Research Article

A Fuzzy Comprehensive Evaluation and Random Forest Model for Financial Account Audit Early Warning

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Financial risk is objective, developmental, and predictable and has an important impact on the development and operation of enterprises. China's economy is currently facing major changes, and with the introduction of the “Made in China 2025” plan, deepening supply-side reform, and the rapid development of artificial intelligence, blockchain, and big data technology, the importance of enterprise financial early warning is becoming increasingly prominent. Therefore, by establishing and studying the changes in some financial indicators and establishing an effective enterprise financial early warning model, the signals of financial crisis can be found in time, to prevent and eliminate the hidden danger of enterprise financial crisis and ensure the financial security of the enterprise. The enterprise financial system and business management system are running well. Based on this, a financial early warning model is proposed in this study. First, financial early warning indicators are constructed, and the existing financial indicators are used to establish an early warning indicator system that can detect and identify the financial risks of the enterprise. Then, the financial early warning model based on the fuzzy comprehensive evaluation model and random forest algorithm for fuzzy comprehensive evaluation is constructed using the advantages and noise resistance of the integrated model of fuzzy comprehensive evaluation model and random forest algorithm. The financial data set is used to verify the model constructed in this study. The experimental results show that the model in this study not only is beneficial for enterprises to control financial crisis but also plays a financial early warning role.

1. Introduction

With the increasingly fierce market competition, the financial crisis will directly affect the survival and development of enterprises. Therefore, establishing an effective financial early warning model and sending a signal to the enterprise management before the financial crisis can make it improve production and operation in time, to prolong the life of enterprises [1]. Financial early warning is based on the enterprise’s financial statements, business plans, and other relevant accounting data, using the theories of accounting, statistics, finance, enterprise management, and marketing, and ratio analysis, comparative analysis, factor analysis, and various methods to analyze and predict the enterprise’s business activities and financial activities, to discover the potential operational and financial risks in the operation and management activities of the enterprise, issue a warning to the enterprise operators before the crisis, urge the enterprise management authorities to take effective measures to avoid the potential risks from evolving into losses, and play a proactive role [2]. Under the new economic conditions, enterprise financial early warning has attracted more and more attention. Therefore, it is very important to build an effective financial crisis early warning model, timely find the problems existing in enterprise financial management, detect the signals of financial crisis as soon as possible, and enable managers to take effective measures and improve management when the financial crisis is latent. It is very important for market participants, such as investors and management. Creditors and other relevant stakeholders have very important practical significance [3]. The significance of financial early warning model can be roughly divided into the following types.
(1) Theoretical Significance: the application of fuzzy comprehensive evaluation method to establish financial early warning models can provide accurate and scientific early warning for enterprises and overcome the inherent limitations of some existing early warning models. It is helpful for managers to find the source of alarm as soon as possible, improve the accuracy of early warning, strengthen financial management, and avoid financial risks [4]. It has the advantages of simplicity, rationality, science, and operability. It is of great significance to the theory of financial management.

