$

$$h_t = \left[h_t^{forward}, h_t^{backward}\right] \tag{17}$$

The Attention mechanism adaptively assigns different weights to different parts of the input data to highlight key features. Different financial indicators in financial data have different impacts on risk prediction. The Attention mechanism can automatically identify and focus on key indicators, enhancing the model's predictive ability.

Self-Attention calculates the weight of each time step and sums them according to the weights to highlight the most important time steps for risk prediction. The Attention mechanism calculates the relevance weight of each part of the input:

$$Attention\_score_t = Soft\max\left(Q_t \cdot K_t^T\right) \tag{18}$$

$Q_t$ and $K_t^T$ are vectors of query and key, respectively, representing different parts of the financial data.

By calculating the Attention weights, the model can assign different importance to each time step in the financial data, and weighted sum to obtain the final feature representation:

$$\bar{h}_t = \sum_{i=1}^{n} Attention\_weight_{t,i} \cdot h_i \tag{19}$$

In Formula 19, $\tilde{h}_t$ is the weighted output and $Attention\_weight_{t,i}$ is the attention weight at time step i.

The final financial risk prediction result is obtained by fusing the weighted output of the Attention mechanism with the LSTM output:

$$h_{final} = Fusion\left(h_t, \tilde{h}_t\right) \tag{20}$$

Through weighted fusion, the model can better focus on the key features in financial data. By designing This paper model, financial time series data can be efficiently processed and risk classification prediction can be performed. CNN extracts local features, BiLSTM captures time dependencies, and the Attention mechanism strengthens the focus on key financial indicators. This model has significant advantages in handling complex financial risk prediction tasks.

### *1.3. Model Training and Evaluation*

The loss function formula is:

$$\mathrm{L} = -\sum_{c=1}^{C} y_c \log\left(p_c\right) \tag{21}$$

The hidden layer dimension in LSTM determines the amount of information that the model can accommodate during learning. Too small a dimension may not be able to fully learn complex financial data features, while too large a dimension may lead to long model training time and overfitting problems.

In the Attention mechanism, the number of heads refers to the number of parallel attention mechanisms, and the dimension refers to the representation dimension of each head. Increasing the number of heads allows the model to learn more feature representations, but it can increase the computational complexity. The batch size determines how many samples are used for a gradient update during each training process, and the batch size is set to 64.

In order to avoid overfitting, Dropout is used to randomly discard some neurons in the neural network during training. Overfitting is prevented by adding L2 regularization terms to the loss function to punish excessive weights. The formula for L2 regularization is:

$$\mathrm{L}_{regularized} = \mathrm{L} + \lambda \sum_{i} w_i^2 \tag{22}$$

In formula 22, $\lambda$ is the regularization strength and $w_i$ is the parameter of the weight in the network.

The initialization parameter settings of the model in this paper are shown in Table 3.

**Table 3.** Initialization parameter settings

| Parameters | Value | Function |
|---|---|---|
| Convolution kernel size | 5×5 | Used to extract local features in financial data. |
| Number of convolution kernels | 64 | Used to extract features at different levels. |
| Pooling layer size | 2×2 | Used to reduce dimensionality and reduce feature dimensions. |
| LSTM hidden layer dimension | 256 | The number of neurons in each hidden layer in LSTM. |
| Number of bidirectional LSTM layers | 2 | Use bidirectional LSTM to learn forward and backward time dependencies simultaneously. |
| Number of attention heads | 8 | The number of heads used in the Attention mechanism, allowing the model to learn multiple different attention features in parallel. |
| Attention dimension | 128 | The dimension of each attention head. A higher dimension enables each head to learn more fine-grained features. |
| Batch size | 64 | The batch size of data input during each training. |
| Learning rate | 0.001 | Controls the step size of gradient updates. Too large a learning rate can lead to unstable training. |
| Epochs | 50 | The number of complete traversals of the training set. Sufficient training rounds help the model converge. |

The accuracy formula is:

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{23}$$

The precision formula is:

$$\Pr ecision=\frac{TP}{TP+FP} \tag{24}$$

The recall rate formula is:

$$\operatorname{Re} call=\frac{TP}{TP+FN} \tag{25}$$

The F1 value formula is:

$$F1=2\times\frac{\Pr ecision\times\operatorname{Re} call}{\Pr ecision+\operatorname{Re} call} \tag{26}$$

