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Research on Personalized Financial Decision Making Based on Random Forest Algorithm in Big Data Environment

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ABSTRACT

The application of big data in modern enterprise finance is becoming more and more common, and the research adopts the random forest algorithm to explore the enterprise financial risk status, so as to make personalized financial decisions. Construct the enterprise financial risk early warning model based on random forest and construct the financial risk early warning index system. The performance of the random forest model is tested by comparing the financial risk early warning effect of the random forest model with other models. Taking M company as an example, by analyzing its financial risk situation from 2019 to 2023, it puts forward targeted financial decision-making suggestions. The random forest model performs best in the financial risk early warning performance experiment, far outperforming other models. The financial risk status of Company M in 2019-2023 is dangerous, sub-safe, general, dangerous, and general. Although it has been improved in general, it is still in a fluctuating state and the development status is unstable. For the specific financial risk status of Company M, financial decision-making suggestions are proposed for the three aspects of solvency, operating capacity and development capacity.

Keywords: big data, random forest algorithm, financial risk warning, financial decision-making

1. Introduction

In this era of data explosion, if enterprises want to maintain a certain competitive advantage in the industry, they must emphasize and pay attention to their own financial decision-making. As an important core of enterprise financial management, financial decision-making is accurate, to a large extent, will affect the development of enterprise financial management work.

Financial decision-making refers to the overall requirements of the enterprise in accordance with the financial management objectives, in order to realize the maximum value of the enterprise, the use of scientific theories and methods, on the fund-raising methods, related financial decision-making selection and development process [1-2]. Its purpose is to develop a financial management plan in line

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with the actual situation of the company and is conducive to the future development of the company's financial decision-making program, scientific and reasonable financial decision-making can make full use of the company's resources to maximize the economic benefits, and create value [3-5]. In the production and operation activities of enterprises, financial decision-making is a very critical content, will have a direct impact on the production and development of enterprises, and in the enterprise market competitiveness enhancement has a decisive role [6]. In the traditional financial decision-making model, enterprise managers may be biased when faced with the massive, cumbersome financial statements and other financial data resources, resulting in their inability to accurately mine the value and true nature of the data behind, or due to physiological, psychological and other personal behavior of the financial decision-making judgments are imprecise, which affects the effectiveness of the decision-making accuracy, resulting in the interests of the enterprise can not be realized according to expectations [7-10]. In addition, the overall requirements of the financial management objectives of each enterprise are not the same, and the financial decisions suitable for the enterprise are not the same. And in addition to the enterprise, the state, individuals, families, university associations, etc. are involved in financial decisions belonging to themselves [11-14]. And the reasons affecting financial decision-making come from all aspects and are divided into internal and external factors. Among them, the external factors are the current economic situation, foreign equity situation, while the internal factors are the composition of the enterprise board of directors, the financial literacy of the financial management team, and the financial decision maker's own reasons [15-18]. Therefore, under the new situation, in order to better financial decision-making, we should abandon the traditional financial decision-making methods, based on financial literacy, supported by big data, oriented to personalized needs, adopt new technologies and new means to integrate financial decision-making with big data, carry out a fundamental reform of financial decision-making mode, reveal the great value stored in financial management data, and provide decision-making related personnel with timely and dynamic Fair value news [19-20].

In a big data environment, there are more and more risks to be avoided in financial management and decision making. Similarly, the development of technology in the big data environment has found solutions to these challenges. Literature [21] constructed a cloud accounting IT auditing model in the context of big data that can accurately identify and determine abnormal data in finance. Literature [22] optimized the financial management capabilities and management strategies of universities using a decision tree classification algorithm. Literature [23] even directly utilized data mining to design a financial decision-making platform for universities. And literature [24] is mentioned that SAS financial analysis model can help micro and small enterprises to make financial decisions, risk avoidance, and strategic development. However, this model does not have comprehensive applicability, and the rapid analysis of multiple datasets ability and alternative decision-making ability of artificial intelligence can make up for this problem, and it improves financial performance [25]. Based on this, literature [26] designed interpretable AI model to predict the credit risk management of lending platforms, and the most accurate prediction results were made through decision tree and random forest algorithms. Among them, the random forest algorithm is an integrated learning algorithm that obtains the final prediction results by constructing multiple decision trees and combining their predictions to vote for the final prediction results [27]. In finance and finance, the random forest algorithm has many applications, such as financial risk prediction [28], enhanced credit card fraud detection [29], and financial crisis early warning [30]. The accuracy of the audit data of enterprises is directly related to financial decision-making, but the audit data are usually complicated and disorganized, and even write useless data. For this reason, the literature [31] uses neighborhood rough sets to remove redundant attributes in the financial decision-making data system, and then optimizes the parameters of the integrated classifier through grid search for model training and use. This approach improves the accuracy of financial decision making.