(2) Practical significance: it is conducive to the investment decision of investors. For investors, they can timely adjust the existing investment portfolio after discovering the bud of the enterprise's financial crisis, or reduce the investment in the enterprise, or dispose of all the investment to avoid greater losses. When investors make investment decisions, they need more information in advance. Therefore, if we can establish an effective financial crisis early warning model, it is of great significance to investors' investment decision-making [5]. It is conducive to the management of the enterprise to take preventive measures. Real financial data can be said to be the most objective report card of enterprise operating performance. The relevant financial ratio analysis can provide the best financial crisis early warning information for the company [6]. Accounting information is of great significance in the performance evaluation and management decision-making of listed companies. If we can establish a scientific and effective financial crisis early warning model of listed companies, it will help the management to take measures in advance, improve vigilance, and reduce the probability of enterprises falling into a financial crisis [7]. It is helpful for creditors to make scientific decisions according to the operation and management of the enterprise. Creditors of enterprises mainly refer to banks and other financial institutions. Although China's capital market has developed greatly and the proportion of direct financing of enterprises has been increasing, indirect financing through banks still accounts for a considerable proportion in the capital structure of enterprises [8]. Creditors are eager to know the future solvency of listed companies and the possibility of financial crisis, to ensure the safety and profitability of loans. Therefore, it is of great significance for creditors to establish a scientific and effective financial crisis early warning model of listed companies. The reason for choosing the fuzzy integrated evaluation model and the random forest algorithm in this study is as follows: the two integrated algorithms, which are inherently more accurate than most individual algorithms, are highly accurate. Due to the introduction of the two randomness, the algorithm does not easily fall into overfitting. In industry, the introduction of the two randomness makes the algorithm have certain anti-noise capability, which has certain advantages over other algorithms. In recent decades, the fuzzy integrated evaluation models and random forest algorithms have been developed rapidly. In the field of bioinformatics, Chen et al. [9] studied protein interactions using related algorithms for research. Smith et al. [10] explored the discriminant analysis method and random forest algorithm for a comparative study of bacterial source tracking data. In the field of economic management, Dincer [11] studied customer churn using the fuzzy integrated evaluation model algorithms with data from bank customers. In addition, random forests have achieved better results in ecology, economics, medical field, criminal investigation field, and pattern recognition field. The main contributions of this study are as follows: (1) this study constructs a financial early warning index and uses existing financial indices to establish an early warning index system that can detect and identify the financial risks of enterprises. (2) Combining the fuzzy comprehensive evaluation model and random forest algorithm, this study proposes a financial early warning model with fuzzy comprehensive evaluation. (3) The real enterprise financial data set is used to verify the model constructed in this study. The experimental results show that the model in this study is not only beneficial to the enterprise to control the financial crisis but also can play the role of financial early warning.

2. Related Work

2.1. Research Status Abroad. As the economy of European and American countries entered industrialization earlier, with the increasingly fierce market economy, more and more companies began to pay attention to corporate financial risk management, and the research results related to financial risk are relatively rich and mature. By collecting and sorting out the research results of foreign financial risk management, it can be divided into the following types.

2.1.1. Financial Risk Identification. Blach identified common risks in BOT projects with the help of his new risk hierarchy model [12]. Beaver pointed out that the financial risk of an enterprise can be effectively identified through the total asset profit margin and quick ratio of the enterprise [13]. Ohlson proposed a financial crisis prediction model based on ant colony optimization, which is divided into two stages: feature selection algorithm based on ant colony optimization and data classification algorithm based on ant colony optimization [14]. The proposed financial risk model was verified using five benchmark data sets combining qualitative and quantitative methods. Sivasankar proposed a boosting ensemble method based on rough set feature...
2.1.2. Financial Risk Measurement. Bao et al. proposed a new financial risk evaluation method, which comprehensively considered evaluation results, risk occurrence probability, and knowledge dimension, and proved that this method is also applicable to traditional risk measurement [17]. The research of financial risk measurement is mainly concentrated in the field of securities market. Pačka and Kondor analyzed the risk performance using a fat-tail risk measurement model that ignored the distribution function under the background of normal distribution rate of return [18]. To evaluate risks more comprehensively, Ruan et al. proposed a method to establish risk measurement based on utility theory [19]. Valaskova et al. established a prediction model based on the important predictors affecting Slovak’s health and future prosperity. Through multiple regression analysis, significant predictors were determined under specific economic conditions to estimate the prosperity and profitability of Slovak [20]. Kolari and Sanz used neural network mapping technology to measure the dynamic nature of banking systemic risk changing over time. The problem of risk measurement for discrete time-controlled partially observable Markov processes is studied [21]. A new concept of conditional random time consistency is proposed, and a financial risk measurement model with this property is derived.

2.1.3. Financial Risk Prevention and Control Measures. Li constructed a management system with three core functions: automatic control, analysis and evaluation, and real-time monitoring [22]. With the help of this system, it can realize the whole-process, comprehensive, and intelligent financial risk source management of relevant enterprises by regulators. Rampini studied the financial risk management of financial institutions with interest rate and foreign exchange risk hedging data. On the basis of the questionnaire survey, Brustbauer established a structural model of risk management of small- and medium-sized enterprises and analyzed the risk management of small- and medium-sized enterprises [23]. The results showed that enterprise size, industry membership, and ownership structure affect the implementation of enterprise risk management. Bodnar et al. showed that personal risk aversion combined with other executive characteristics played a key role in hedging and that risk-averse executives were more likely to rely on (more conservative) thick-tailed distributions to estimate risk exposure [24]. By analyzing the financial risks of financial institutions, Butaru et al. concluded that supervision and regulation of financial institutions should adopt a more personalized approach [25].

