Retraction

Retracted: Analysis and Risk Assessment of Corporate Financial Leverage Using Mobile Payment in the Era of Digital Technology in a Complex Environment

Journal of Mathematics

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets 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 own 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] W. Wei and B. Li, "Analysis and Risk Assessment of Corporate Financial Leverage Using Mobile Payment in the Era of Digital Technology in a Complex Environment," *Journal of Mathematics*, vol. 2022, Article ID 5228374, 9 pages, 2022.

Research Article

Analysis and Risk Assessment of Corporate Financial Leverage Using Mobile Payment in the Era of Digital Technology in a Complex Environment

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The study aims to improve the enterprise's ability to respond to financial crises and find some countermeasures to prevent potential financial risks. The enterprise financial risk is assessed, and the automatic summary function of mobile payment platforms based on long short-term memory (LSTM) is performed to extract the structured data and unstructured texts from its annual report. On this basis, the early warning system model of financial risks is implemented and its accuracy is improved. The structured data and unstructured text in the company's annual report are extracted. The enterprise financial risk early warning system model is constructed. The accuracy of the enterprise financial risk early warning system has been improved. Firstly, we use the convolutional neural network (CNN) to establish a financial risk prediction system using financial data and test various indicators of the system. Secondly, the financial annual report of the listed company is obtained from the Internet. The required financial statements are obtained in two ways. The first is to set high special treatment (ST) sample weights and delete some non-ST samples. The second is to delete punctuation marks, interjections, numbers, and so on and process the collected text data. The financial risk prediction model is established using the financial text, and the LSTM + attention mechanism is used to optimize the model. Finally, combining structured financial data and unstructured financial text to establish a forecasting model, the model uses LSTM. Combined with a single-layer neural network or CNN model, the comparison experiment is carried out in two ways. Experiments show that the CNN or LSTM attention mechanism cannot significantly improve the performance of the system only using financial data or texts. Using the financial data and financial text using the LSTM + CNN model, the $F1$ value reached 85.29%. Financial data and other indicators in the text have also been greatly improved, and the overall performance is the best. In summary, LSTM using financial data and financial texts combined with CNN to establish a risk prediction system can help investors and companies themselves find possible financial crises in listed companies as soon as possible and help companies deal with their financial risks in a timely manner.

1. Introduction

With the rapid development of the global economy, many companies have gone public in various countries. In the expansion of production and operation of the enterprise, a series of problems have followed one after another. Among them, financial risk prediction is a problem that every company must face [1]. From the perspective of investors, the interests of investors are directly related to the financial status of the company. If investors can predict the financial risks of a company in time, they can stop losses in time. As early as 1930, most Western companies had already begun research on financial risk early warning systems. In today's information age, financial analysis methods continue to mature [2].

Scholars have also conducted a lot of research on financial risk prediction systems. In used to collect data through the company's ten-year annual financial report and researched and applied the z-model to study financial performance [3]. With the development of neural network models, various fields have begun to study using neural network models. Wu and Wu established a financial forecasting and early warning model using neural network [4]. Li and Quan showed that the judgment and analysis of

manufacturing financial risks can help promote the healthy development of the real economy. They used improved particle swarm optimization to establish a financial risk early warning model using neural networks [5]. Song and Wu used genetic algorithm, neural network, and principal component analysis methods to collect and process data in order to improve the ability of trade finance companies to deal with the risk of excessive financialization. The risk assessment model of excessive financialization of financial enterprises was constructed in [6]. Malakauskas and Laktutien used logistic regression, artificial neural networks, and random forest techniques to estimate a binomial classifier for financial distress prediction. They used the random forest algorithm with additional factors to achieve the highest prediction accuracy [7]. Matin et al. established a model using convolutional recurrent neural network (RNN) combined with unstructured text data, which provided a statistically significant improvement in the performance of financial distress prediction [8].

Financial issues are the key concern of every listed company. The establishment of a financial risk prediction system can effectively avoid the company's financial crisis and promote the company's sustainable development [9]. If the financial risks that the company will face in the future can be predicted, the company can greatly avoid losses and protect the company's interests. Because of the importance of financial risk control, companies and investors are extremely concerned. It is relatively simple to analyse one's own financial risks from the company's perspective [10]. From the perspective of investors, we extract structured and unstructured information from the annual reports of listed companies, establish financial risk prediction models using neural networks, and compare different models to conduct experiments. The proposed method greatly improves the forecasting effect and provides a reference for investors to discover the financial risks of listed companies in time and avoid losses. For the organization of the paper, we have arranged the paper such that Section 2 constructs the prediction model by using the neural network. In Section 3, the financial data and tests are used to analyse the experimental outcomes. In the end, the paper is concluded in Section 4 which presents the conclusion of the study.