In this paper, first of all, risk early warning and analysis of the enterprise's financial situation, on the basis of which personalized and targeted financial decision-making is proposed. Firstly, the random forest algorithm is chosen to construct the financial risk early warning model, screen the financial risk indicators, and construct the financial risk early warning indicator system. Then the Random Forest financial risk early warning model in this paper is compared with other classical financial risk early warning models, and the risk early warning performance of the Random Forest model is detected by indicators such as accuracy, precision, recall, specificity, F1-score and AUC value. Subsequently, an example study is conducted to deeply analyze the financial risk status of Company M in the past five years, quantify its financial risk and classify its early warning level. Finally, targeted suggestions for corporate financial decision-making are proposed.

2. Random forest-based financial risk early warning modeling

2.1. Financial decision-making

Financial decision-making refers to the overall requirements of the enterprise in accordance with the financial management objectives, in order to realize the maximum value of the enterprise, the use of scientific theories and methods, on the fund-raising methods, related financial decision-making selection and formulation process [32]. Its purpose is to develop a company in line with the actual situation and is conducive to the future development of the company's financial decision-making program. Scientific and reasonable financial decision-making can make full use of the company's resources to maximize the economic benefits and create value. In the production and operation activities of enterprises, financial decision-making is a very critical content, will have a direct impact on the production and development of enterprises, and in the enterprise market competitiveness enhancement has a decisive role.

The success of an enterprise's operation and whether it has the ability to survive and develop, the core lies in the implementation of good or bad financial management work, specifically depends on the accuracy of financial decision-making. The success of financial decision-making is the result of the combination of various elements (decision-makers, information, theories and methods, etc.). In the context of the big data era, enterprises must change the previous lagging management mode, realize process reengineering, and optimize the traditional business model, and only in this way can they obtain better development. In order to realize the development of enterprise management to the goal of internationalization and leaning, enterprises need to realize that the backward analysis means will constrain the enterprise's every financial decision-making problem, and according to the requirements of the background of the big data era, appropriate financial decision-making adjustments should be made.

Financial decision-making is the core of enterprise financial management, is built on the basis of financial forecasting, the correct financial decision-making can make the enterprise back from the dead, the wrong decision-making can lead to the destruction of the enterprise, and its success is directly related to the rise and fall of the enterprise success or failure. This paper takes financial risk prediction as an entry point, through the prediction of the enterprise's financial risk, so as to warn the enterprise to adjust the financial decision-making in time, in order to avoid financial crisis.

2.2. Random Forest Model

Random Forest (RF) is an integrated learning method that incorporates Decision Trees and Bagging. Each decision tree in the random forest model can be regarded as a base classifier, and each decision tree will be trained to produce a classification result, and a large number of decision trees converge into a “forest”. Combined with the integration idea of Bagging, the model will vote on the classification results of multiple decision trees, and based on the principle of majority rule, the final classification results will be integrated. In this section, the principles of Random Forest are explained in detail from three parts: CART decision tree, Bagging algorithm and Random Forest method.