The macro precision calculates the precision for each class and then takes the average of these precisions:

$$MP=\frac{1}{N}\sum_{i=1}^{N}\Pr ecision_i \tag{27}$$

The macro recall is to calculate the recall for each class and then take the average of these recalls:

$$MR=\frac{1}{N}\sum_{i=1}^{N}\operatorname{Re} call_i \tag{28}$$

$$MF1=\frac{1}{N}\sum_{i=1}^{N}F1_i \tag{29}$$

### 1.4. Risk Prediction System

This paper applies This paper model to accurately identify and classify various risk types in corporate FM. A corporate FM risk prediction system is constructed. Through CNN-BiLSTM-Attention, the financial status of the enterprise is monitored and analyzed in real time, and potential financial risks are accurately identified and classified. It helps enterprises to identify various financial risks such as financial liquidity risk, debt repayment risk, profitability risk, etc., as early as possible, and take timely countermeasures. Through data-driven prediction capabilities, it improves the decision-making efficiency of decision makers in FM, avoids blind decisions or losses caused by information lags. It enhances the automation and intelligence level of FM, and improves the transparency of the overall FM and risk control capabilities of enterprises. Through this system, enterprises can maintain stable development in a dynamic market environment.

The interface of the enterprise FM risk prediction system constructed in this paper is shown in Figure 1.

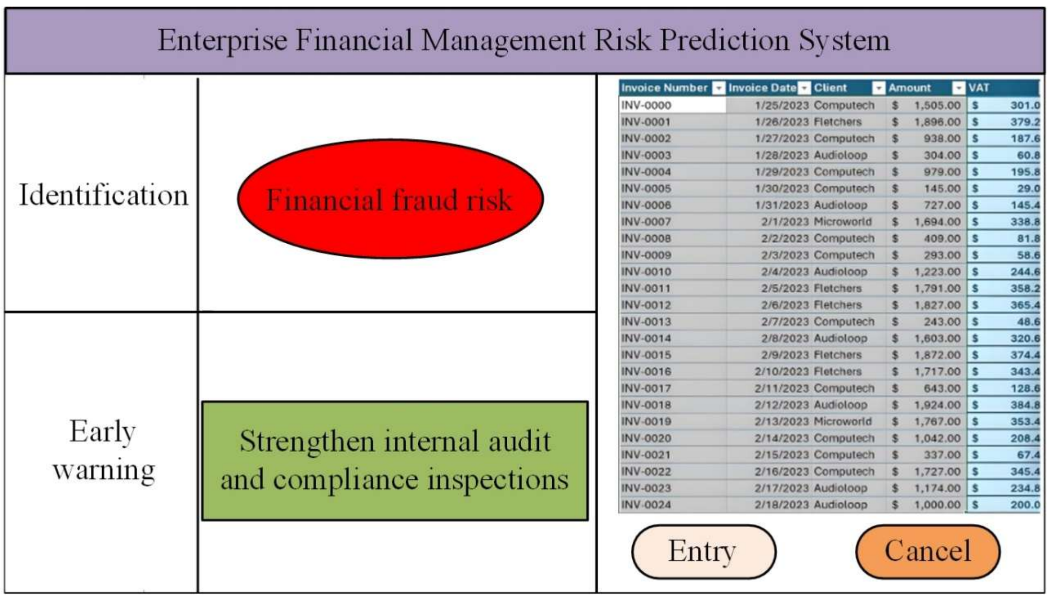


**Fig. 1.** Enterprise FM risk prediction system interface

Using CNN-BiLSTM-Attention, the system can accurately identify and classify different types of financial risks. The system can automatically analyze the financial data of each enterprise and output risk categories through the trained risk classification model based on the financial status and historical data of each enterprise. For each risk type, the system can calculate the probability of its occurrence and provide corresponding warning information.

The system is not only a simple financial risk classification, it also has a multi-category risk warning function. When it is detected that the enterprise is facing a certain type of financial risk, the system can provide personalized response suggestions through the decision support module. If the system finds that the company's debt ratio has increased abnormally, the system can recommend strengthening debt repayment management and adjusting the debt structure; if there is a risk of financial fraud, the system can prompt to strengthen internal audits and compliance inspections. The system can also assess the company's current financial health based on historical data and industry benchmarks, helping decision makers make more scientific and accurate financial decisions.

## 2. Results

### *2.1. Risk Classification Performance*

The number of rounds is set to 50, and the changes in accuracy and loss are shown in Figure 2.