2. Construction of Prediction Model Using Neural Network

2.1. Recurrent Neural Network (RNN). Using the RNN algorithm, a variant algorithm of the RNN is proposed, and research experiments on intrusion detection and knowledge extraction are carried out. When the traditional neural network processes some sequence data, especially when the sequence data have upper and lower connections, it is prone to problems, so the cyclic neural network came into being. The advantage of RNN is that it has a memory mechanism, which can fully analyse the relationship between these data when dealing with these serial data-related problems with upper and lower connections, so that the whole is more optimized [11]. Figure 1 shows the structure of RNN.

x represents the input at the current time h; ? represents the instant hidden node state; ? represents the output (RNN processing), as shown in equations (1) and (2):

$$s_t = f\left(U_{x_h} + W_{s_{h-1}} + b\right) \tag{1}$$

$$o_t = \text{softmax}\left(V_{s_h} + c\right) \tag{2}$$

Sigmoid is an activation function; *U, W* represent the weight matrix between layers; *b, c* represent the bias value. The advantage of RNN is that model parameters are shared at different moments and can handle long-term dependence problems; the disadvantage is that model parameter updates are unstable, there are gradients that explode or disappear, and there is only short-term memory.

2.2. Long Short-Term Memory (LSTM). Long short-term memory (LSTM) is an improvement of the RNN model. In terms of structure, a "door" structure has been added. In this way, the problems caused by the long distance can be solved, even if the data sequence length is different [12]. There are four neurons in the LSTM model: the cell state, output gate, input gate, and forget gate. The working method of the forget gate is as follows: the sigmoid function assigns the weighted calculated value of the input p_t at the current time t and the output n_{t-1} at the time t-1 and uses the above to control the influence of the previous output sequence information on the input stream, as shown in the following equation:

$$g_t = \sigma\left(W_f \bullet [n_{t-1}, p_t]\right) + b_{g.} \tag{3}$$

The sigmoid function is used to weight the input p_t and the output n_{t-1} at the time t_-1 to obtain the value s, as shown in equation (4). The new unit state candidate value $\widetilde{A}_t$ is generated by the non-linear tanh function, as shown in equation (5). The new state A_t of the unit only needs to add the two and then pass through the forget gate and the input gate, as shown in equation (6):

$$s_t = \sigma\left(W_i \bullet [n_{t-1}, p_t]\right) + b_s, \tag{4}$$

$$\widetilde{A}_t = \text{tann}\left(W_c \bullet [n_{t-1}, p_t]\right) + b_A, \tag{5}$$

$$A_t = g_t \bullet A_{t-1} + s_t \bullet \widetilde{A_t}. \tag{6}$$

The q_t value of the output gate needs to be weighted to calculate the input p_t and the output n_{t-1} at t_-1 using the sigmoid function, as shown in equation (7). The output of the LSTM unit is calculated and controlled by the non-linear tanh function, and finally the output value n_t is obtained, as shown in equation (8). The advantage of LSTM is that it can solve the data problem due to the long distance.

$$q_t = \sigma\left(W_q \bullet [n_{t-1}, p_t]\right) + b_q, \tag{7}$$

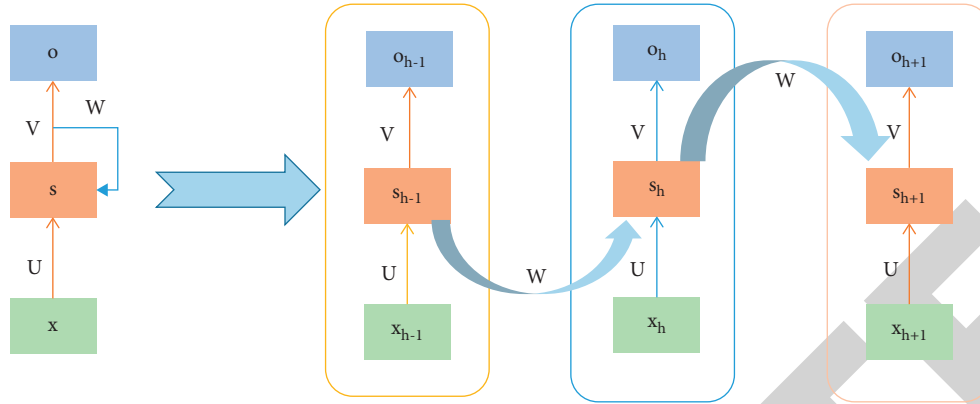$$n_t = q_t \bullet \text{tann}\left(A_t\right) \tag{8}$$

FigURE 1: Structure diagram of RNN.

CNN is a feed-forward neural network, which has excellent performance for large-scale image processing [13]. Figure 2 shows the CNN model structure. The picture is first convolved by the convolutional layer, and then the pooling operation is performed. Repeat convolution and pooling and input the obtained feature information into the fully connected layer. Finally, it enters the output layer, and the size of the output layer is determined by the task of the CNN.

