

Retraction

Retracted: Research on Intelligent Prediction Method of Financial Crisis of Listed Enterprises Based on Random Forest Algorithm

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1].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

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

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

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

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

References

- [1] M. Jiang and X. Wang, "Research on Intelligent Prediction Method of Financial Crisis of Listed Enterprises Based on Random Forest Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 3807480, 7 pages, 2021.

Research Article

Research on Intelligent Prediction Method of Financial Crisis of Listed Enterprises Based on Random Forest Algorithm

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Traditional financial crisis prediction approaches have a tough time extracting the properties of financial data, resulting in financial crisis prediction with insufficient accuracy. As a result, based on the random forest algorithm, an intelligent financial crisis prediction approach for listed enterprises is proposed. The random forest method is used to mine the characteristics of financial data based on financial index data from publicly traded companies. This research develops a financial crisis prediction index system based on the findings of data feature mining. The CCR model is used to assess the efficiency of listed firms' decision-making units with more input and output, and the efficiency index of each decision-making unit is calculated. The efficiency evaluation index of publicly traded companies is used to divide the severity of the financial crisis. The experimental results reveal that, when compared to standard prediction methods, this method's forecast accuracy is commensurate with the actual state of businesses, and it can reduce the time it takes to predict financial crises.

1. Introduction

The domestic economic environment is fast expanding as China's economic development enters the new normal and the government encourages "mass innovation and entrepreneurship" [1]. Government regulators, professional financial institutions, enterprise decision makers, and investors must be able to grasp the most recent enterprise data information in a timely manner, expect to predict the enterprise's future development direction from current financial data, and plan ahead of time. This necessitates the creation of a financial crisis forecasting system that can be dynamically examined using previous data [2].

The likelihood of a financial crisis for publicly traded companies is gradually increasing as market competition becomes more intense. One of the most pressing concerns among the listed company operators, investors, creditors, and other stakeholders is whether they can properly foresee the financial crisis. Financial crisis forecasting has a long history of more than 80 years, including two stages: statistical analysis and data mining. Support vector machines

and artificial neural networks based on artificial intelligence have been widely applied in the field of financial crisis prediction in recent years, which has improved prediction efficiency significantly. These methods, however, are challenging to generate satisfying results due to the imbalance of financial forecasting difficulties and the complexity of data noise and distribution [3–5]. Financial crisis prediction entails an analysis of an enterprise's situation based on financial statements, business plans, and other relevant accounting materials provided by the enterprise, as well as the use of accounting, statistics, finance, enterprise management, factor analysis, comparative analysis, and other analysis methods to timely address problems identified in the enterprise. Furthermore, financial crisis prediction refers to the development of relevant models using financial indicators that can comprehensively and accurately depict the financial position of businesses and then using the model to anticipate the likelihood of a financial crisis [6]. Prediction and evaluation in this manner can give timely decision-making basis for business managers, have a positive impact on business development, and reduce business risks. A

financial crisis prediction approach based on particle swarm optimization algorithm and nuclear limit learning machine is proposed in reference [7]. Particle swarm optimization algorithm is used to optimize the parameters of nuclear limit learning machine and choose features at the same time, taking into account the interaction between parameter optimization and feature selection in the classification prediction process. As a result, the ideal kernel limit learning machine model is found, as well as a representative feature subset. Finally, the new dataset is trained and predicted using the proposed optimal kernel limit learning machine model. A financial crisis prediction system based on the Benford logistic model is proposed in reference [8]. Effective factors describing the quality of financial data are introduced to the logistic model of financial risk prediction by using Benford law. Benford law is used to assess the quality of financial data, create the Benford factor, and combine it with financial factors to create a Benford logistic model for predicting financial risk. Reference [9] proposes a financial crisis prediction method based on rs-lssvm, builds an index system of influencing factors of financial crises of publicly traded companies combined with financial crisis theory, and builds a financial crisis prediction model of publicly traded companies based on rough set theory and least squares support vector machine method. In order to increase the operational stability of listed organizations, it is vital to accurately foresee financial crises, allowing businesses to assess their own financial status and devise financial crisis avoidance or resolution methods as quickly as feasible. As a result, based on the random forest algorithm, this research provides a financial crisis prediction approach for the listed enterprises.

2. Intelligent Prediction of Financial Crisis of Listed Enterprises Based on Random Forest Algorithm

Financial prediction of publicly traded companies is the process of predicting whether or not a publicly traded firm will experience a financial crisis based on financial and nonfinancial variables. It is essentially a classification issue. The goal of this study is to create an intelligent financial crisis prediction model using financial index data from publicly traded companies and the random forest algorithm in order to generate an accurate prediction of the financial state of target publicly traded companies.