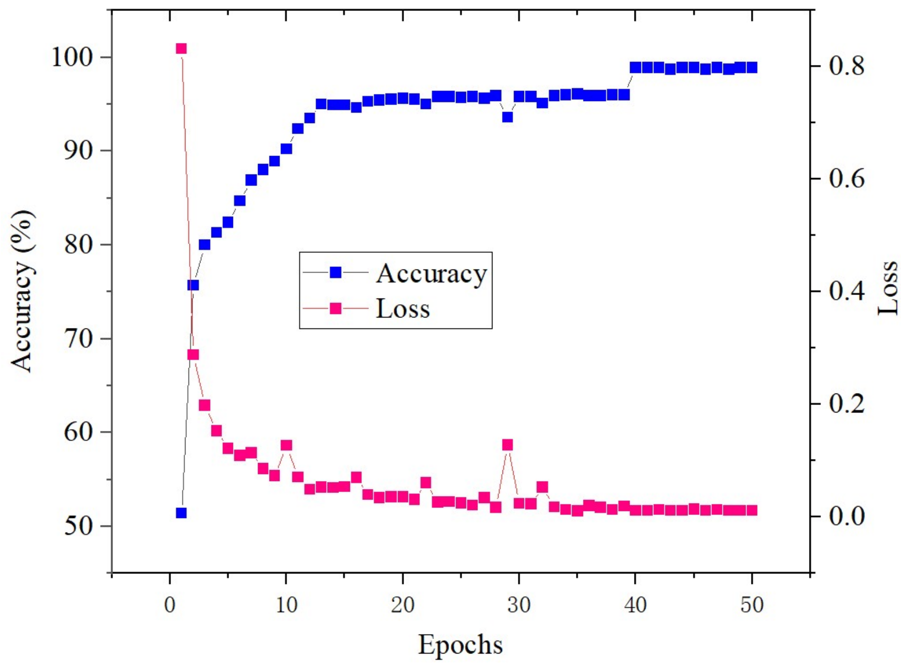


**Fig. 2.** Changes in accuracy and loss

The changes in accuracy and loss are very small when Epochs are 40-50, and they basically reach convergence. When Epochs is 50, the accuracy of risk classification is 98.9% and the loss value is 0.012. This paper model in this paper can perform very accurate financial risk classification due to its unique structural design and mechanism. Through multi-level feature extraction, time-dependent modeling, and adaptive weighting of key features, it significantly improves the accuracy of financial data risk classification. The CNN part extracts local features from the original financial data through convolutional layers and pooling layers. This processing method can capture the complex nonlinear relationship between various indicators in the financial statements, including the dynamic relationship between revenue, liabilities and cash flow. CNN automatically learns features at different levels through multiple convolution kernels to ensure that deep patterns that are helpful for risk prediction can be mined. BiLSTM effectively captures long-term trends and short-term fluctuations in time series data by considering the dependencies between the past and future data. BiLSTM uses both past and future data for modeling, which enhances the understanding of the temporal characteristics of financial data, including the impact of seasonal fluctuations, economic cycles and other factors on financial conditions. The Attention mechanism assigns different weights to different financial indicators, allowing the model to autonomously identify and focus on the most critical financial features, including the importance of debt ratio, liquidity and other factors in risk classification. This mechanism avoids the problem of treating all features equally, improves the model's ability to identify key risk indicators, reduces the interference of irrelevant features, and effectively improves the accuracy of risk classification.

In order to further analyze the classification performance of the model in this paper, comprehensive macro indicators are analyzed, and the results are shown in Figure 3.