2.3. Attention Mechanism.

The attention mechanism simulates the attention model of the human brain, which is essentially a resource allocation model. The working principle of the attention mechanism is to allocate the attention resources rationally. More resources should be allocated to the key parts and fewer resources should be given to the rest, reducing or eliminating the adverse effects caused by too many key parts [14]. Commonly used scoring methods: the soft attention scoring function in the hard attention scoring functions are used. Three kinds of weight value calculations are experimented [15]. The first is to input all attention models to score and sum, as shown in the following equation:

$$\alpha_t = \frac{\exp\left(\mathrm{score}\left(h_t\right)\right)}{\sum_{i=1}^{T} \exp\left(\mathrm{score}\left(h_t\right)\right)} \quad (9)$$

where α_t indicates the weight value of the t-th input, h_t indicates the t-th input, and $score$ () indicates the score of the input. The second is to calculate and input h_t first. The calculated y_t is input into the model, as shown in the following equation:

$$y_t = \tan \mathrm{h}\left(W h_t\right) \quad (10)$$

$$\alpha_t = \frac{\exp\left(\mathrm{score}\left(y_t\right)\right)}{\sum_{i=1}^{T} \exp\left(\mathrm{score}\left(y_t\right)\right)} \quad (11)$$

where y_t is calculated from h_t, W is the output obtained by inputting h_t into a single-layer neural network, and α_t is the input weight value. The first two methods are employed after being figured out and multiplied by, as shown in the following equation:

$$S_t = \sum_{i=0}^{n} \alpha_t h_t \quad (12)$$

where S_t is the output of the h_t-th input model. The third method is obtained by adding the output of the input model of the second method, and its expression is shown in the following equation:

$$S_t = \sum_{i=0}^{n} \left(\alpha_t h_t + h_t\right) \quad (13)$$

2.4. Experimental Model Performance Indicators.

The performance evaluation indicators for the two-class problem are model prediction accuracy, sensitivity, specificity, precision, and $F1$ [16]. Accuracy: m is the sample size, D is the training set, X_i is the sample, and Y_i is the mark. The prediction accuracy of model f is shown in the following equation:

$$\mathrm{acc}\left(f: D\right) = \frac{1}{m} \sum_{i=1}^{m} I\left(f\left(x_i\right) = y_i\right). \quad (14)$$

Piecewise function: I, $I\left(1\right) = 1$, $I\left(0\right) = 0$, which indicates the proportion of correctly classified samples to the total number of samples. For a binary classification task, Figure 3 shows a framework diagram of the confusion matrix.

TP refers to true example, FP refers to false positive example, TN refers to true negative example, and FN refers to false negative example; $F1$-score represents the harmonic average of precision and recall [17]. It is one of the main indexes for model evaluation with specificity.

Recall rate:

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \quad (15)$$

Specificity:

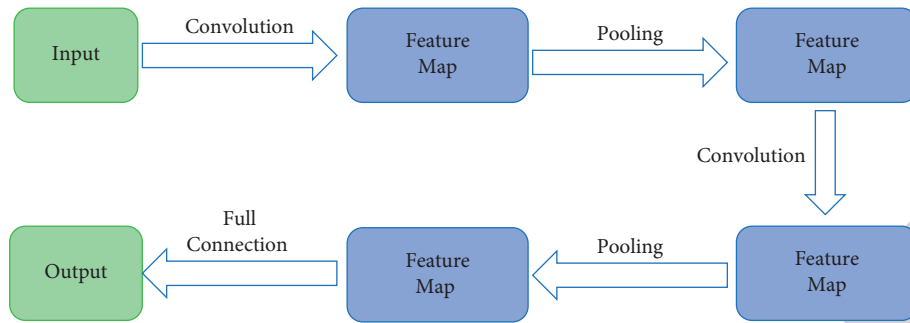$$K = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \quad (16)$$
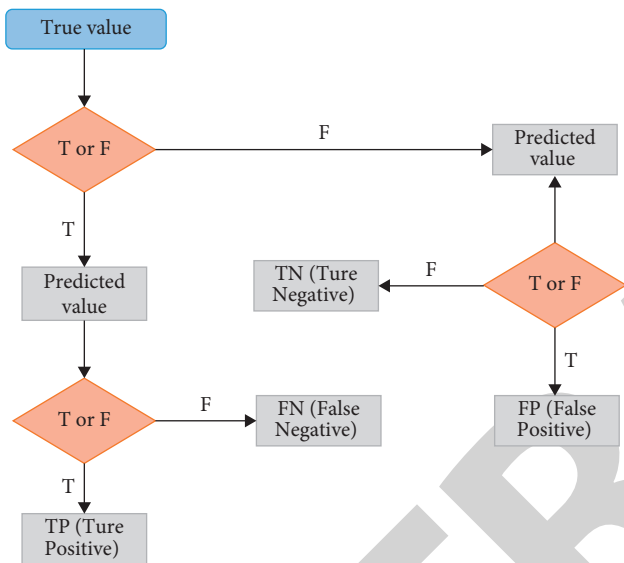
Figure 2: Schematic diagram of the CNN model.

