Enhanced Financial Performance Classification Using an Improved ID3 Algorithm with Decision Coherence

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The evaluation of enterprise financial performance is of great significance to investors, creditors and managers. Through the performance evaluation, we can judge the comprehensive strength of the enterprise and then take corresponding countermeasures. The study mainly quantifies the three financial performance factors of profitability, operating ability and solvency in segments. At the same time, variables are constructed for the statement subjects other than the performance factors. In addition, an iterative binary tree three-generation algorithm model based on decision coordination degree is introduced to classify and measure the financial performance of enterprises. The study used 528 financial statements from a manufacturing industry and employed a mean imputation strategy and Z-score standardization method for preprocessing. Ultimately, 19 variables were selected for financial performance evaluation. Using the model's construction time, classification accuracy, and area under the curve as evaluation indicators, verify the performance advantages of the proposed model in financial performance evaluation. The results show that when the sample size is 300, the construction time of the improved model is only 120ms, and out of 50 financial statements, only 7 financial statements with "poor" profitability are misclassified as "excellent". The average classification accuracy of the improved model is 87.57% and the average area under the curve is 0.8369. In the solvency test, the average classification accuracy of the improved model in the solvency indicator is 84.21%. In the test of operating capacity indicators, the mean value of classification accuracy of the improved model proposed by the Institute in operating capacity indicators is as high as 85.16%. The results show that the classification model proposed by the Institute has the least construction time and the highest classification accuracy. It provides reliable technical support for the rational allocation of corporate asset structure and the effective decision-making of financial institutions.

Povzetek: V članku je predstavljen izboljšan algoritem ID3 za klasifikacijo finančne uspešnosti, kar poveča kvaliteto klasifikacij in zmanjša čas izgradnje modela, ter tako izboljša zanesljivost poslovnega odločanja.

1 Introduction

Enterprise financial performance evaluation refers to the process by which enterprises assess the performance of operators and the effectiveness of capital operations. Generally speaking, performance evaluation is mainly carried out by referring to the industry standard values pre-measured by the national government and adopting certain mathematical means and scientific principles to construct the index system. Then, a comprehensive qualitative and quantitative comparative analysis of the operator performance and capital operation efficiency of the enterprise within a certain period of time is carried out, so as to make a more objective and accurate judgement [1-2]. At present, the construction of the evaluation index system is mainly based on the performance factors under the three ability indicators of profitability, debt servicing and operation. At the same time, various evaluation methods or models are used to rank the performance of enterprises, and then the contribution of the three capability indicators in the financial performance of enterprises is analysed [3]. However, most of the indicators in this type of research are biased towards the development of the enterprise itself and involve only a small number of financial statement subjects. For investors and creditors, the characteristics of each subject of an enterprise's financial statements reflect the asset structure of the whole enterprise, so it is necessary to focus on the performance measurement of financial statements [4]. Based on this, the study takes profitability, operating capacity, and solvency as the three financial performance evaluation contents, and quantifies the performance factors under them in segments. Meanwhile, the comparative analysis and factor analysis methods in financial statement analysis are used as references to construct variables for statement subjects other than performance factors. In addition, the Iterative Dichotomiser 3 (ID3) model, which is an iterative binary tree three-generation algorithm based on decision coordination, is introduced to classify the financial performance of the firms. The contribution of the study lies in the practical integration of financial statement subjects and the construction of variables for statement subjects other than the performance factors, which is conducive to improving the understanding of the firms by the relevant stakeholders. At the same time, the study improves on the ID3 model, which helps to reduce the computational cost.

The research includes four main parts, the first part provides an overview of corporate performance measurement methods and ID3 algorithms, and the second part proposes a method to measure corporate financial performance based on the ID3 model of decision coordination degree. The third part takes a company as an example to validate the proposed measurement scheme of the study. The fourth part discusses the results of the study and presents the future outlook.