2.2. Domestic Research Status. With the development of China’s economy and society, Chinese companies are paying more and more attention to financial early warning. Therefore, we first investigated the status of related research within China (domestic denotes within China). Due to the short time since the founding of the People’s Republic of China and the planned economy adopted before 1978, domestic enterprises at this stage did not have a strong sense of market competition. Since the reform and opening up in 1978 and China’s accession to the WTO in 2001, enterprises are facing more and more fierce competition at home and abroad. Therefore, more and more enterprises begin to pay attention to internal management and external management. As an important part of enterprise internal management, financial risk management has attracted more and more scholars’ attention in recent years. Through collecting and sorting out relevant research results, this study focuses on the following aspects of financial risk management in China.

Zhao took the new media industry as the research object, made an in-depth analysis of the main causes of financial risks in this industry, and put forward some measures to control financial risks in this industry through systematic analysis [26]. Lan-Min [27] believes that corporate financial risks are mainly caused by corporate financial activities, such as financing, investment, distribution, and other links. Once these financial activities have problems, corporate financial risks may occur. Ru-Fei pointed out that the current financial risks of the banking system by regulators are mainly the traditional deposit and loan business, and this index cannot effectively reflect the new financial risks to the banking system in the Internet era [28]. Hong-Hai proposed to identify the risks of financial outsourcing from two dimensions and five specific aspects based on the current financial outsourcing adopted by circulation enterprises [29]. Zhang comprehensively considered 4 first-level evaluation factors and 47 second-level evaluation factor subordinate to them, set corresponding alert value and risk value based on historical data, and constructed the evaluation of enterprises’ false opening and false offset financial risk using the above factors and setting value [30].

2.3. Review of Domestic and Foreign Research Status. However, although the relevant research abroad is mature and in-depth, the relevant theoretical results are difficult to be directly applied to the research related to real estate risk management in China because of the great difference between the macro- and microenvironments of Chinese enterprises and that of foreign countries. By drawing on the research of domestic scholars and studying advanced theories from abroad, breakthroughs and improvements have been made to the research related to financial risks in China, but most of the current research is mainly focused on macrostudies on the definition, characteristics and preventive measures of financial risks, and there are still relatively few studies with specific real estate enterprises as the research objects.
3. Fuzzy Comprehensive Evaluation Model

3.1. Basic Theory of Fuzzy Comprehensive Evaluation. In view of the limitations of the existing financial early warning models, this study constructs a financial early warning model with the help of fuzzy comprehensive evaluation theory to effectively predict the financial risk of enterprises [31]. Firstly, a comprehensive financial index evaluation system is established, which is a collection of different attribute indexes reflecting the operation status and development prospect of the enterprise according to a certain hierarchical structure to analyze and evaluate the enterprise’s finance and operation status [32], so as to provide relevant financial information to the users of financial statements. There are many financial indicators, but the content and importance of financial information reflected by each indicator are different [33]. A large weight indicates that the indicator has a great impact on the whole finance; otherwise, the impact is small. Next, three elements of fuzzy comprehensive evaluation are introduced.

First, the evaluation factor set $U = \{u_1, u_2, \ldots, u_n\}$ is established. The evaluation factors are composed of factor set $U$, and $U$ is divided into several groups. The mathematical expression is as follows:

$$U = \bigcup U(U, \cap U, = \emptyset, i - j).$$  \hspace{1cm} (1)

Then, there are subfactor sets $U_i = \{u_{1i}, u_{2i}, \ldots, u_{ni}\}$, and each subset contains a different number of factors. So, there is the following mathematical expression:

$$U = \{u_{11}, u_{12}, \ldots, u_{1n}; u_{21}, u_{22}, \ldots, u_{2n}; u_{31}, u_{32}, \ldots, u_{3n}; \ldots; u_{m1}, u_{m2}, \ldots, u_{mn}\}. \hspace{1cm} (2)$$

$V$ is defined as a set which is composed of all the indicators, and $V$ is a subset of one-level factor set $U$. Then, the evaluation set $V = \{v_1, v_2, \ldots, v_m\}$ is established. Single-factor evaluation on the factors in $U = \{u_1, u_2, \ldots, u_n\}$ is conducted, the membership function is determined, the membership degree is obtained, and fuzzy mapping is established. The mathematical expression is as follows:

$$\overline{f}_i: U_i \longrightarrow F(v),$$

$$\overline{f}_i(u_k) = (r_{k1}^{(i)}, r_{k2}^{(i)}, \ldots, r_{kt}^{(i)}) \in F(v). \hspace{1cm} (3)$$