2.1. Financial Data Extraction of Listed Enterprises Based on Random Forest Algorithm. Because random forest has excellent generalization and noise robustness, as well as the particular features of abnormal sample diagnosis and variable importance calculation, this study will use it to anticipate and simulate the financial crises of publicly traded companies. Figure 1 depicts the random forest structure. It is a multiclassifier. The bagging method is used to assemble a set of CART decision trees (base classifier). Finally, each tree's classification results are compiled, and the final classification results are established through "voting."

The random forest approach is used to produce a similarity matrix by measuring the similarity of financial data samples from publicly traded companies. Clustering, abnormal sample identification, missing value filling, and data presentation are all possible using the matrix. The similarity matrix might be considered one of the most useful random forest tools [10–13]. For the financial dataset of listed enterprises with N samples, first generate an $N \times N$ zero matrix, which is recorded as $P = \{p_{ij}\} (i, j = 1, 2, \dots, N)$. After the growth of a tree in the model is completed, the dataset is brought into the tree for classification and prediction. If sample i and sample j are at the same leaf node, their similarity increases by 1, that is, p_{ij} and p_{ji} increase by 1 at the same time. Repeat the above process until all m trees in the model grow well, and the corresponding matrix is obtained. Finally, divide p_{ij} by the number of trees m in the model to obtain the final correlation matrix. It can be seen that the similarity matrix is a symmetric matrix with a main diagonal of 1, and the upper bound of each element is 1, which is similar to the correlation sparse matrix.

The similarity matrix, often known as distance, calculates the degree of similarity between samples. The financial data of publicly traded companies can be projected into low-dimensional space using this matrix, allowing for a better understanding of sample distribution. Random forest's data presentation is built on the concept of "multidimensional scaling." Let the similarity matrix $\{\text{prox}(n, k)\}$ be formed from the similarity between sample n and sample k so that $\text{prox}(-, k)$ is the matrix on the first coordinate $\text{prox}(n, k)$, $\text{prox}(n, -)$ is the matrix on the second coordinate $\text{prox}(n, k)$, and $\text{prox}(-, -)$ is the matrix on two coordinates $\text{prox}(n, k)$. Then, there is a matrix:

$$cv(n, k) = 0.5 \times (\text{prox}(n, k) - \text{prox}(n, -) - \text{prox}(-, k) + \text{prox}(-, -)). \quad (1)$$

The matrix shown in formula (1) is the inner product matrix of distance and is also a positive definite symmetric matrix. Let the eigenvalue of matrix cv be $\lambda(j)$ and the eigenvector be $v_j(n)$. Then, there is a vector:

$$x(n) = \left(\sqrt{\lambda(1)}, v_1(n), \sqrt{\lambda(2)}, v_2(n), \dots \right). \quad (2)$$

The square of the distance between two samples can be obtained, and its value is the same as $1 - \text{prox}(n, k)$. The value of $\sqrt{\lambda(j)}, v_j(n)$ in formula (2) is the value of vector $x(n)$ on the j -th scaling coordinate.

In the process of matrix scaling, the goal is to estimate vector $x(n)$ through the first few scaling coordinates. In order to achieve this goal, the random forest extracts several maximum eigenvalues and corresponding eigenvectors from matrix cv [14].

In general, the ideal way to present financial data from publicly traded companies is to project it onto a binary plane formed of the first two scaling coordinates.

The sample points of the principal data subject are commonly referred to as remote samples. They are classified