2 Literature review

Corporate financial performance is one of the most important concerns of many stakeholders, and a large number of measurement methods are available. For the establishment and measurement of corporate financial performance indicators, scholars such as Abdel-Basset proposed a multi-objective decision-making model, which is mainly based on neutral hierarchical analysis, optimisation methods, and similarity ranking of ideal solutions. The results show that in the assessment of the top ten Egyptian steel companies based on specific financial ratios, the resulting company rankings are basically the same [5]. In order to analyse the financial performance of the ICT sector in Turkey, Aldalou and Perçin proposed a fuzzy ID3 algorithm. In order to avoid subjectivity in the decision-making process, weights were assigned to the evaluation criteria and then the alternatives were evaluated and ranked using the Fourier method. The results show that the proposed model of the study is significantly better than the rest of the models [6]. In order to assess the financial performance and service quality of low-cost airlines, Durmaz and other researchers evaluated six low-cost centres on the basis of seven service quality and ten financial attributes. Due to the multidimensional nature of the performance phenomenon, the team introduced an integrated multi-criteria decision-making approach. The results showed that an increase in service quality had a negative impact on financial performance and the applicability of the proposed methodology was confirmed [7]. In order to analyse the impact of government size, balanced funding and economic growth on the financial performance of Indonesian regions, Lubis and other researchers used a simple regression analysis model for data analysis and performance measurement. The results show that government size has a positive effect on regional financial performance, balanced fund has a negative effect on regional financial performance, and economic growth has a negative effect on regional financial effectiveness [8].

ID3 algorithm is widely used in detection and measurement tasks in various fields of society. In order to enable big data inspection of healthcare information to identify hidden patterns that predict diseases, researchers such as Agarwal have proposed an improved ID3 algorithm. The algorithm is based on a simple model of decision tree algorithm which reduces time complexity and complex computation by applying entropy calculation and arithmetic operations for obtaining information. The results showed that the method achieved excellent results in the testing of confusion matrix [9]. Li and other scholars found that intrusion detection system plays an important role in network security, so a hybrid intrusion detection method using adaptive synthesis and decision tree based on ID3 algorithm was proposed. The method uses ID3 algorithm to build a decision tree model. The results show that the combined model designed by the team has higher accuracy and lower false alarm rate, which makes it more suitable for intrusion detection tasks [10]. In order to achieve more efficient early detection of breast cancer, Idris and Ismail introduced the Bagging fuzzy ID3 algorithm. This method combines fuzzy system, ID3 algorithm and bagging technique. The results showed that the adopted bagging technique improved the generalisation ability and reduced the overfitting phenomenon. At the same time, the method effectively improves the classification accuracy of breast cancer [11]. Harti and other researchers introduced the ID3 algorithm for decision tree creation in order to make predictions about potential trade disasters and tsunamis in waters. The experimental results showed that ID3 model was able to achieve accurate classification of the risk of sea level with 88% accuracy [12]. Hameed introduced ID3 classifier algorithm for the problem of diagnosis of gestational diabetes mellitus. Also, the study used Pima Indians diabetes dataset for algorithm performance validation. The results show that the model has a classification accuracy of 94% in the confusion matrix test [13].

In summary, researchers at home and abroad have proposed a variety of methods for the financial performance measurement of enterprises, and have achieved certain results. However, few scholars have adopted the decision tree algorithm to solve such problems. Therefore, the study introduces the improved ID3 algorithm to analyse the financial statements of enterprises. In order to bring certain ideas and application value for the performance evaluation mechanism of enterprises.

3 Fusing iterative binary tree three-generation algorithms with decision coordination for performance measurement

The study firstly selects profitability index, solvency index and operating capacity index as the target variables for segmented quantitative treatment. Then, financial statement subjects are used to construct relevant financial variables for constructing the classification model of enterprise performance evaluation. Subsequently, the study introduces the ID3 algorithm and describes its tree-building steps. Finally, the algorithm was improved to enhance its performance.

3.1 Variable construction for corporate financial performance measurement

Generally speaking, researchers generally tend to adopt the three major capability indicators of profitability, debt servicing and operation as the basis for the construction of performance factors in the selection of variables for the evaluation of corporate financial performance. At the same time, some scholars have also incorporated development ability indexes or non-financial indexes on this basis, and ranked the performance of enterprises through a variety of methods or models [14-15]. Based on this, the study firstly identifies profitability indicators, solvency indicators and operating capacity indicators as the dependent variables for segmented quantitative treatment. Subsequently, relevant financial variables were constructed using financial statement subjects for the classification model construction of enterprise performance evaluation. Among them, the profitability indicator, operating capacity indicator and solvency indicator as well as the performance factor situation are shown in Figure 1.