Finally, the establishment of single-factor judgment is a fuzzy judgment for each factor in the factor set according to the evaluation set. The mathematical expression is as follows:

$$\overline{f}: U \longrightarrow F(U \times V),$$

$$u_i \mapsto \overline{f}(u_i) = (r_{1i}, r_{12}, \ldots, r_{im}) \in F(V). \hspace{1cm} (4)$$

The fuzzy relation $R_f \in F(U \times V)$ can be induced by $\overline{f}$, where $R_f(u_i, u_j) = f(u_i) = j$, and the fuzzy matrix can be formed by $R_f$, and its mathematical expression is as follows:

$$R = \begin{bmatrix}
    r_{11} & r_{12} & \cdots & r_{1n} \\
    r_{21} & r_{22} & \cdots & r_{2n} \\
    \cdots & \cdots & \cdots & \cdots \\
    r_{ml} & r_{m2} & \cdots & r_{mn}
\end{bmatrix}. \hspace{1cm} (5)$$

3.2. General Steps of the Comprehensive Evaluation Mathematical Model. The mathematical model of fuzzy comprehensive evaluation is roughly divided into the following steps:

Step 1: determine the evaluation object set, factor set, and comment set.

Step 2: establish the weight distribution vector of $M$ evaluation factors. Generally, there are subjective weighting method and objective weighting method. According to the previous analysis, this study uses the expert survey method in the subjective weighting method. The specific steps are as follows:

Step 2.1: through the analysis of experts, determine the importance of each financial index and form the investigation results

Step 2.2: summarize all survey information

Step 2.3: calculate the weight coefficient of financial indicators

Step 3: determine the evaluation membership matrix.

Step 4: operator analysis of the fuzzy comprehensive evaluation model: in the process of fuzzy comprehensive evaluation, the synthesis process is an important link affecting the conclusion of comprehensive evaluation. Different operators will lead to different evaluation models. The types of operators used in fuzzy comprehensive evaluation mainly include “take the small and take the large” operator, multiplication and addition (weighted average) operator, product one take the large operator, comprehensive restriction operator, balanced average operator, and so on.

Step 5: carry out graded evaluation, including the first-level evaluation and the second-level evaluation, respectively.

Through the above steps, the construction of fuzzy comprehensive evaluation model can be realized. The overall structure of the model is shown in Figure 1.

4. Improved Random Forest Algorithm

Random forest (RF) is a combinative classifier. It uses the bootstrap resampling method to extract multiple samples from the original samples, conducts decision tree modeling for each bootstrap sample, and then combines these decision trees together to obtain the final classification or prediction result through voting [10]. A large number of theoretical and empirical studies have proved that the random forest algorithm has high prediction accuracy, has good tolerance to outliers and noise, and is not prone to overfitting. This study intends to summarize and sort out the theoretical research of random forest, which is conducive to the subsequent optimization research. However, the study of random forest must involve decision tree, because the base classifier of random forest is decision tree without pruning [11]. A decision tree is a single classifier classification technique. A decision tree is a typical single classifier. The generation and
decision-making process of the classifier are divided into three parts. First, a tree structure like an inverted tree is generated through recursive analysis of the training set [34]. Then, the path of the tree from the root node to the leaf node is analyzed to generate a series of rules. Finally, the new data are classified or predicted according to these rules. In essence, the classification idea of decision tree is actually a data mining process by generating a series of rules and then analyzing data through these rules.

As can be seen from the algorithm implementation, following the traditional decision tree algorithm can produce many different decision trees. This is mainly because when selecting the root node, the traditional decision tree algorithm does not have a fixed rule to decide which attributes should be selected as the root node; this practice makes the algorithm somewhat blind and makes the use of the algorithm curtailed. In view of the uncertainty caused by the traditional decision tree algorithm, which does not specify which test attribute to use, this study improves it. The significant difference from the traditional decision tree algorithm is that the algorithm in this study abides by a fixed rule when selecting attributes. This rule is to compare the attributes by introducing information entropy and determine which attribute is the splitting node by comparing the size of information entropy.