Figure 3: Framework diagram of confusion matrix.

Precision rate:

$$P = \frac{TP}{TP + FP}. \tag{17}$$

$F1$-score:

$$F1 = \frac{2PR}{P + R}. \tag{18}$$

2.5. Financial Risk Forecast Modelling Using Financial Data. The basic financial status of a company can be understood by analysing financial indicators [18]. In recent years, experts in the financial field generally use computer methods to analyse financial data, establish simple models, and analyse the extracted financial indicators. The CNN model is used to carry out financial risk prediction modelling using financial data, and the listed companies are used as the forecast target to predict the financial risks that exist in these companies. Listed companies are divided into ST companies and non-ST companies.

Index Acquisition. From the JoinQuant database (JQData), the cash flow statement, income statement, and balance sheet of each listed company from 2005 to 2021 are obtained.

Meanwhile, 36 financial indicators that are not in the three tables are obtained. Among them, the three basic tables are called financial indicators, and the other 36 are collectively called non-financial indicators.

Data Cleaning. It is the process of re-examining and verifying data with the purpose of removing duplicate information, correcting existing errors, and providing data consistency.

Selecting Data That Meet the Indicators. The missing value of a financial index that reaches more than 30% is cleared. Compensation for missing data: when collecting data by hand, the financial indicators issued by various companies are different, resulting in serious data missing in most companies' financial indicators. According to the distribution of financial index values, replanting is carried out. The specific calculation is shown in the following equation:

$$M = A + R \times A, R \in \{-0.3, 0.3\} \tag{19}$$

where M is a missing value; A is the mean value; and R is a random number. Filtering data: when processing data, set the sample lack threshold, and the threshold is set to 50%; when the missing value exceeds, delete the sample, delete the severely missing data, and ensure the availability of the data [19].

In the end, there are 17,107 data that can be used in the financial measurement standard indicators of each company. In order to ensure the integrity of the financial measurement standard indicators during the experiment, the existing data must be compared with the experiment first. Select all existing companies' public financial measurement standards for experimentation, and there are no missing values for 47 public financial measurement standards of all companies. It is also necessary to continue the experiment to compare and analyse whether the data supplement has an impact on the experimental results. The financial measurement indexes are sorted into two collections, and there are 146 indexes in collection 1 and 47 in collection 2. Using the same model, Figure 4 shows the statistical results of the indicators.

2.6. Construction of Forecasting Model Using Financial Data. Financial risk prediction is a two-class problem. The CNN model performs well on the classification problem [20], so
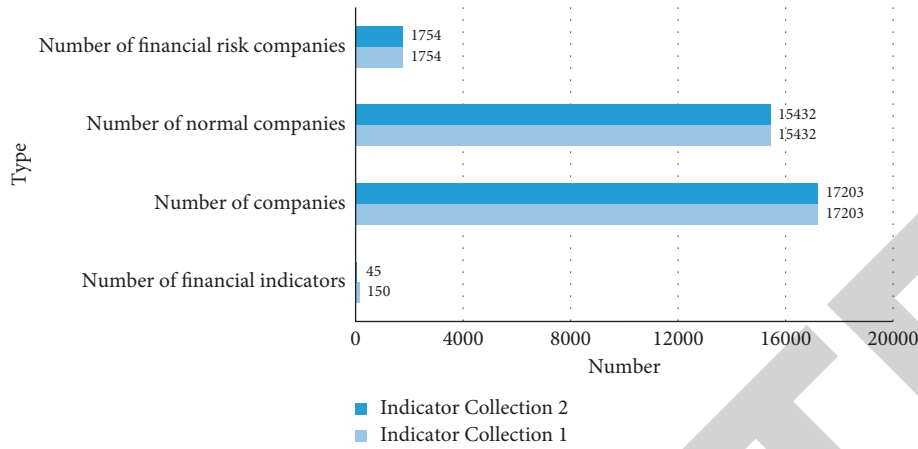
FIGURE 4: Indicator statistics chart (indicator collection 1 has a complementary value, and indicator collection 2 has no complementary value).

the CNN model is selected to build the model. Figure 5 shows a flowchart of index processing.