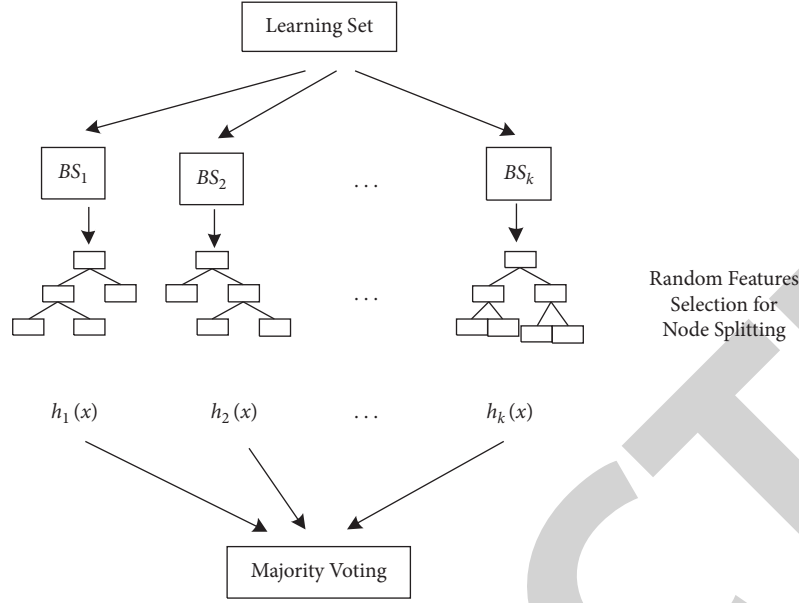


FIGURE 1: Random forest structure.

by the random forest as samples having little resemblance to all other samples in the financial data of publicly traded companies. For example, the similarity between the abnormal samples of financial category j of listed enterprises and other samples in this category is small. The measurement process of abnormal samples is as follows:

The average similarity between sample n in category j and other samples in this category is defined as

$$\bar{P}(n) = \sum_{d(k)=j} \text{prox}^2(n, k). \quad (3)$$

Then, the original abnormal sample measurement of sample n is

$$\text{rawoutlier} = \frac{n\text{sample}}{\bar{P}(n)}. \quad (4)$$

In the formula, $n\text{sample}$ represents the number of samples of financial data category j of the listed enterprises. It can be seen from the above formula that the smaller the average similarity $\bar{P}(n)$, the larger the measurement value rawoutlier of the original abnormal sample. Calculate the rawoutlier of all sample points in the financial data category j of the listed enterprises, and calculate the mean μ and variance σ between them, through the formula:

$$\text{outlierm} = \frac{(\text{rawoutlier} - \mu)}{\sigma}. \quad (5)$$

The final abnormal sample measurement value, referred to as abnormal degree [15], can be obtained by standardizing the initial abnormal sample measurement of financial data of listed firms. The numerical disparities generated by financial sample data of multiple categories of listed firms can be minimized through standardization, making it easier to compare aberrant sample measurements of different categories. Construction of financial data feature classification

mining function of the listed enterprises based on random forest algorithm:

$$H_R(x) = \arg \max_j \sum_{m=1}^M (I(H(x; \theta_m) = j)). \quad (6)$$

Through the above calculation, the feature extraction of financial data of listed enterprises can be completed.

2.2. Intelligent Prediction of Financial Crisis of Listed Enterprises. This article creates financial crisis prediction indicators based on the above extracted financial data feature extraction results of listed firms to complete the financial crisis prediction.

The reliability of prediction results is directly tied to the indicators used to predict financial crises. It can accurately portray the financial state of publicly traded companies and distinguishes between crisis and noncrisis companies. The following are the criteria for selecting financial crisis prediction indicators for publicly traded companies: (1) the comparability principle. There are two types of financial indicators: absolute indicators and ratio indicators. Absolute number indications are frequently fairly varied among businesses of various sizes, and they are not comparable when it comes to assessing financial health. Because the ratio index is unaffected by the size of the company, it can more objectively depict the financial status of publicly traded companies. For example, overall profits may range significantly among businesses of various sizes, perhaps by an order of magnitude, but earnings are nearly identical. As a result, the absolute number index is not taken into account in this study.

(2) In order to avoid omitting indicators that make significant contributions to the prediction model, preliminary screening of indicators should be done using a variety

of indicators that can reflect the financial status of listed firms. (3) The importance principle. The more the indicators, the worse it is. Selecting several representative indicators from each sort of indicator indicating the financial situation is adequate. Too many indicators will cause noise and impair the prediction model's performance. (4) The principle of availability. Nonfinancial variables such as the macro-economy, industry prospects, and enterprise leadership quality may be related to the financial problems of listed enterprises, although these indicators are typically difficult to gather and quantify. As a result, the selection scope for this article is financial indicators released by publicly traded companies.

According to the above prediction index selection principles, the selected prediction indexes are shown in Table 1.

The CCR model is used to assess the efficiency of listed firms' decision-making units with more input and output, and the efficiency index of each decision-making unit is calculated. The efficiency evaluation index of publicly traded companies is used to divide the severity of the financial crisis.