The algorithm in this study takes the information entropy corresponding to the attribute value as the criterion for selecting node splitting. The algorithm starts from the calculation of information entropy, calculates the information gain rate of each attribute, and then uses the size of information gain to compare which attribute to choose for node splitting. The calculation process of information gain is as follows. Firstly, the information entropy of the node is calculated, and its mathematical expression is as follows:

\[
\text{Info}(D) = -\sum_{i=1}^{m} P_i \log_2 P_i.
\]  

(6)

Then, based on the expected information required for the sample classification of \( D \) according to \( A \), the formula is as follows:

\[
\text{Info}_A(D) = \sum_{j=1}^{v} \left( \frac{|D_j|}{|D|} \right) \cdot \text{Info}(D_j),
\]

(7)

where \(|D_j|/|D|\) acts as the weight of the \( j \)th partition. The smaller \( \text{Info}_A(D) \) is, the more pure the division is. The information gain can be obtained from formulas (6) and formulas (7), which are as follows:

\[
\text{Gain}(A) = \text{Info}(D) - \text{Info}_A(D).
\]

(8)

\( \text{Gain}(A) \) indicates the expected reduction in information requirements caused by the value of \( A \), that is information gain. The algorithm selects the attribute that maximizes \( \text{Gain}(A) \) as the test attribute. In addition, this algorithm also introduces the window method for incremental learning to solve the problem of too large instances. The specific steps are as follows:

Step 1: obtain training set \( X \). If all samples in the current training set belong to the same category, or the sample attribute set in the training set is empty, then leaf nodes are generated and the algorithm ends. Otherwise, go to Step 2.

Step 2: according to the training set \( X \), calculate the information gain of all attributes in \( Q \).

Step 3: select the attribute \( B \) with the largest information gain in \( Q \) as the split attribute. If there are \( N \) values of attribute \( B \), then \( x \) is divided into \( N \) disjoint subsets by \( B \). In this way, \( N \) branches are generated from attribute \( B \).

Step 4: place the root node of each branch, and then, go to Step 1.

The algorithm in this study makes up for the deficiency of the traditional decision tree algorithm in randomly selecting attributes, so that when generating the decision tree, the generated rules are fixed and reproducible, and the depth of the final decision tree is very small. Then, it introduces the problems of decision tree in classification. Since decision tree adopts a single classifier decision mode, it has its insurmountable disadvantages: (1) complex classification rules; (2) converges to a nonglobal local optimum; and (3) excessive fitting. To overcome the above disadvantages of decision trees, and with reference to the idea of combining single classifiers into multiple classifiers, it is easy to think of a way to generate more decision trees that do not need to have a high classification accuracy, and let all the decision trees make decisions by voting. This is the idea at the heart of random forests. The construction of random forest mainly includes the following three steps:

Step 1: each decision tree is sampled to generate a training set. Each decision tree corresponds to a training set. To build \( N \) decision trees, it is necessary to
generate a corresponding number of training sets. Generating N training subsets from the original training set involves statistical sampling technology.

The final output of the algorithm adopts the majority voting method. According to the randomly constructed N decision subtrees, a certain test sample will be classified, and the results of each subtree will be summarized. The classification result with the most votes will be the final output result of the algorithm. The schematic diagram of random forest algorithm is shown in Figure 2.

The random forest algorithm proposed in this study can improve its classification accuracy and can be applied in some areas where the classification accuracy is strict. However, because only binary trees can be generated, the decision tree generated by this algorithm method can only be binary bifurcation, which makes the algorithm only suitable for binary classification data sets when applied, which needs to be further studied in the future, to achieve better results.

5. Financial Early Warning Model Construction

Due to the relatively weak theoretical basis of financial early warning and the lack of specific economic theoretical guidance in the selection of variables, it is difficult to fully describe it with a few simple financial ratios. Usually, only different variables can be selected to represent different aspects of the financial situation of listed companies [35]. Some of the financial indicators are unrealistic or uneconomical, which is difficult to play a real early warning role. Therefore, according to the principle of selecting the above indicators and the analysis of indicators, after consulting relevant experts, the impact evaluation indicators are analyzed and selected one by one [36], and finally, a set of universal comprehensive evaluation index system composed of several effective indicators is formed. These indicators mainly reflect the four aspects of the enterprise’s financial situation, namely 15 financial indicators in the four aspects of solvency, operating ability, profitability, and growth ability, and rebuild a systematic and scientific three-tier financial evaluation index system, as shown in Figure 3.