2.2.1. CART Decision Tree. Decision tree is a class of machine learning methods based on the tree structure for decision making, through the "decision" of each node, to achieve accurate classification or regression on the task. Typically, a decision tree contains a root node, a number of internal nodes and a number of leaf nodes. Decision trees include CART decision tree, ID3 decision tree, CHAID decision tree and C4.5 decision tree, etc. Different decision tree algorithms have different classification criteria for optimal attributes. Among them, CART decision tree utilizes the Gini coefficient to classify the attributes, ID3 decision tree's core idea is to measure the selection of attributes through information gain, CHAID decision tree uses Bonferroni method to test the significance, and C4.5 decision tree selects the gain ratio as a criterion to classify the data attributes. Among the different decision trees mentioned above, ID3 decision tree cannot deal with continuous variables, and scholars have already found that the classification accuracy of CART decision tree is higher than that of ID3 decision tree and C4.5 decision tree, so in this paper, we choose the CART decision tree in the standard random forest method as the base classifier, and the principle of the CART decision tree algorithm will be analyzed in the following.

CART decision tree is proposed by Breiman et al. using the Gini coefficient minimization criterion as a guiding theory to improve the efficiency of generating decision trees [33]. Assuming that the number of classes in the current sample set M is set to be T and the probability size of a sample point being in class t is p_t, the Gini value of the data set M can be expressed as:

$$Gini(M) = 1 - \sum_{t=1}^{T} p_t^2 \tag{1}$$

In the above equation, $Gini(M)$ reflects the probability that two samples are randomly drawn from the data set M with different category labels, and the Gini value indicates the purity of the model; the smaller the $Gini(M)$ value, the higher the purity and the better the features.

Assuming that the discrete attribute a has Z possible values $\{a^1, a^2, ..., a^Z\}$, if the sample set M is divided by a, Z branch nodes are created, and the Zth branch node contains all the samples in the sample set M that have a value of a^Z on the attribute a, which can be denoted as M^Z. Since the number of samples contained in different branch nodes is different, the branch node is assigned a weight, denoted as $|M^Z|/|M|$, and the Gini of attribute a can be denoted as value can be denoted as:

$$Gini_{index}(M, a) = \sum_{z=1}^{Z} \frac{|M^z|}{|M|} Gini(M^z) \tag{2}$$

For the attributes in the attribute set A, the attribute with the smallest Gini value after division will be selected as the final divided attribute, denoted as:

$$a_* = \underset{a \in A}{\arg\min}\, Gini_{index}(D, a) \tag{3}$$

2.2.2. Bagging Algorithm. The Bagging algorithm is based on Bootstrap sampling and was proposed by Bremian [34]. Bootstrap is sampling with put-back, which assumes that in a collection of m samples, one sample is randomly selected at a time, and that sample is put back into the original dataset, implying that these samples may be selected repeatedly. After m random samples, a new dataset containing m samples is obtained. Based on this, N Bootstrap sampling of the training samples, then N new datasets containing m samples can be sampled, based on the different datasets can be trained N base learners, and finally these base learners are integrated, which is the basic process of the Bagging algorithm. The combined model generated by Bagging weightless sampling approach will have better modeling results than the model using a single raw data. As far as the classification problem is concerned, the final classification prediction is determined using the simple voting method.

2.2.3. Random Forests. Random Forest as an integrated method combines multiple decision trees as base classifiers using Bagging algorithm and finally the final classification prediction is obtained by the minority-majority voting method, which makes the results of the model have higher accuracy [35]. During the training process of different decision tree models, the random forest method introduces random attribute selection, which converges to a lower generalization error as the number of base learners increases. The random forest approach increases the variability among classification models by constructing different training sets thereby increasing the predictive power of the combined classification model. From the model construction process of random forest, through I training, different decision tree model sequences $\{h_1(x), h_2(x), \ldots, h_i(x)\}$ are obtained, different decision tree models are integrated and the final classification is decided by the simple voting method, which is formulated as follows:

$$H(x) = agr\max_{t \in T} \sum_{i=1}^{I} I(h_i(x) = t) \tag{4}$$

where, $H(x)$ denotes the combined classification model, $h_i(x)$ denotes each decision tree model, t denotes the target variable i.e. belonging to class t, I denotes the number of decision trees and $I(\,)$ denotes the schematic function. The random forest classification process is shown in Figure 1.