Assuming that the data include the system structure, there are n decision-making units, and each decision-making unit has m input variables (recorded as x) and s output variables (recorded as y). Each input/output variable has a weight coefficient. The weight coefficient is a measure of the corresponding input/output variable, which is recorded as f and g , respectively. The value of ownership coefficient is not less than 0. Among them, the decision-making unit corresponds to the financial data of a listed enterprise in a certain year, the input variable x and the output variable y correspond to the input/output items, respectively, and the weight coefficients f and g are set by the system rather than by the user.

Let h be the efficiency evaluation index of each decision-making unit, then the calculation formula of h is

$$h_j = \frac{f^T y_j}{g^T x_j} = \frac{\sum_{r=1}^s f_r y_{rj}}{\sum_{i=1}^m g_i x_{ij}}, \quad j = 1, 2, \dots, n. \quad (7)$$

The sum of the product of each decision-making unit's output item value and its corresponding weight coefficient divided by the sum of the product of each decision-making unit's input item value and its corresponding weight coefficient is the efficiency index of each decision-making unit. The system can always obtain many combined weight coefficients because the weight coefficient is not selected subjectively.

$$h_j \leq 1, \quad j = 1, \dots, n. \quad (8)$$

It is necessary to consider as much as possible the maximum h value of each decision-making unit when taking different weight coefficients. Taking the efficiency index of j_0 decision-making units as the target and the efficiency index of all decision-making units as the constraint, the generated data include the CCR model as follows:

$$\begin{cases} \max h_{j_0} = \frac{\sum_{r=1}^s f_r y_{rj_0}}{\sum_{i=1}^m g_i x_{ij_0}}, \\ \text{s.t. } \frac{\sum_{r=1}^s f_r y_{rj_0}}{\sum_{i=1}^m g_i x_{ij_0}} \leq 1, \quad j = 1, 2, \dots, n, \\ f \geq 0, g \geq 0. \end{cases} \quad (9)$$

It is generally believed that when the maximum efficiency index of the decision-making unit is equal to 1, the decision-making unit is DEA efficient or weakly efficient. When it is less than 1, the decision-making unit does not reach DEA efficiency.

The degree of financial crisis will be split into four categories based on the efficiency index of each firm in each year: "safe," "safer," "generic," and "crisis." In general, the impact is optimal when the principle of equal depth is applied. Obviously, a high efficiency index indicates that the company has traded a lesser investment for a higher financial return this year, and the financial condition is stable, implying that the degree of financial crisis is low. The severity of the financial crisis will steadily worsen as the efficiency index falls. After obtaining the financial crisis degree of all samples, the financial crisis degree of year T shall be corresponding to the financial historical data of year $T - 1$, so as to achieve the purpose of financial crisis prediction. The best way is to add the financial crisis degree of the enterprise in year T as a new attribute to the records of the enterprise in year $T - 1$. The decision tree is currently being used to construct a financial crisis prediction model for publicly traded companies. It is simple to produce excessive development and overfitting of the tree when there are many prediction factors, hence it is vital to screen the prediction variables. Because association rules do not require that the sample data be continuous, have a normal distribution, or pass the correlation test, they have a wider range of applicability. At the same time, the degree of financial crisis is substantially connected with the prediction variables screened by association rules. While reducing the number of prediction variables, it can ensure a certain accuracy of the prediction model. Therefore, the financial historical data of $T - 1$ year and association rule technology can be used to screen out important prediction variables.

In association rules, X deduces the support of Y , which represents the variables containing both X and Y in all records. The formula is

$$\text{support}(X \rightarrow Y) = \text{count} \frac{(X \cup Y)}{|D|}. \quad (10)$$

The confidence of Y derived from X represents the ratio of the number of records containing X and Y to the number of records containing X , which means that when a record has X attribute, it also has the probability of Y attribute. The formula is

$$\text{confidence}(X \rightarrow Y) = \text{support}(X \rightarrow Y) = \text{support}(X). \quad (11)$$

TABLE 1: Financial crisis prediction indicators.