Identifying the index system is not the ultimate objective, but with the use of the established financial index system. The secondary fuzzy comprehensive evaluation method is used to realize the financial early warning research of Cologne Company. In the fuzzy comprehensive evaluation method, when evaluating the financial situation and comprehensively considering multiple factors, each factor is evaluated separately, and then, each influencing factor is comprehensively evaluated, which is a comprehensive evaluation problem.

6. Experiments and Results

This study will take 46 ST enterprises and 184 non-ST enterprises in the ratio of 1:4 as samples to construct the financial early warning model, including the comparison between the financial early warning model based on SVM and the algorithm in this study. We split the training and test sets in a ratio of 5:1 including positive and negative samples.

To verify the predictive ability of the proposed algorithm, we set the pruning threshold between 0 and 30 and the number of decision trees between 0 and 100 in steps of 10 and record the value with the highest accuracy as the model parameter. The model is trained for 10 rounds. The experimental environment of this study is as follows: the hardware environment is NVIDIA GTX 1080Ti; the software environment is Linux system, Python3.7, sklearn0.20.1, and other toolkits.

6.1. The Experimental Results of the Model Are Presented in This Study. The value of the index system composed of 22 financial indicators of 230 sample enterprises for 10 years from 2006 to 2015 is calculated. Since the selection of samples is random, we can only order the number of samples selected. To maintain consistency, the financial index data of half of the ST enterprises and non-ST enterprises are also selected as the training samples for building the model, and the remaining ST enterprises and non-ST enterprises are used as the prediction samples. According to the training samples, the model uses program statements and the black box function of MATLAB software to find and establish the relationship between these 22 indicators and whether the enterprise will have a financial crisis, that is, whether it will be ST (assigned 0 by ST enterprises and 1 by non-ST enterprises). After the model is established, it will predict whether the remaining enterprises will be ST according to the data of 22 indicators of the prediction sample. Comparisons are made with the actual results of the forecast sample to derive the accuracy of the model’s judgement of
whether a firm will experience a financial crisis. Next, let us look at the experimental process of the financial early warning model constructed in this study. 2015 is taken as an example, as shown in Figure 4. The experimental process in other years is the same as that in that year.

As it can be seen from Figure 4, the error of sample data in 2015 showed a slow fluctuating downward trend, with the lowest falling below $10^{-8}$, but the highest not exceeding $10^{-4}$, indicating that the establishment of the model is effective. Next is the recognition rate chart of the financial early warning model, still taking 2015 as an example, as shown in Figure 5.

As can be seen from Figure 5, the training set accuracy and verification accuracy of the model established in 2015 have reached 100%, the test set accuracy has reached 83.516%, and the weighted recognition rate has reached 96.971%, mainly because the accuracy simulated by the training set has reached 100%. Therefore, from the perspective of model accuracy, ANN model is effective for judging whether enterprises are going to fall into financial crisis. Next, 2015 is taken as an example to analyze the prediction result of the model on the sample enterprises of the test set, as shown in Figure 6.

In Figure 6, the red representation represents the results predicted by the proposed random forest model, and the blue markers represent the actual results of the enterprise runs. The abscissa in Figure 6 shows the serial number of 115 sample enterprises in the test set: the first 20 are ST enterprises and the last 95 are non-ST enterprises. Its ordinate represents the category of sample enterprises, including two categories, “0” represents ST enterprises and “1” represents non-ST enterprises. It can be found from the above figure that there are 15 ST enterprises and 19 non-ST enterprises with identification errors; that is, the accuracy rate of the model to judge whether an enterprise will have a financial crisis in 2015 is 70.4348% (81/115), which is acceptable.

Next, taking the number of ST enterprises and non-ST enterprises in the test set identified by the model in 2016 as the standard of recognition rate, this study analyzes and compares the recognition rate from 2006 to 2015. The empirical results are shown in Table 1.

Through Table 1, we can find that the financial early warning model established in this study has a high accuracy in judging whether an enterprise will have a financial crisis. Except for 2011, it is 70% or more in other years. Combined with the training error and its own accuracy of the model in the experimental process, it is enough to show that the established financial early warning model is effective and once again shows that the financial crisis can be predicted.