After obtaining the financial metrics, the data are cleaned. Financial metrics are converted. After the characteristic representation is converted, a financial vector is established with each financial measurement standard indicator corresponding to each example, and the financial measurement standard indicators are unified and normalized for all the examples, as shown in the following equation:

$$x' = \frac{x - \min(x)}{\max(x) - \max(x)}, \tag{20}$$

where $\max(x)$ indicates the maximum value of financial measurement standard indicators in all examples; $\min(x)$ indicates the minimum value of financial measurement standard indicators in all examples; x' represents the normalized financial measurement standard indicator value of the example; and x indicates the value of the financial measurement standard before the example is normalized. Meanwhile, due to the good classification effect of the CNN model, the CNN model is used to classify the financial measurement standard indicators.

2.7. Financial Text Processing. First, text data are cleaned, including 2791 samples from 379 ST and 18917 from 2781 non-ST enterprises. Then, two methods are used during the experiment, and some measures are used to balance the dataset distribution. Two ways: set the weight of the loss function category. The weight of ST samples is set to be higher than that of non-ST samples. Some non-ST samples have been deleted, making the ratio of the two samples closer to reasonable. Measures: delete interjections, punctuation marks, tabs, dates, amounts, etc.

After the financial text is obtained, the presentation of the financial text needs to be considered. The financial text needs to be converted into a vector. Then, classify and sort the vectors. It can be divided into word vectors and document vectors. Word vector refers to a vector in which words or phrases from the vocabulary are mapped to real numbers. Text vector is a whole paragraph of text. Word
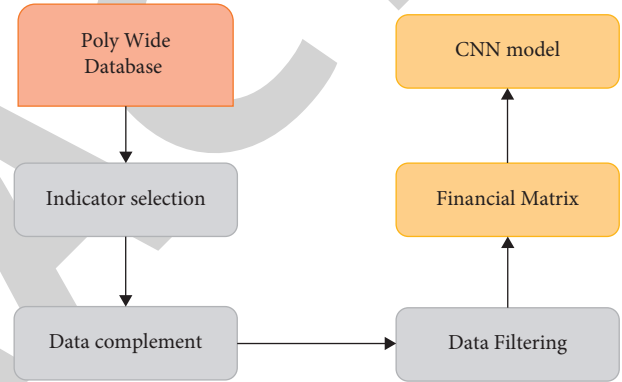

FIGURE 5: Flowchart of indicator processing.

vectors are all words, so word vectors can form document vectors. In general, the training of the word vector is carried out first, and then the word vector is expressed as a text vector by means of summation [21].

The word2vec model using skip-gram is used for text representation. The advantage of the skip-gram model is that it can predict the relationship between a word and surrounding words.

$$\max \frac{1}{n} \sum_{t=1}^{n} \sum_{j=-c, j \neq 0}^{b} \log p(w_{t+j}|w_t) \tag{21}$$

where b represents the number of words around the word that needs to be considered now. Here, b takes 5. Log p is calculated using negative sampling, and the subsampling of words is proportional to their inverse frequency. In word2vec, the relationship between words also has an impact. For example, when the semantics are similar, these words all have a high cosine similarity, and vector calculations can also be performed on the words.

2.8. Construction of Forecast Model Using Financial Text. The financial risk prediction model using financial texts uses LSTM as the main body and cooperates with the attention mechanism. Figure 6 shows a basic process diagram.
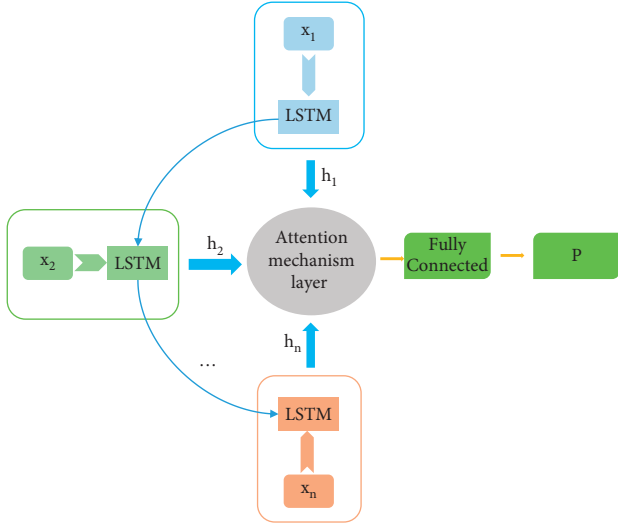
FIGURE 6: Flowchart using financial text processing.