Indicator type	Indicator name	Calculation formula
Profitability	Return on net assets (weighted)	Net profit/weighted shareholders' equity in the current period
	Return on assets (X_2)	EBIT * 2/(total assets at the beginning + total assets at the end of the period)
	Net interest rate of assets	The total net profit/average assets
	Net profit margin on sales	Net profit/operating income
	Gross profit margin of sales	(Operating revenue-operating cost)/operating revenue
	Operating profit margin	Operating profit/total main operating income
Solvency	Volatility ratio	Current assets/current liabilities
	Quick ratio	(Current assets - inventory)/current liabilities
	Equity ratio	Total liabilities/shareholders' equity
	Cash flow liability ratio	Net operating cash flow/current liabilities
Growth ability	Growth rate of operating revenue	Current year's turnover/last year's turnover - 1
	Operating profit growth rate	Total operating profit of the current year/total operating profit of the previous year - 1
	Net profit growth rate	Net profit of this year/net profit of the same period last year - 1
	Growth rate of net assets	Assets at the end of the year/net assets at the same period last year - 1
	Growth rate of total assets	Total assets at the end of the period/total assets in the same period last year - 1
Cash flow	Cash sales ratio	Net operating cash flow/main business income
	Cash recovery rate of total assets	Net operating cash flow/average total assets
Capital structure	Asset liability ratio	Total liabilities/total assets

If the “prediction variable $A1 < x$ ” deduces that the support of “crisis” meets the minimum support and the confidence meets the minimum confidence, it shows that when the prediction variable $A1 < x$, the degree of financial crisis of the enterprise next year is more likely to be “crisis,” so the prediction variable $A1$ will become a qualified prediction variable.

Association rules can only filter out relevant prediction variables, but they cannot create a readable and verifiable prediction model. As a result, decision tree technology is utilized to create a financial crisis prediction model for publicly traded companies. By evaluating the information gain of each attribute, the decision tree will identify the priority categorization attributes. The information gain is for a variable attribute, which means that the system interpolates the information when the variable is carried and when it is not carried. Therefore, in the decision tree, the calculation of information is particularly important. Suppose there is a variable X , its possible values are

$$(X_1, X_2, \dots, X_n). \quad (12)$$

The probability of each channel is

$$(P_1, P_2, \dots, P_n). \quad (13)$$

Then, its information content is

$$H(X) = - \sum_{i=1}^n P_i \log_2 P_i. \quad (14)$$

The attribute variables with the largest information gain are always prioritized by the decision tree. The financial index data of listed firms in year $T - 1$ is the decision tree model's prediction variable. Starting from all training samples, multiple branches are formed according to different discrimination conditions. The final classification

result is the financial crisis degree of enterprises in year T . After the tree model is obtained, when the financial data of a listed enterprise in the S year is available, the classification result obtained by substituting the tree model is the prediction result of the financial crisis degree of the listed enterprise in the $S + 1$ year.

3. Experimental Verification

In the above process, the research on financial risk prediction of listed enterprises is completed from the theoretical part, and the practical application performance of the prediction method will be verified in this part.

3.1. Experimental Data. Due to the difficulty in obtaining financial data for general listed firms, this study uses the financial data of an enterprise listed in Shenzhen and Shanghai as the research object, with 7 listed enterprises with normal finances and 5 listed enterprises in financial crisis. The financial statistics of 12 publicly traded companies are from the previous five years. The financial crisis of the above 12 firms is forecasted based on financial data from the previous five years combined with the business situation of each enterprise.

3.2. Experimental Scheme. The following is the overall experimental plan: using the accuracy of financial data feature mining, financial crisis prediction accuracy, and financial crisis prediction time as experimental comparison indicators, this method is compared to the financial crisis prediction method based on particle swarm optimization algorithm and nuclear limit learning machine proposed in reference [7], as well as the financial crisis prediction method based on Benfinger algorithm proposed in reference [8].

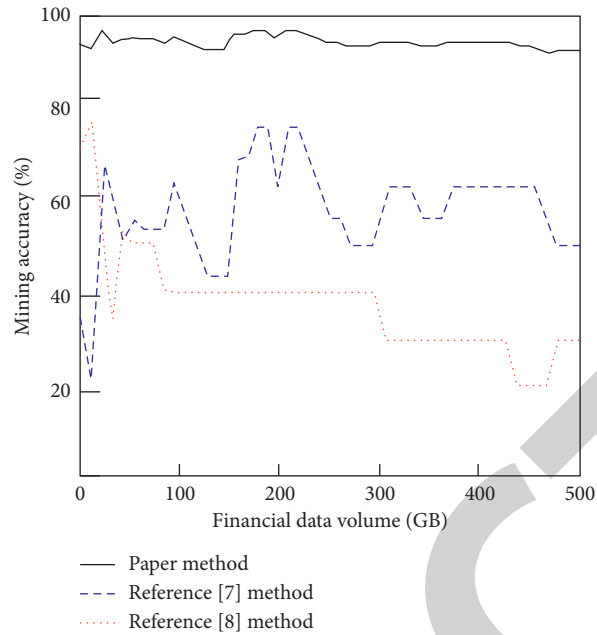


FIGURE 2: Accuracy of financial data feature mining.