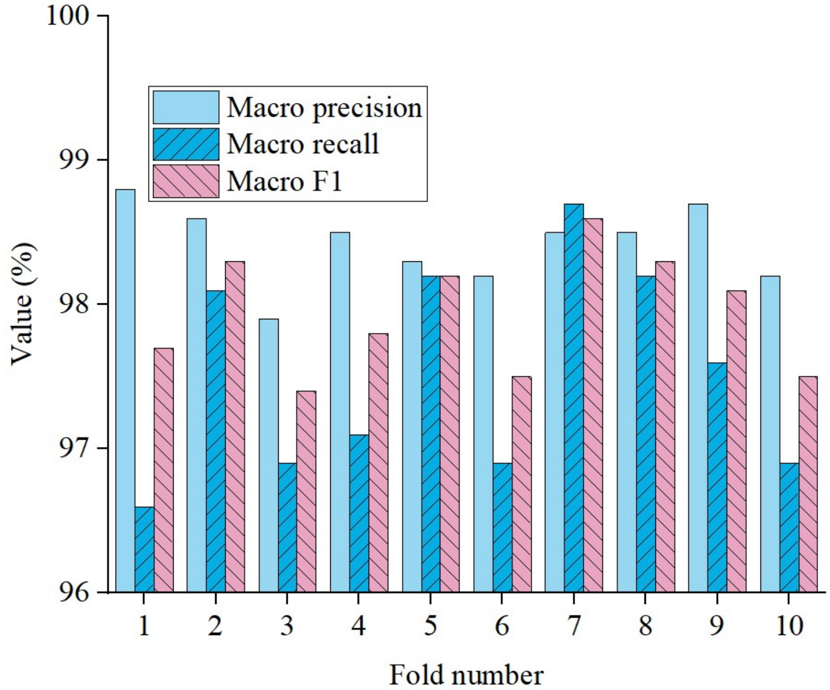


**Fig. 3.** Classification performance

From the performance data of This paper model on 10-fold cross validation, its performance in macro precision, macro recall and macro F1 value is very good, indicating that the model has stably made accurate financial risk classification in multiple training and validation. Specifically, the macro precision of the model has always remained between 97.9% and 98.8%. This shows that the model is not only highly accurate in identifying various types of financial risks, but also can better balance the prediction of positive and negative samples, avoiding overfitting or bias towards a certain type of risk. The excellent performance of macro precision and macro recall is attributed to the multi-level structure of This paper model. The CNN layer can effectively extract local features in financial data, capture the nonlinear relationship between various financial indicators, and enhance the learning ability of complex financial data. The BiLSTM layer helps discover long-term trends and cyclical fluctuations in financial data by capturing the dependencies between the past and the future in the time series, improving the model's overall grasp of historical and future financial conditions, thereby improving the stability and accuracy of predictions. The Attention mechanism helps the model focus on the most critical financial indicators through adaptive weighting, thereby making more accurate judgments on risk factors during the classification process. The combination of these technologies enables the model to perform well in different trade-offs, ensuring the stability and efficiency of the classification results. Overall, This paper model achieved such excellent results in the 10-fold cross validation, thanks to its powerful feature extraction capabilities, time-dependent modeling capabilities, and adaptive weighting capabilities for key indicators. It can fully explore the complex relationships in financial data, thus providing highly accurate and stable support for financial risk prediction.

### *2.2. Classification Effect of Specific Categories*

Classification analysis of specific categories helps to accurately identify and distinguish different types of financial risks, and then provide targeted management measures for enterprises. Through detailed classification, the unique characteristics and potential impact of each risk can be revealed, helping decision makers to formulate more precise strategies and effectively prevent and mitigate the impact of different risks on the financial health of enterprises. The classification effect of specific categories is shown in Figure 4.