T_t characterizes the word at the t-th position in the document, T_{wt} embodies the word vector converted from the word at the t-th position, and h_t represents the output of the unit LSTM at the t-th position. The calculation equation selected in the experiment is as follows:

$$y_t = \tan h\left(Wh_t\right) \tag{22}$$

$$\alpha_t = \frac{\exp\left(\text{score}\left(y_t\right)\right)}{\sum_{i=1}^{T} \exp\left(\text{score}\left(y_t\right)\right)} \tag{23}$$

$$S_t = \sum_{i=0}^{n} \alpha_t h_t. \tag{24}$$

Score function represents a single-hidden-layer neuron calculation. W stands for the weight of the input h_t. The attention weight α_t of the output h_t of each LSTM unit is obtained by normalizing the scalar by the softmax function. T indicates the step length between step 1 and step t. S_t signifies the final output of the experiment. The experiment uses the attention model mechanism. The attention model can effectively focus the attention on the text and describe not much, but the more important parts of the text can be better described.

2.9. Construction of Forecasting Model Combining Financial Text and Financial Data.

Figure 7 shows a framework diagram of the financial data and financial text forecasting model. There are two parts of model input: financial data and financial text. The processing of financial data and financial text in the model is to combine the two, but instead of inputting individual financial data and financial text into the model separately, they are input at the same time.

The right side of Figure 7 shows the processing methods of the two financial measurement standard indicators. The first method: firstly, the financial data $C1$ are processed by the feature engineering into a financial vector $C2$. Then, input a single-layer neural network for processing to obtain a word
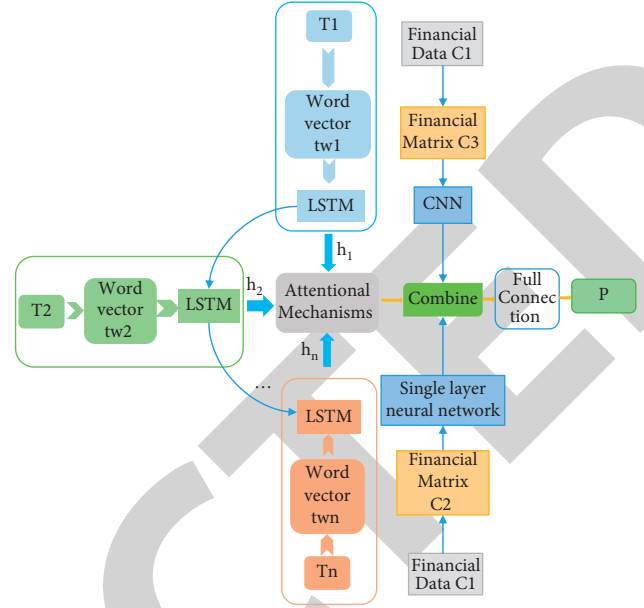

FIGURE 7: Schematic diagram of financial data combined with financial text model.

vector with the same dimension as the output of the attention model. Finally, it is combined with unstructured information to enter the fully connected layer. The second method: firstly, perform characteristic engineering processing on the financial data $C1$ to obtain a financial matrix $C3$. Then, input the CNN model to summarize and extract the key information. Finally, combine the processed information of the financial text and enter the fully connected layer.

3. Analysis of Experimental Results Using Financial Data and Financial Text

3.1. Experimental Results and Analysis of CNN Model Using Financial Data.

The range of CNN model parameters is as follows: convolution kernel (size) $D \in \{3, 4, 5, 6, 7, 8, 9\}$, convolution kernel (number) $H \in \{64, 100, 128, 256, 300, 500, 1000\}$, pooling layer (size) $C \in \{3, 4, 5\}$, CNN (number of layers) $K \in \{2, 3, 4, 5, 6\}$, and fully connected layers (number of neurons) $n \in \{64, 128, 256, 300, 512, 1024\}$. After many experiments, the final parameters are determined: the sizes of the convolution kernel are $4*4$, $5*5$, and $6*6$, respectively, the size of the pooling layer is $4*4$, the number of convolution kernels is 300, and the number of the layers is 4. The numbers of neurons in the fully connected layer are 128 and 64, respectively, and its weight of loss function is 0.6 and 0.4, respectively. Figure 8 shows the experimental results.