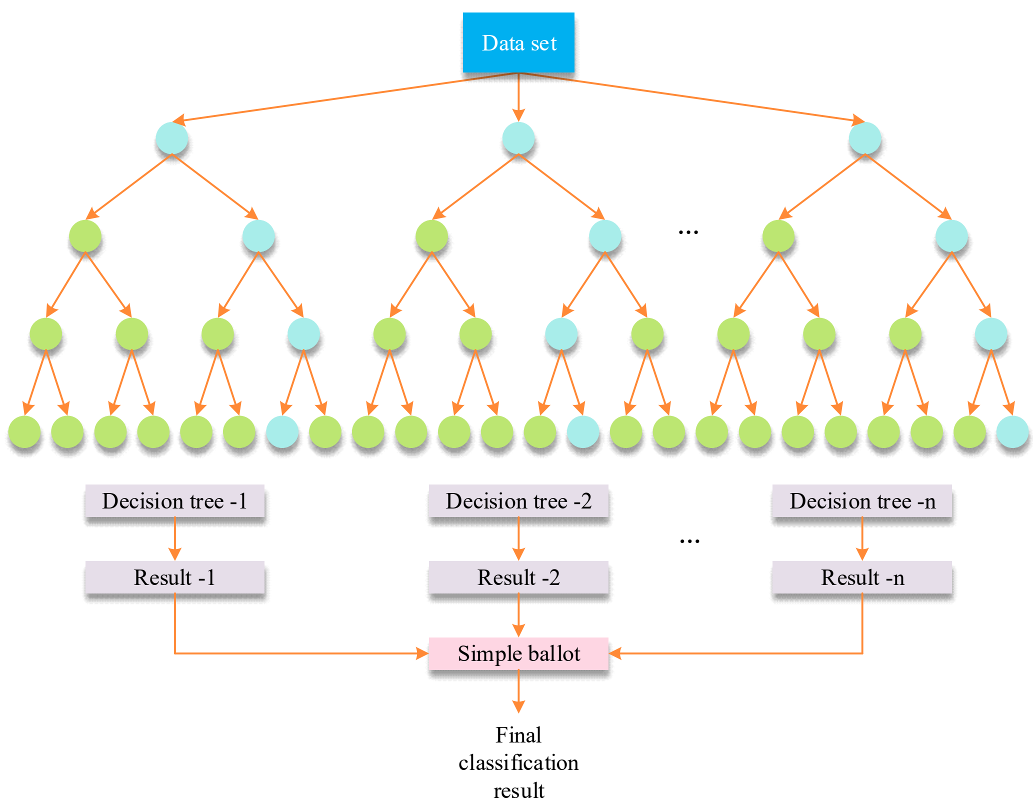

Fig. 1. The process of random forest algorithm

In layman's terms, when using a random forest to make a categorical prediction, it is a number of decision trees that make up the forest that make separate categorical predictions, and each decision tree makes a prediction about which category the sample belongs to. Each tree predicts which class the sample belongs to. The final classification prediction of the random forest is based on which class is chosen the most by the voting method.

2.3. Construction of financial risk early warning indicator system

2.3.1. Indicator system. For the quantitative data and financial text processing, 15 financial and non-financial indicators and 300×300 word vector matrix of each listed company are obtained as inputs to the model, and the quantitative indicators obtained are shown in Table 1.

Table 1. Quantitative model input index system

Index	Name	Code
Debt-paying ability	Quick ratio	X1
	Cash flow ratio	X2
	Asset liability ratio	X3
	Times interest earned	X4
Operating capacity	Accounts receivable turnover rate	X5
	Inventory turnover rate	X6
	Current asset turnover	X7
	Total asset turnover	X8
Profitability	Operating margin	X9
	Return on total assets	X10
	Return on equity	X11
	Profit margin of the cost and expense	X12
Development capacity	Sales growth	X13
	Sales profit growth rate	X14
	Asset growth rate	X15

2.3.2. Model evaluation indicators. The model evaluation metrics in this section are constructed using the constructed model by predicting the sample companies and comparing the final prediction results with the real labels of these sample companies. The most common of these evaluation metrics are described below:

1) Accuracy. The accuracy for a particular model f is defined as follows: if the sample size of a test set is n, where the ird sample is assumed to be X_i, and the true label corresponding to this sample X_i is Y_i, then the prediction accuracy formula for this model is as follows:

$$\text{Accuracy} = \frac{1}{n}\Sigma_1^n I(f(X_i) = Y_i) \tag{5}$$

In the above expression, I represents the segmentation function of $I(0)=0$ and $I(1)=1$. The accuracy rate represents the proportion of samples that are successfully and accurately predicted out of all the samples predicted by the model.