6.2. Comparison of Experimental Results. Through empirical research, it is found that the two types of financial crisis early warning models can effectively predict whether the company will fall into financial crisis, but on average, the recognition rate of this model is lower than that of SVM model, as shown in Figure 7.

In Figure 7, the horizontal coordinate represents the year and the vertical coordinate represents the accuracy rate. As it can be seen from the above figure, over time, the recognition rate of SVM model for whether the enterprise will be ST shows an upward trend, while the recognition rate of ANN model fluctuates around 70%. Through this figure, it can be clearly seen that the accuracy of SVM model in judging whether the enterprise will fall into financial crisis is higher than that of this model. Next, the effectiveness of the two models in predicting the test set will be compared and analyzed through quantitative indicators. First, a brief description of the three indicators that distinguish the prediction effect of the two models is given, as shown in Table 2.

As shown in Table 2, through the description of the above three indicators, we can know that the smaller the
three indicators, the better, indicating the better prediction effect of the model. Next, let us take a look at the performance of the statistical indicators of the two models. Table 3 shows that the MAE and MSE indexes of the two models are relatively small, indicating that the two models are more effective in predicting the test set. The MAE index of the two models shows a downward trend as a whole, while the MSE index of the SVM model shows a downward trend as a whole, and the downward trend of the index of the model in this study is not obvious. In terms of $\eta$ index, the value of this
The index of the two models is larger than that of MAE and MSE indexes, but it is still relatively small in terms of absolute quantity and shows a downward trend as a whole, indicating that the two models are more effective in predicting the test set. As for the average values of the three indexes, the average values of SVM model are smaller than those of this model.

### Table 1: Comparison of actual classification and predicted classification of the model test set.

<table>
<thead>
<tr>
<th>Years</th>
<th>ST</th>
<th>ST sum</th>
<th>Non-ST</th>
<th>Non-ST sum</th>
<th>Average rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>2</td>
<td>23</td>
<td>81</td>
<td>92</td>
<td>72.17</td>
</tr>
<tr>
<td>2007</td>
<td>2</td>
<td>25</td>
<td>86</td>
<td>90</td>
<td>76.52</td>
</tr>
<tr>
<td>2008</td>
<td>0</td>
<td>30</td>
<td>84</td>
<td>85</td>
<td>73.04</td>
</tr>
<tr>
<td>2009</td>
<td>1</td>
<td>24</td>
<td>87</td>
<td>91</td>
<td>76.51</td>
</tr>
<tr>
<td>2010</td>
<td>1</td>
<td>24</td>
<td>82</td>
<td>91</td>
<td>72.17</td>
</tr>
<tr>
<td>2011</td>
<td>3</td>
<td>27</td>
<td>74</td>
<td>88</td>
<td>66.95</td>
</tr>
<tr>
<td>2012</td>
<td>0</td>
<td>19</td>
<td>91</td>
<td>96</td>
<td>79.13</td>
</tr>
<tr>
<td>2013</td>
<td>3</td>
<td>26</td>
<td>90</td>
<td>95</td>
<td>80.86</td>
</tr>
<tr>
<td>2014</td>
<td>2</td>
<td>28</td>
<td>82</td>
<td>97</td>
<td>73.04</td>
</tr>
<tr>
<td>2015</td>
<td>5</td>
<td>20</td>
<td>76</td>
<td>95</td>
<td>70.43</td>
</tr>
<tr>
<td>Average rate</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>74</td>
</tr>
</tbody>
</table>

### Table 2: Description of the statistical indicators.

<table>
<thead>
<tr>
<th>Index</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n}</td>
</tr>
<tr>
<td>MSE</td>
<td>$\text{MSE} = \frac{1}{n} \sum_{t=1}^{n} e_t^2$</td>
</tr>
<tr>
<td>$U$</td>
<td>$U = \sqrt{\frac{1}{n} \sum_{t=1}^{n} f_t^2 / \sqrt{\frac{1}{n} \sum_{t=1}^{n} y_t^2}}$</td>
</tr>
</tbody>
</table>
Table 3: Comparison of MAE, MSE, and U indexes of the two models in each year.