The experimental results in Figure 8 show that the accuracy and recall rate of the CNN model are high, but the specificity and $F1$ value are low. In the predictive model, K and $F1$ are more important, so they need to be improved. The CNN model is more likely to overfit the categories with more data when the data are unbalanced, but there is no more in-depth information on the financial indicators. The CNN model's ability to extract information is limited, so in deeper information extraction, it does not bring more benefits.
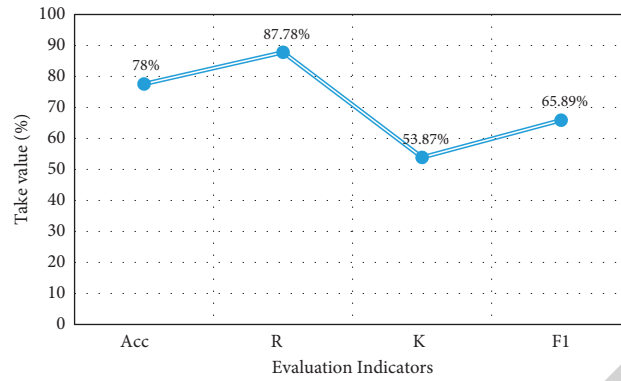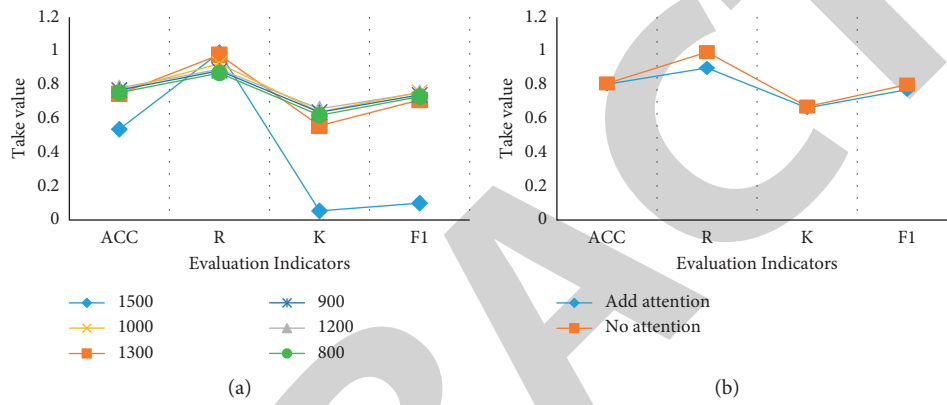
Figure 8: CNN model experimental results.

(a)

(b)

Figure 9: Some parameters after the experiments ((a) 100-word vector dimensions without the attention mechanism; (b) 200-word vector dimensions with the word length of 1200).

3.2. Analysis of Model Experiment Results Using Financial Text.

Figure 9 shows the experimental results of selected experimental parameters.

Figure 9 shows that the attention model has a greater effect on improving the $F1$ value. Different word vector dimensions and word lengths have an impact on the results of the experiment. When the word length is 1300 and 1500, the R value increases, but the K value decreases with a larger amplitude, so the word length 1200 is selected for the attention model experiment. First, make sure the word length is 1200. Then, change the word vector dimension from 100 to 200, and the R value and the K value are slightly improved, indicating that the improvement of the word vector dimension is helpful. Figure 10 shows a comparison diagram of the experimental results of dimensional changes and attention mechanism changes.

The dotted line in Figure 10(a) indicates that the used word vector has a dimension of 200, and the solid line indicates that the used word vector has a dimension of 100. When the word length is 1200 and the word vector dimension is 200, the experimental results of the attention model and the non-attention model are added in Figure 10(b). When the word length is 1200 and the word vector dimension is 200, after adding the attention model, the accuracy rate, R, K, and $F1$ are all improved, indicating that the attention model is very helpful for improving the

index. Using the above experiments, select the parameters that can produce the best results for the experiment. Figure 11 shows the experimental results of the model.

In Figure 11, the risk prediction model using financial data is not as effective as the model using financial text. There are two reasons for the conclusion: there is interference between individual financial data, and the proportion of non-ST text is too large. Although the overall effect of the financial text-based model is good, K is only 66.71%, and the $F1$ value is not high. Continue to conduct model experiments using the combination of financial data and text.

3.3. Model Experiment Results Combining Financial Text and Financial Data.

Figure 12 shows the optimal results of the two methods.