2) Accuracy rate. The accuracy rate, also known as the check accuracy rate. In this paper, whether a listed company is implemented by the stock exchange ST as a measure of whether the company has financial risk, for this dichotomous problem, assuming that “ST” is a positive category, non-“ST” is a negative category, then according to the model sample prediction results and the real label value of the sample there are Sample real label value there are the following four cases: true class (TP), false positive class (FP), true negative class (TN), false negative class (FN), according to the actual situation into the table, you can get the confusion matrix shown in Table 2.

Table 2. Confusion matrix

Real label	Model predict results	
	Positive class (ST)	Negative class (Non ST)
Positive class (ST)	TP	FN
Negative class (Non ST)	FP	TN

Then, based on the above confusion matrix, the accuracy rate can be derived as:

$$\Pr ecision = \frac{TP}{TP + FP} \times 100\% \tag{6}$$

The accuracy rate represents the percentage of all samples that were predicted to be positive cases that were actually positive, and it is also possible to represent the accuracy rate proposed above based on the confusion matrix as:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \tag{7}$$

3) Recall rate. Recall rate, also known as true positive rate. Similarly, the recall rate is calculated by the formula:

$$\operatorname{Re} call = TPR = \frac{TP}{TP + FN} \times 100\% \tag{8}$$

Recall and precision are in a contradictory and unified relationship, if the goal is to increase the precision, the model should make a prediction of a sample as a positive sample only when the "certainty" is higher. In other words, when the threshold for a sample to be positive is higher, it is "more certain". However, setting the threshold too high, i.e., judging a sample to be positive only when the model output probability is very high, may result in incorrect prediction of many samples that are actually positive, leading to a decrease in the recall value of the recall rate. That is, in general, the precision rate and the recall rate are inversely related. In this paper, the cost of incorrectly identifying ST companies as non-ST companies is much larger than the cost of incorrectly identifying non-ST companies as ST companies, and the more listed companies that are actually ST companies are accurately identified, the better, i.e., the higher the ratio of the actual positive class predicted to be the positive class is the better, and therefore the recall rate is also an important model evaluation index.

4) Specificity. Specificity is also known as the true negative rate, and the formula for specificity is as follows:

$$Specificity = \frac{TN}{FP + TN} \times 100\% \tag{9}$$

Specificity indicates the proportion of all samples that are actually in the negative category that are correctly predicted to be in the negative category.

5) F1 value. As the recall and accuracy are in the situation of this and that, in order to better measure the effectiveness of the model, the F-Score method is used to combine the accuracy and recall, which is the weighted summed average of the two as shown in Equation (6) for the precision and Equation (8) for the recall, and the higher the value of the F-Score, the better the performance of the model is:

$$F1\text{-}score = \frac{2}{\frac{1}{\Pr ecision} + \frac{1}{\operatorname{Re} call}} = \frac{2 \times \Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{10}$$

3. Financial risk early warning and decision analysis

3.1. *Financial risk early warning performance*

The Random Forest model is compared with other classical financial risk warning models to explore their risk prediction performance. The risk discrimination effect of the trained random forest model and other models (Logistic model, support vector machine model, XGBoost model, LightGBM model, Stacking model) is tested on the test set, and the probability of financial crisis after two years is obtained for each test set sample, if the probability is greater than or equal to 0.5, it is judged that it will have financial crisis after two years, and if the probability is less than 0.5, it is judged that it will not have financial crisis after two years. The confusion matrix of the discriminant results is shown in Table 3.

As seen in Table 3, all models are able to accurately predict most of the ST and non-ST samples, but obviously Logistic model, Support Vector Machine model, XGBoost model, LightGBM model, and Stacking model are stronger in identifying the non-ST samples, and accurately judged 234, 228, and 236 out of 250 healthy companies, respectively, 225, and 240, but the identification ability of ST samples is relatively weak, only 164, 185, 179, 193, and 203 out of 250 ST enterprises are judged accurately, and 86, 65, 71, 57, and 47 are judged as normal enterprises, respectively, without identifying their potential financial risks. Whereas, the random forest model identified the largest number of healthy firms (245) among non-ST firms and risky firms (243) among ST its firms.