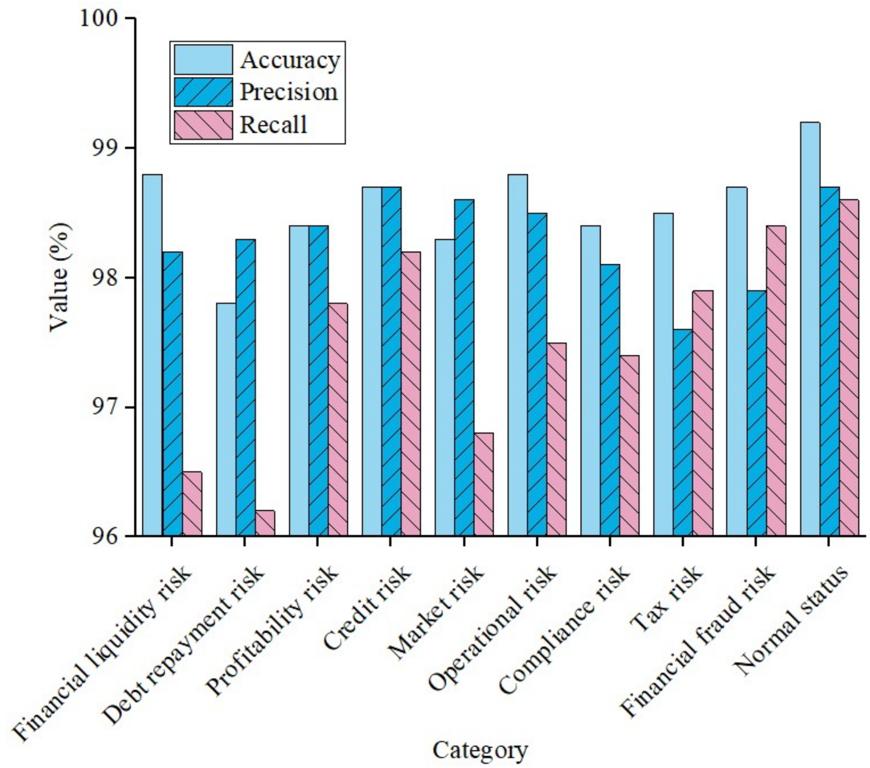


**Fig. 4.** Classification results of specific categories

From the perspective of classification results of specific categories, this paper model has shown extremely high accuracy, precision, and recall in the classification of all financial risk categories, reflecting the model's excellent ability in distinguishing various types of financial risks. The model in this paper performs best in the "normal state" category, with an accuracy of 99.2%, precision and recall of 98.7% and 98.6% respectively. This shows that the model can accurately distinguish between normal and risky states, and its prediction of normal state is very stable. Secondly, for important financial risks such as "financial liquidity risk" and "operational risk", the model also showed extremely high accuracy, reaching 98.8% accuracy. The precision rates were 98.2% and 98.5% respectively, and the recall rates were 96.5% and 97.5%, indicating that when dealing with such risks, the model can accurately identify and distinguish, and performs well in avoiding false positives and false negatives. In the "Credit Risk" category, the model's precision and recall rates were 98.7% and 98.2%, demonstrating its ability to accurately classify credit risk categories. The model can effectively handle various types of complex financial risks and achieve high predictive power and classification accuracy in most categories. This paper model has balanced and stable classification performance in different financial risk categories. It can accurately distinguish various risks and avoid overfitting or bias towards a certain category. This further proves the excellent performance and adaptability of the model under multivariate complex data, and is suitable for accurate risk classification tasks in corporate financial risk management.

### *2.3. Risk Binary Classification Performance*

The binary classification of normal and other risks helps to simplify the problem and improve classification efficiency. In practical applications, companies often focus on whether there are financial risks. Therefore, combining "normal status" and "other risks" into a binary classification problem can quickly identify potential financial problems and take early warning and intervention measures in a timely manner.

In order to more comprehensively analyze the performance of this model, this model is compared with CNN-BiLSTM, Transformer, and CapsNet. The confusion matrix comparison is shown in Figure 5.