<table>
<thead>
<tr>
<th>Years</th>
<th>MAE SVM</th>
<th>MSE SVM</th>
<th>U SVM</th>
<th>MAE Our model</th>
<th>MSE Our model</th>
<th>U Our model</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>0.1913</td>
<td>0.3808</td>
<td>0.1913</td>
<td>0.2074</td>
<td>0.4864</td>
<td>0.6933</td>
</tr>
<tr>
<td>2007</td>
<td>0.2174</td>
<td>0.3263</td>
<td>0.2174</td>
<td>0.1907</td>
<td>0.5301</td>
<td>0.6007</td>
</tr>
<tr>
<td>2008</td>
<td>0.2193</td>
<td>0.3672</td>
<td>0.2193</td>
<td>0.2095</td>
<td>0.4864</td>
<td>0.6701</td>
</tr>
<tr>
<td>2009</td>
<td>0.2413</td>
<td>0.3413</td>
<td>0.2413</td>
<td>0.1886</td>
<td>0.4864</td>
<td>0.6145</td>
</tr>
<tr>
<td>2010</td>
<td>0.2193</td>
<td>0.3733</td>
<td>0.2193</td>
<td>0.2063</td>
<td>0.4864</td>
<td>0.6702</td>
</tr>
<tr>
<td>2011</td>
<td>0.2413</td>
<td>0.3953</td>
<td>0.2413</td>
<td>0.2334</td>
<td>0.4864</td>
<td>0.7350</td>
</tr>
<tr>
<td>2012</td>
<td>0.1652</td>
<td>0.2817</td>
<td>0.1652</td>
<td>0.1666</td>
<td>0.4664</td>
<td>0.5256</td>
</tr>
<tr>
<td>2013</td>
<td>0.1913</td>
<td>0.3248</td>
<td>0.1913</td>
<td>0.1803</td>
<td>0.4996</td>
<td>0.6001</td>
</tr>
<tr>
<td>2014</td>
<td>0.1913</td>
<td>0.3799</td>
<td>0.1913</td>
<td>0.2585</td>
<td>0.5042</td>
<td>0.7289</td>
</tr>
<tr>
<td>2015</td>
<td>0.0783</td>
<td>0.3083</td>
<td>0.0783</td>
<td>0.2605</td>
<td>0.3556</td>
<td>0.6586</td>
</tr>
<tr>
<td>Average</td>
<td>0.1800</td>
<td>0.3479</td>
<td>0.1800</td>
<td>0.2102</td>
<td>0.4788</td>
<td>0.6497</td>
</tr>
</tbody>
</table>

To sum up, it is found that both models can effectively judge whether an enterprise will fall into a financial crisis. However, in terms of the prediction accuracy of the test set, the financial early warning model based on SVM is inferior to the financial early warning model in this study. As we all know, for the same financial index, different industries may have different reasonable ranges, which reduces the fitting degree of SVM model and then reduces the recognition rate.

7. Conclusion

Based on the combination of theoretical analysis and empirical research, starting from the environment and existing financial problems faced by China’s listed companies, this study establishes an innovative comprehensive accounting index system by reviewing the financial crisis early warning theory and relevant classical literature and constructs a nonlinear financial early warning model using fuzzy comprehensive evaluation and random forest model. It also makes an empirical analysis and comparative analysis on the effectiveness of the model.

According to the relevant theories of financial crisis early warning, this study takes the A-share listed companies that were ST in 2016 as an example, matches the corresponding non-ST companies according to the screening conditions according to the ratio of 1:4, and takes all ST companies and the matched non-ST companies, a total of 230 A-share listed companies as a sample. The data of the comprehensive financial index system are constructed by the combination of the Altman index and dynamic accounting index from 2006 to 2015, and the financial early warning model is established using the sample data. From the results of empirical analysis, there is a nonlinear relationship between the financial index data and whether the company will fall into financial crisis, but most things in the world are the combination of linear relationship and nonlinear relationship.

The application value of this study lies in the following: first, for the owners of listed companies, it can help listed companies establish two effective nonlinear financial early warning models. The shareholders of listed companies can choose the corresponding financial early warning model according to the characteristics of the invested enterprises, to strengthen the risk prevention and internal control of enterprises. The aim is to achieve a higher return on investment. Second, for the management of listed companies, the financial early warning model established in this study can help them improve the identification of financial risks and enhance the risk prevention awareness of the management, so as not to make the enterprise on the verge of crisis without knowing it, improve their management ability and performance, and obtain the support and corresponding remuneration of shareholders. In the future, we plan to carry out research on financial early warning models based on convolutional neural networks.

Data Availability

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

References