Table 3. The confusion matrix of the test results

		Real value	
		Non ST	ST
Predict value of logistic model	Non ST	234	86
	ST	16	164
Predict value of SVM model	Non ST	228	65
	ST	22	185
Predict value of XGBoost model	Non ST	236	71
	ST	14	179
Predict value of LightGBM model	Non ST	225	57
	ST	25	193
Predict value of Stacking model	Non ST	240	47
	ST	10	203
Predict value of random forest model	Non ST	245	7
	ST	5	243

To further analyze the risk warning effect of the model, this paper calculates the accuracy, precision, recall, specificity, F1-score and AUC values of the random forest model and other models on the test set based on the confusion matrix, and the results are shown in Table 4.

Observing Table 4, it can be found that the random forest model selected in this paper achieves the best performance in accuracy, precision, recall, specificity, F1-score and AUC value, which reaches 98.84%, 98.74%, 96.35%, 99.13%, 98.57% and 0.9666, respectively, and it is clear that the random forest model performs better than the other models.

Table 4. Model warning performance comparison

Model	Accuracy	Precision	Recall	Specificity	F1-score	AUC
Logistic	89.96%	90.51%	68.42%	88.39%	87.15%	0.9083
SVM	88.81%	92.26%	65.97%	94.16%	92.62%	0.8994
XGBoost	88.07%	90.55%	88.46%	85.98%	93.63%	0.9479
LightGBM	93.22%	91.49%	90.35%	94.47%	95.26%	0.9221
Stacking	91.38%	93.21%	84.07%	93.93%	91.76%	0.9418
Random forest	98.84%	98.74%	96.35%	99.13%	98.57%	0.9666

3.2. Financial early warning results

Taking M listed company as the research object, based on the data of M's public annual report from 2019-2023, the analysis is conducted by using the random forest model to determine its financial risk situation and make recommendations for financial decision-making accordingly.

According to the financial risk model constructed in Chapter 2, the corresponding financial index data of Company M are imported into the model, and the model index data of Company M in the past five years are shown in Table 5, in which X1~X15 represent the quick ratio, cash flow ratio, asset-liability ratio, interest earned multiple, accounts receivable turnover ratio, inventory turnover ratio, current asset turnover ratio, total asset turnover ratio, operating profit margin, return on total assets, return on net assets, cost profit margin, sales growth rate, sales profit growth rate, and asset growth rate.

Table 5. Company M financial model index value

Year	X1	X2	X3	X4	X5
2019	1.39	-0.08	63.16	3.24	6.74
2020	1.23	-0.23	75.65	-1.54	5.64
2021	1.21	-0.21	81.23	0.46	9.76
2022	0.42	-0.49	197.84	-25.23	7.43
2023	1.68	-0.22	64.38	17.95	12.06
Year	X6	X7	X8	X9	X10
2019	28.93	3.62	2.85	0.48	2.81
2020	20.42	1.35	1.44	-3.86	-2.74
2021	21.65	1.03	0.93	-2.58	0.04
2022	12.45	0.88	0.71	-129.36	-79.84
2023	10.43	1.54	0.92	79.84	65.48
Year	X11	X12	X13	X14	X15
2019	2.34	0.42	21.26	11.65	16.85
2020	-13.48	-3.48	-52.74	-578.84	31.06
2021	-6.84	-1.96	-19.72	26.33	5.84
2022	0.00	-129.84	-43.35	-3156.84	-53.48
2023	0.00	52.41	-23.84	149.58	-21.51

Substituting the above relevant financial data of Company M from 2019 to 2023 into the random forest model, the evaluation coefficients of each index and the comprehensive evaluation coefficients of each year are calculated from 2019 to 2022 for Company M. The financial risk score values for the years 2018-2023 are shown in Tables 6 to 10.