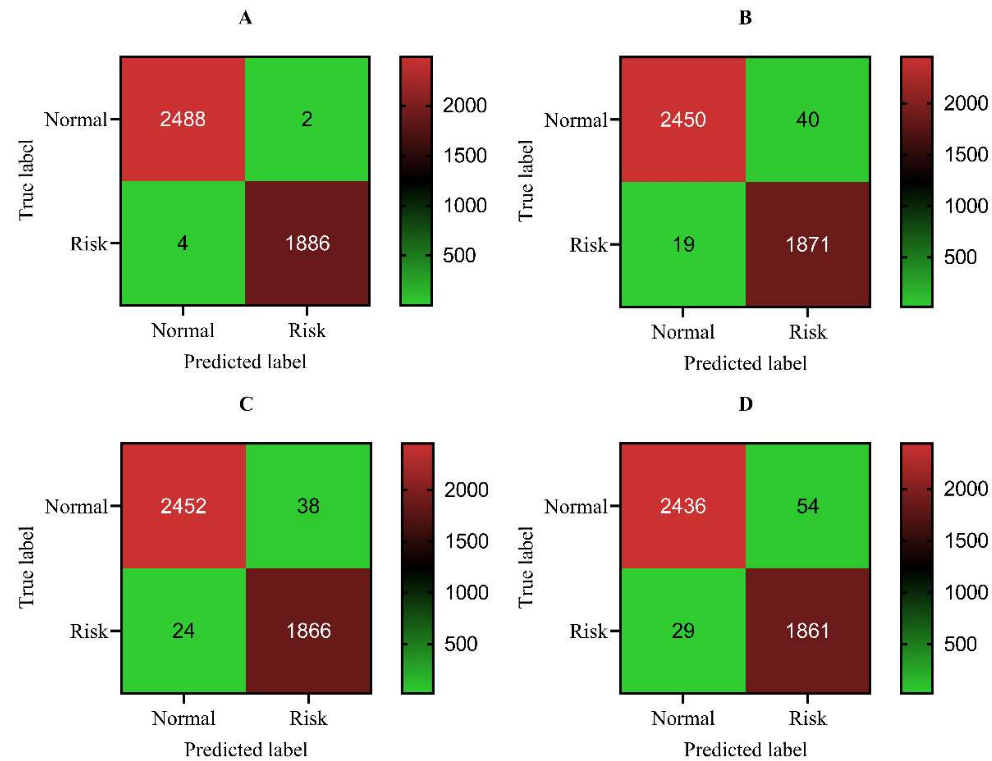


**Fig. 5.** Confusion matrix

(A) Model of this paper; (B) CNN-BiLSTM model; (C) Transformer model; (D) CapsNet model

From the confusion matrix results, CNN-BiLSTM-Attention has better performance in identifying risks and normality than the other three models. There are 2490 normal samples in total, and the number of correctly classified normal samples of the proposed model is 2488, with only 2 samples being misclassified as risks. There are 1890 risk samples in total, of which 1886 are correctly classified as risky and 4 are incorrectly classified as normal. In Figure 5(B), Figure 5(C), and Figure 5(D), the number of samples classified incorrectly is 59, 62, and 83, respectively.

This paper model performs better than CNN-BiLSTM, Transformer, and CapsNet in the normal and risk binary classification task, mainly because it combines the advantages of CNN, BiLSTM, and Attention. In contrast, although CNN-BiLSTM can effectively extract the spatial and temporal features of time series data, its focus on important information is not fully optimized. The introduction of the Attention mechanism enables the model to dynamically adjust the weight of attention to different financial indicators according to the context of the input data, significantly improving the ability to focus on key financial features, which is particularly important for the classification of financial risks. Compared with the traditional CNN-BiLSTM model, although Transformer can handle long-term dependencies through the self-attention mechanism, its ability to process the features of input data and optimize weights is not as good as CNN-BiLSTM-Attention. Although CapsNet has advantages in processing complex patterns and spatial relationships, it is not as good as CNN-BiLSTM-Attention in modeling time series data and mining specific features of financial data. In summary, this paper model has an advantage in the binary classification of financial risks by efficiently extracting spatial and temporal features and combining an adaptive attention mechanism, showing higher accuracy.

The ROC (Receiver Operating Characteristic) curve is drawn to more intuitively compare the classification performance of different models. The results are shown in Figure 6.