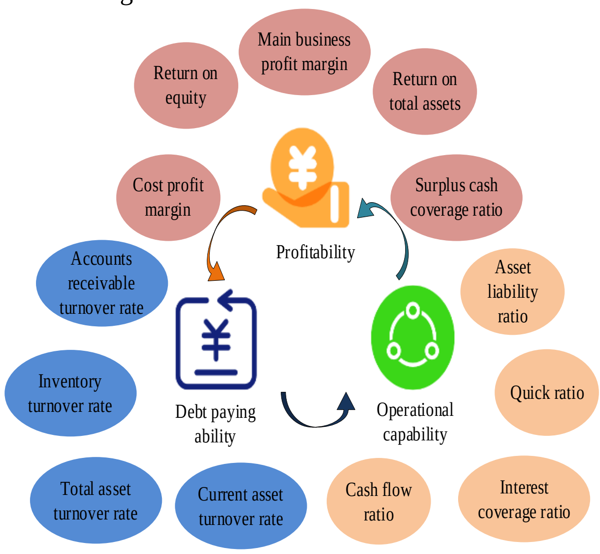

Figure 1: Three ability indicators and performance factors.

In Figure 1, corporate profit is the focus of attention of all stakeholders, and the profitability behind it is a direct reflection of an enterprise's ability to make a profit in a specific period of time. This indicator is crucial for internal management, creditors and investors. Profitability not only reflects the problems that may exist in the operation and management process of the enterprise, but also directly relates to the enterprise's debt repayment ability. Once an enterprise faces debt problems, especially long-term debt, creditors and investors will often rejudge the creditworthiness of the enterprise by assessing its solvency, and then decide whether to borrow or invest, and the amount of investment or borrowing. The solvency of an enterprise refers to its ability to use its assets and its own earnings to pay off its debts. This capacity is directly related to the ability of the enterprise to successfully repay its short-term and long-term debts, or to meet its debt obligations through cash payments [16]. In addition, the operating capacity reflects the efficiency, effectiveness and profitability of the operating assets of the enterprise, which reflects the problems that may exist in the process of operation of the enterprise, and can be a useful complement to the indicators of profitability and solvency. This indicator can help enterprises to assess their operating conditions more comprehensively, so as to formulate more scientific and reasonable business strategies [17]. In order to quantify the three indicators and realise the dichotomy problem, the study quantifies profitability, operating capacity and solvency into corresponding grades with reference to the performance classification of annual national enterprise performance standard values. Let P_{ij} be a performance factor, and p_{ij} denote the value of the corresponding factor. Then a threshold value h is set to divide the performance factor into two ends, and the quantitative definition is shown in Equation (1).

$$P_{ij} = \begin{cases} 1, & p_{ij} > h \\ 0 & p_{ij} \le h \end{cases} \tag{1}$$

After quantitatively taking the values of the performance factors of the three enterprise performance evaluation indexes, it then sums them up and divides the three abilities into two levels of strength and weakness respectively. In the segmented quantification of profitability indicators, the threshold value is taken as the industry good value, and the values of different performance factors are shown in Figure 2.

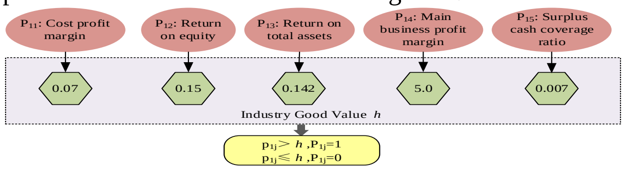

Figure 2: Performance factor values for profitability indicators.