Table 6. Financial risk index score of Company M in 2019

	Index	Single index evaluation coefficient	Index sort evaluation coefficient	Overall evaluation coefficient
Debt-paying ability	X1	0.95	0.96	0.42
	X2	0.93		
	X3	0.96		
	X4	0.98		
Operating capacity	X5	0.00	0.14	
	X6	0.15		
	X7	0.33		
	X8	0.08		
Profitability	X9	0.78	0.44	
	X10	0.56		
	X11	0.24		
	X12	0.18		
Development capacity	X13	0.46	0.15	
	X14	0.00		
	X15	0.00		

Table 7. Financial risk index score of Company M in 2020

	Index	Single index evaluation coefficient	Index sort evaluation coefficient	Overall evaluation coefficient
Debt-paying ability	X1	0.89	0.95	0.70
	X2	0.95		
	X3	0.98		
	X4	0.96		
Operating capacity	X5	0.56	0.59	
	X6	0.68		
	X7	0.57		
	X8	0.53		
Profitability	X9	1.00	0.52	
	X10	0.38		
	X11	0.35		
	X12	0.33		
Development capacity	X13	0.53	0.72	
	X14	1.00		
	X15	0.63		

Table 8. Financial risk index score of Company M in 2021

	Index	Single index evaluation coefficient	Index sort evaluation coefficient	Overall evaluation coefficient
Debt-paying ability	X1	0.66	0.52	0.50
	X2	0.52		
	X3	0.48		
	X4	0.42		
Operating capacity	X5	0.33	0.39	
	X6	0.47		
	X7	0.36		
	X8	0.40		
Profitability	X9	0.91	0.46	
	X10	0.47		
	X11	0.22		
	X12	0.24		
Development capacity	X13	0.93	0.64	
	X14	0.00		
	X15	1.00		

Table 9. Financial risk index score of Company M in 2022

	Index	Single index evaluation coefficient	Index sort evaluation coefficient	Overall evaluation coefficient
Debt-paying ability	X1	0.55	0.47	0.33
	X2	0.46		
	X3	0.45		
	X4	0.43		
Operating capacity	X5	0.00	0.13	
	X6	0.16		
	X7	0.22		
	X8	0.14		
Profitability	X9	0.76	0.56	
	X10	0.48		
	X11	0.51		
	X12	0.47		
Development capacity	X13	0.46	0.15	
	X14	0.00		
	X15	0.00		

Table 10. Financial risk index score of Company M in 2023

	Index	Single index evaluation coefficient	Index sort evaluation coefficient	Overall evaluation coefficient
Debt-paying ability	X1	0.43	0.51	0.68
	X2	0.49		
	X3	0.57		
	X4	0.55		
Operating capacity	X5	0.53	0.67	
	X6	1.00		
	X7	0.62		
	X8	0.54		
Profitability	X9	1.00	0.70	
	X10	0.54		
	X11	0.56		
	X12	0.68		
Development capacity	X13	0.76	0.83	
	X14	1.00		
	X15	0.74		

By summarizing and organizing the results of financial risk scores in each year, the specific results of the financial risk evaluation coefficients of M Company for 2019-2023 are shown in Table 11. In the financial risk early warning level classification in this paper, the early warning score [0.85,1] corresponds to no alarm, that is, the risk status is safe. [0.7,0.85) corresponds to light alarm, the risk status is sub-safe. [0.5,0.7) corresponds to medium alarm. The risk status is fair. [0.3,0.5) corresponds to Heavy Alert, with a sub-dangerous risk status. [0,0.3) corresponds to huge alarm and the risk status is dangerous. Based on the evaluation coefficient values of each type of financial risk in Table 12, and also combined with the corresponding financial risk early warning level classification criteria, the financial risk early warning level of Company M for 2019-2023 is summarized as shown in Table 12.

As can be seen from Table 12, the financial status of Company M in the past five years shows fluctuations and ups and downs, and generally improves, shifting from a heavy warning level in 2019 to a medium warning level in 2023, and changing the risk status from dangerous to average. However, it is worth noting that during the period 2020-2022, the financial status of Company M decreases from a light alert rating to a heavy alert rating, and the risk status deteriorates from sub-safe to dangerous, indicating that the company's financial decision-making has suffered from a huge error during these three years.