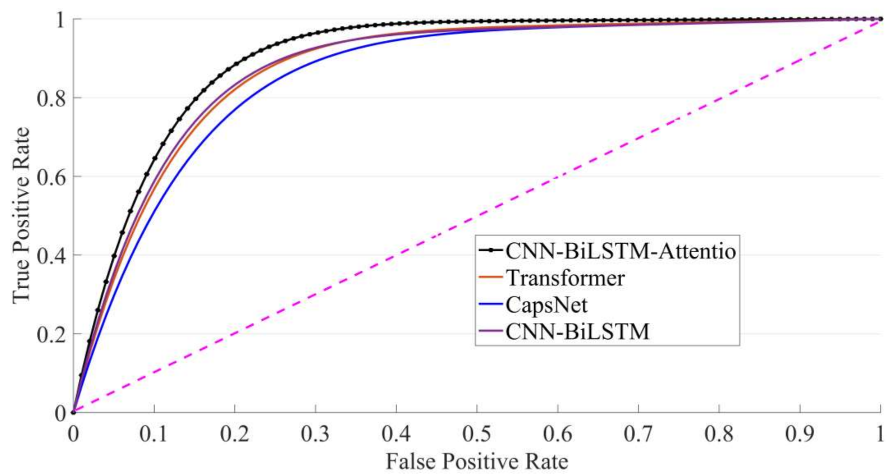


**Fig. 6.** ROC curve comparison

By comparing the four curves, the ROC curve of CNN-BiLSTM-Attention is closer to the upper left corner point, and the area enclosed under the curve is the largest. This means that the model combining CNN, BiLSTM, and Attention can more accurately classify normal and risk data, and improve the recognition effect of financial risk data. This paper model has better classification results than the other three models, mainly due to its unique structural design and mechanism. CNN effectively extracts local features in financial data through convolution operations, including the relationship between key indicators in financial statements, and can automatically discover low-order patterns in input data. BiLSTM can capture historical and future time dependencies by processing time series data in both directions, further improving the model's understanding of dynamic financial changes, and is particularly suitable for complex time series data in the financial field. A simple CNN-BiLSTM cannot efficiently identify key features, especially when processing multi-dimensional information. This adaptive feature selection capability is particularly important in financial risk classification and can effectively improve the accuracy of classification. Compared with Transformer, although Transformer performs well in capturing long-distance dependencies, it lacks a feature selection mechanism for specific tasks and is easily disturbed by redundant information. Although CapsNet has stronger spatial relationship modeling capabilities, it does not perform as well as CNN-BiLSTM-Attention when processing time series and dynamic features. This paper model has obvious advantages in multi-level feature extraction, time-dependent modeling, and feature weight adjustment, making it perform better in financial risk classification.

### *2.4. Response Time*

The risk prediction system constructed in this paper is compared with the traditional risk prediction system, and the real-time performance is analyzed by comparing the response time. The results are shown in Figure 7.

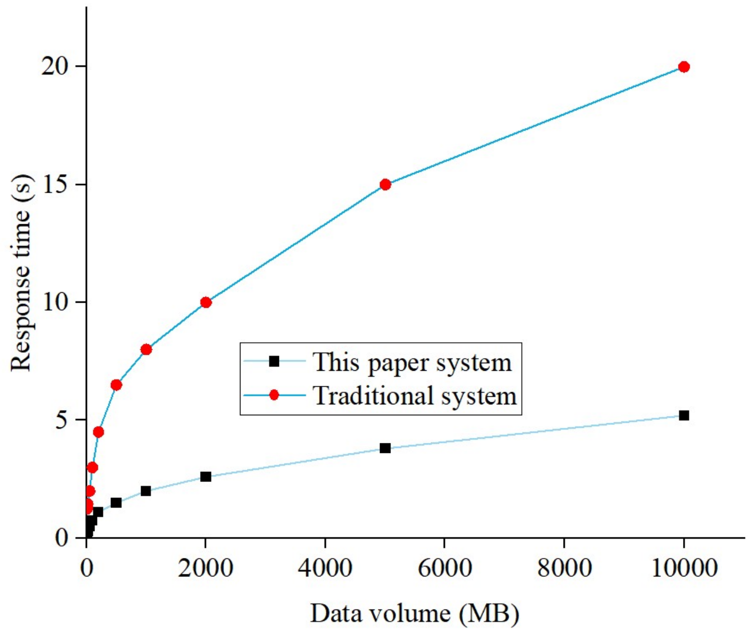


**Fig. 7.** Comparison of response time

This paper model combines the advantages of CNN in local feature extraction and can automatically extract important features from data efficiently. Compared with the traditional system that relies on manual feature selection and rule reasoning, CNN can learn and process features in a more efficient and automated way, thereby reducing the amount of calculation and speeding up the processing process. The BiLSTM layer in the model optimizes the modeling of time series by capturing the dependencies between the previous and next time series data. This enables the system to better process the time series information in financial data and avoids the inefficiency and complexity of time series data processing in traditional systems. The model in this paper uses a modern deep learning framework to make the processing of large-scale data more parallel and efficient, greatly shortening the response time. Traditional systems often need to process data step by step and rely on traditional statistical methods or rule engines, which often cannot fully utilize parallel computing and hardware acceleration, resulting in slower computing speeds. The system in this paper can rely on the efficient feature extraction and time series modeling capabilities of deep learning to ensure the steady growth of response time when the amount of data increases. The system in this paper shows excellent performance when processing large-scale data, which makes the response time of this model significantly better than that of traditional systems and meets the needs of real-time and efficiency in corporate FM.

## 3. Conclusions

Based on This paper model, this paper builds an efficient and accurate enterprise FM risk prediction system and achieves remarkable results. This paper innovatively combines CNN, BiLSTM and attention mechanism, giving full play to their respective advantages, improving the model's feature extraction ability, time series modeling ability and adaptive learning ability of important features. This contribution promotes the application of deep learning technology in the field of FM, and also provides a useful reference for the design of risk prediction models in other fields. This study can provide enterprises with more accurate and timely risk warnings, help them identify potential financial crises, optimize financial decisions, and enhance their ability to resist risks.