Figure 12 shows that adding financial text to the forecasting system, combined with the financial matrix, greatly improves the performance of the CNN model. In terms of accuracy, R, K, and $F1$ values, CNN model experimental results are higher than those of single-hidden-layer experimental results. There are two reasons for the conclusion: the CNN model is more suitable for the combination of financial matrix and text, and the combination of financial vector and financial text will cause noise interference to part of the data of the vector. The CNN model has better information
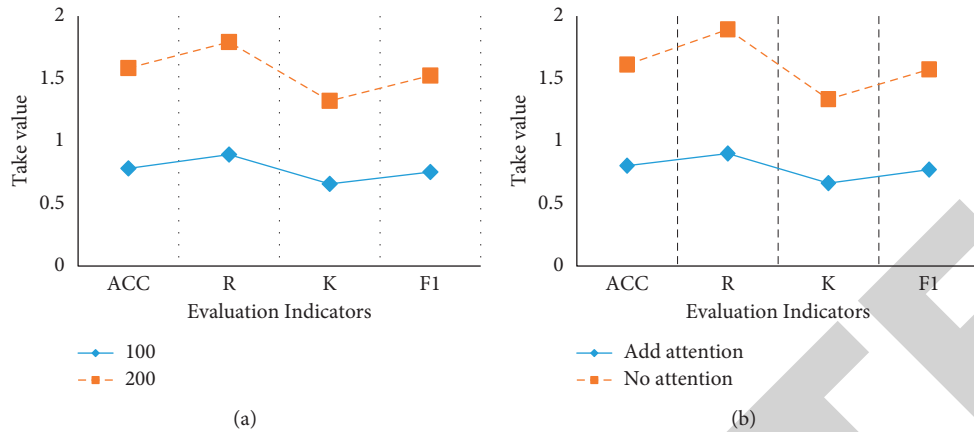
FIGURE 10: Comparison results ((a) comparison results between 100 and 200 dimensions; (b) comparison between the results with or without the attention mechanism).
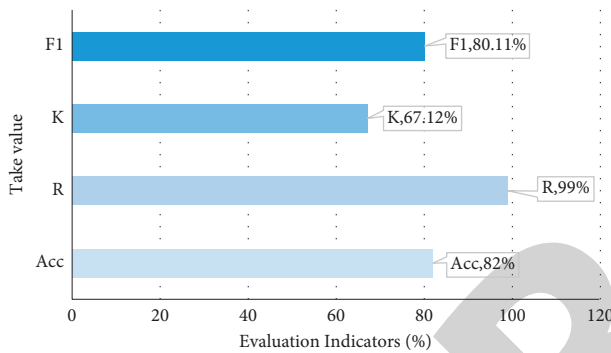

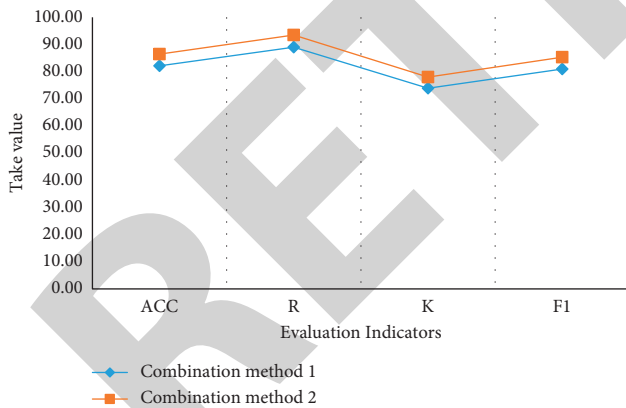FIGURE 11: Model prediction results.
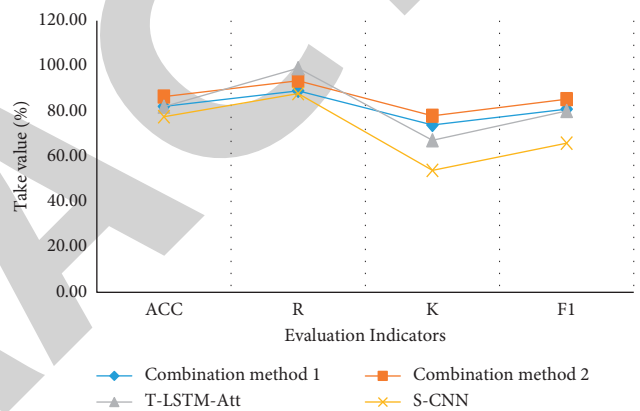

FIGURE 12: The optimal result of the experiment.

FIGURE 13: Comparison of experimental results of each model.

important information the system can select. The prediction model based on the combination of financial texts and data has better performance than the model using only financial data or financial texts.

4. Conclusion

On a mobile payment platform, the use of automatic summarization technology on an LSTM network established a financial risk prediction system. In this paper, three methods were used: (i) CNN using financial data to establish a system; (ii) LSTM + attention model, which uses financial documents to establish a system; (iii) a combination of two methods, combining financial data with financial documents. The last method uses CNN + LSTM and a single-hidden-layer neural network + LSTM to establish a system. The system that combines financial documents and financial data has a different improvement over the forecasting system that only uses unstructured text and structured text. Compared with financial data to establish a model, the addition of financial documents increased $F1$ by an average of 14%, which greatly improved the accuracy of the financial risk prediction system. However, only part of the information in the financial report is extracted here, and not all

extraction effect. Figure 13 shows the final comparison chart of the experimental results of all models.

Figure 13 shows that the performance of the financial matrix combined with the financial text using the CNN model is much higher than that of the financial matrix using the CNN model. Although R is not as good as a model using financial text using LSTM and attention mechanism, it is better in terms of accuracy, K, and $F1$. The results show that the more times the financial text data are trained by the CNN model, the better the performance of the system is, and more

the information can be mined out. Meanwhile, only one annual report is considered. If the model can combine more chapters of the annual report with the historical annual report, its performance can be better improved.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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