TABLE 2: Comparison results of financial crisis prediction accuracy.

Enterprise number	Actual crisis degree	Degree of financial crisis		
		Paper method	Reference [7] method	Reference [8] method
1	General	General	General	Safer
2	Crisis	Crisis	General	Safer
3	Crisis	Crisis	General	Crisis
4	Crisis	Crisis	Safety	Crisis
5	Crisis	Crisis	Safer	Crisis
6	Crisis	Crisis	Safer	General
7	General	General	Crisis	Safety
8	General	General	Crisis	General
9	Safer	Safer	Crisis	General
10	Safer	Safer	Crisis	Crisis
11	Safer	Safer	Crisis	Crisis
12	Safety	Safety	Safer	Safety

3.3. Analysis of Experimental Results

3.3.1. *Accuracy of Financial Data Feature Mining.* The comparison results of financial data feature mining accuracy of the three methods are shown in Figure 2.

By examining the financial data feature mining accuracy comparison results in Figure 2, it can be seen that as the amount of financial data grows, the financial data feature mining accuracy of this method always exceeds that of the two literature [7, 8] comparison methods, and the financial data feature mining accuracy of this method is always greater than 90%.

3.3.2. *Financial Crisis Prediction Accuracy.* The comparison results of financial crisis prediction accuracy between this method and the two comparison methods are shown in Table 2.

Table 2 shows that the financial crisis prediction results of the method in this paper are consistent with the actual financial situation of each enterprise, whereas the financial crisis prediction results of the two literature comparison methods are slightly different from the financial crisis situation of each enterprise, implying that the method in this paper is more accurate than the two literature comparison methods. As a result, it demonstrates that this strategy can accurately estimate a company's financial status.

3.3.3. *Financial Crisis Prediction Takes Time.* The time-consuming comparison results of the three methods are shown in Figure 3.

By examining the time-consuming outcomes of financial crisis prediction displayed in Figure 3, it can be shown that this technique's maximum prediction time is no more than 6

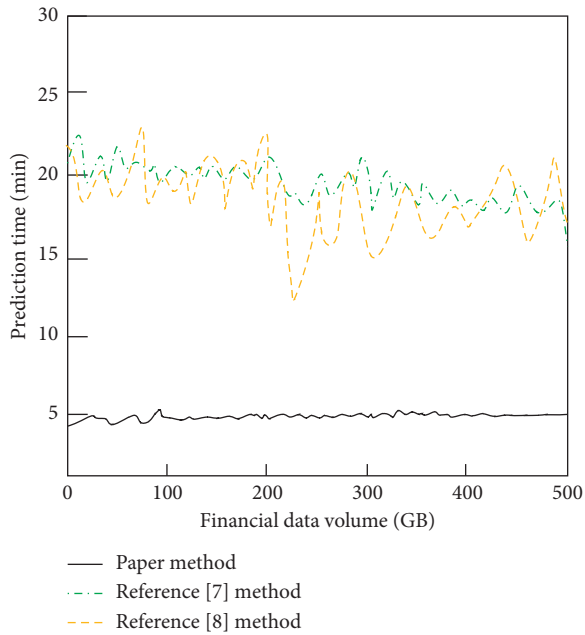


FIGURE 3: Time consuming for financial crisis prediction.

minutes, but reference [7] and reference [8] methods' maximum prediction time is more than 20 minutes. As a result, this strategy can drastically minimize the amount of time it takes to foresee a financial catastrophe.

4. Conclusion

More and more new entrepreneurial forces emerge against a social backdrop in which the government strongly fosters "mass entrepreneurship and innovation." They encourage the development of conventional sectors while pursuing angel investor financial support. Meanwhile, as Internet plus thinking has evolved, this concept has been applied to products and services in a variety of sectors of society, promoting the deep integration of the Internet and traditional industries. Enterprises must increase their risk control capabilities, comprehend the company's financial situation in real time, and improve their management and control level in order to gain a firm foothold in the quickly expanding market environment. As a result, investors, business decision makers, and professional financial institutions must be able to quickly and accurately grasp the most recent enterprise data, expect to predict future enterprise development based on current financial data and management mode, and plan ahead of time for the next step. As a result, it is critical to put in place a quick and effective financial crisis prediction system that can be dynamically assessed using previous data.

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 they have no conflicts of interest.

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