## Funding

This work was supported by Liaoning Province Education Science “14th Five-Year Plan” 2022 Annual Project: Research on the Modernized Operating Mechanism of Industry-Academy Colleges in Higher Education Based on the OBE Concept (JG22DB023); Guangzhou Xinhua University: “Research on the Development and Construction of the Course 'Risk Management and Internal Control' in the Digital and Intelligent Era” (2024J069); Dongbei University of Finance and Economics University-Level Project (Special Program for Scientific Research Platform Development): Multidimensional Evaluation of Green Bond Financing Effectiveness and Information Disclosure under the Dual-Carbon Strategy, Project Number PT-Y202218.

## References

[1] Li, Q., & Zhou, Z. (2020, April). Influence analysis of accounting informatization on enterprise financial management. In Journal of Physics: Conference Series (Vol. 1533, No. 2, p. 022029). IOP Publishing.

[2] Kondratenko, N. O., Novikova, M. M., & Spasv, N. Y. (2021). Developing an adaptive financial management system at an enterprise. The Problems of Economy, 1(47), 78-84.

[3] Zhou, X. (2022, June). Enterprise Financial Management Informatization under Cloud Computing Environment. In 2021 International conference on Smart Technologies and Systems for Internet of Things (STS-IOT 2021) (pp. 101-106). Atlantis Press.

[4] Dudin, M., Lyasnikov, N., Yahyaev, M., & Kuznecov, A. (2014). The organization approaches peculiarities of an industrial enterprises financial management. Life Science Journal, 11(9), 333-336.

[5] Jankensgård, H. (2019). A theory of enterprise risk management. Corporate Governance: The international journal of business in society, 19(3), 565-579.

[6] Yi, Y. (2024). The Role of Financial Informatization in Enhancing Enterprise Risk Management: Strategies and Case Studies. Frontiers in Management Science, 3(6), 46-55.

[7] Anton, S. G., & Nucu, A. E. A. (2020). Enterprise risk management: A literature review and agenda for future research. Journal of Risk and Financial Management, 13(11), 281.

[8] Tkachenko, V., Kwilinski, A., Kaminska, B., Tkachenko, I., & Puzyrova, P. (2019). Development and effectiveness of financial potential management of enterprises in modern conditions. Financial and credit activity problems of theory and practice, 3(30), 85-94.

[9] Musah, A., Gakpetor, E. D., & Pomaa, P. (2018). Financial management practices, firm growth and profitability of small and medium scale enterprises (SMEs). Information management and business review, 10(3), 25-37.

[10] Mazur, N., Khrystenko, L., Pásztorová, J., Zos-Kior, M., Hnatenko, I., Puzyrova, P., & Rubezhanska, V. (2021). Improvement of Controlling in the Financial Management of Enterprises. TEM journal, 10(4).

[11] Wei, R., & Yao, S. (2021). Enterprise financial risk identification and information security management and control in big data environment. Mobile Information Systems, 2021(1), 7188327.

[12] Deng, Y. (2022). Construction of a digital platform for enterprise financial management based on visual processing technology. Scientific Programming, 2022(1), 7666110.

[13] Li, L. (2018). A study on enterprise risk management and business performance. Journal of Financial Risk Management, 7(1), 123-138.

[14] Xie, W. (2022). Study on enterprise financial risk prevention and early warning system based on blockchain technology. Mobile Information Systems, 2022(1), 4435296.

[15] Feng, Q., Chen, H., & Jiang, R. (2021). Analysis of early warning of corporate financial risk via deep learning artificial neural network. Microprocessors and Microsystems, 87, 104387.

[16] Liao, S., & Liu, Z. (2022). Enterprise financial influencing factors and early warning based on decision tree model. Scientific Programming, 2022(1), 6260809.

[17] Wei, H., & Wang, X. (2024). Financial Risk Management Early-Warning Model for Chinese Enterprises. Journal of Risk and Financial Management, 17(7), 255.

[18] Cao, Y., Shao, Y., & Zhang, H. (2022). Study on early warning of E-commerce enterprise financial risk based on deep learning algorithm. Electronic Commerce Research, 22(1), 21-36.

[19] Drobyazko, S., Barwinska-Malajowicz, A., Slusarczyk, B., Chubukova, O., & Bielialov, T. (2020). Risk management in the system of financial stability of the service enterprise. Journal of Risk and Financial Management, 13(12), 300.