Table 11. Summary results of financial risk evaluation coefficient of Company M (2019-2023)

	2019	2020	2021	2022	2023
Debt-paying ability	0.96	0.95	0.52	0.47	0.51
Operating capacity	0.14	0.59	0.39	0.13	0.67
Profitability	0.44	0.52	0.46	0.56	0.70
Development capacity	0.15	0.72	0.64	0.15	0.83
Warning score	0.42	0.70	0.50	0.33	0.68

Table 12. M company's financial risk warning level from 2019 to 2023

	2019	2020	2021	2022	2023
Debt-paying ability	No	No	Medium	Heavy	Medium
Operating capacity	Severe	Medium	Heavy	Severe	Medium
Profitability	Heavy	Medium	Heavy	Medium	Light
Development capacity	Severe	Light	Medium	Severe	Light
Warning score	Heavy	Light	Medium	Heavy	Medium

3.3. Financial decision-making

Based on the analysis of Company M's financial situation, it can be found that the company's profitability is relatively stable. However, its solvency, operating capacity and development capacity have a greater impact on its financial position, and the development of these three capacities has not been stable, leading to the unstable financial position of Company M in the past five years. Therefore, the following initiatives are proposed with a view to improving its financial situation and assisting its financial decision-making.

1) Optimize capital structure and form diversified financing channels. Company M has a strong reliance on traditional indirect financing channels mainly based on bank loans, and debt financing brings potential risks while bringing economic benefits to the company. The singularity of financing channels can easily lead to irrational debt structure of the enterprise, reduce the efficiency of capital utilization, and lead to a more concentrated financial risk. In the enterprise before the financing, you can commission a professional organization of the various channels of the cost and risk of each fund and its return on a multi-faceted and comprehensive analysis, optimize the ratio of equity capital and debt capital, according to the actual changes in the market as well as the enterprise's own situation, constantly optimize the adjustment, the establishment of the financing structure in line with the development of their own, and at the same time in the process of fund-raising should be scientifically measured to detect the benefits and risks.

2) Optimize manpower management and improve the company's operating efficiency. In the solution of manpower risk, on the one hand, a perfect management system should be established, and company managers should constantly go to the grassroots, observe the relevant state of the company's employees, and adjust the company's human resources related system with the actual situation and the state of the employees, to prevent the company from disconnecting because of the theory and the actual inability to connect. On the other hand, to improve the company's basic security and staff management system, the company should increase the budget for staff remuneration, and continuously improve the company's staff remuneration management mechanism, and formulate a reasonable range of salary increase. Clearly defined employee assessment and promotion mechanisms should be put in place to enhance employee motivation, vitality and efficiency, thereby improving the company's overall operational efficiency.

3) Increase investment in R&D to realize high-quality and sustainable development. Company M's average R&D investment level is slightly lower than the industry average, so the company should increase investment in R&D and innovation, improve the machinery and equipment used in R&D, attract and select excellent R&D talents, and cooperate with universities in related fields. By strengthening R&D to improve the development capability of Company M, it will realize the long-term sustainable development of the company.

4. Conclusion

The article chooses the random forest algorithm to warn the financial risk situation of the enterprise, and constructs the financial risk warning model based on random forest. After analyzing the financial risk situation of the enterprise, it puts forward corresponding financial decision-making suggestions for the enterprise to improve its financial status.

In the financial risk early warning performance experiments, the random forest model in this paper shows the best results in accuracy, precision, recall, specificity, F1-score and AUC value, and achieves 98.84%, 98.74%, 96.35%, 99.13%, 98.57% and 0.9666 respectively.

Taking Company M as an example study, its financial risk warning scores for 2019-2023 are 0.40, 0.70, 0.50, 0.33, and 0.68, which correspond to the risk statuses of dangerous, sub-safe, fair, dangerous, and fair, respectively. The company's overall financial risk profile has improved, shifting from a heavy alert stage to a medium alert stage, but remains generally volatile and the financial position of Company M is in a state of continuous deterioration during the period 2020-2022. In view of the warning value of each dimension of Company M, we propose feasible financial decision-making suggestions for its solvency, operating capacity and development capacity respectively.

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