The score for the profitability indicator is calculated as shown in Equation (2).

$$F_1 = P_{11} + P_{12} + P_{13} + P_{14} + P_{15} \tag{2}$$

In Equation (2), F_1 represents the total score of the profitability indicator. In order to realise the binary classification problem, the study further treats the score as a 0-1 variable, which is calculated as shown in Equation (3).

$$y = \begin{cases} 1, & 3 \le F_1 < 5 \\ 0 & 0 \le F_1 < 3 \end{cases} \tag{3}$$

In Equation (3), y represents the value of the profitability indicator, and a value of 1 indicates that the enterprise has a strong ability to make profits, and vice versa. The segmented quantification process of solvency and operating capacity indicators is similar to that of profitability, and the values of their performance factors are shown in Figure 3.

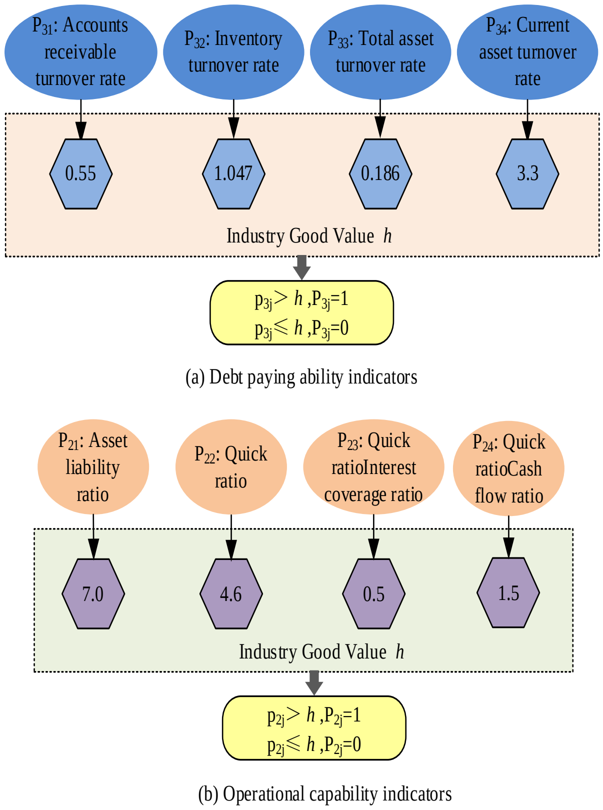

Figure 3: Value of performance factors for debt repayment and operational capacity indicators.

After completing the quantitative processing of indicators, the construction of variables for financial performance evaluation is then carried out. The study mainly starts from the perspective of enterprise operators, investors and creditors, and constructs commonly used financial indicators and non-usable financial indicators through the relationship between the sections of financial statements. Among them, financial statements can comprehensively reflect the enterprise's financial position, operating results and cash flow. Financial statement analysis is to obtain information from the statement that meets the analysis purpose of the statement user. Methods of analysis include comparative analysis and factor analysis [18]. Comparative analysis can be divided into financial ratios, structural percentages and aggregate indicators, while factor analysis mainly breaks down the whole into parts for analysis.

3.2 Improved ID3 algorithm for fusing decision coordination degrees

The study constructed the corresponding variables through the segmented quantitative treatment of the three financial capability indicators. The study next introduced Variance Inflation Factor (VIF) analysis to screen the constructed variables and perform classification model construction. Among other things, VIF characterises the degree of existence of multicollinearity between independent variables. In linear regression analysis, the Variance Inflation Factor is calculated as shown in Equation (4).

$$VIF = (1 - R^2)^{-1} \tag{4}$$

In Equation (4), R^2 denotes the decidable coefficient of multiple independent variables assisted regression, and the larger its value, the larger the variance inflation factor, and the more serious the multicollinearity between the variables. VIF can judge whether there is multicollinearity between the variables, and each independent variable corresponds to a variance inflation factor. In order to achieve the performance measurement of corporate financial capability, the study introduced the ID3 algorithm for classification model construction. The study takes the relationship between climate and suitable outdoor sports as an example, and uses the ID3 algorithm to construct a decision tree [19]. The target of the assessment is whether it is suitable for outdoor sports in a specific climate, and the class attributes contain positive and negative examples. The initial split has four attributes to be selected, and its tree structure is shown in Figure 4.

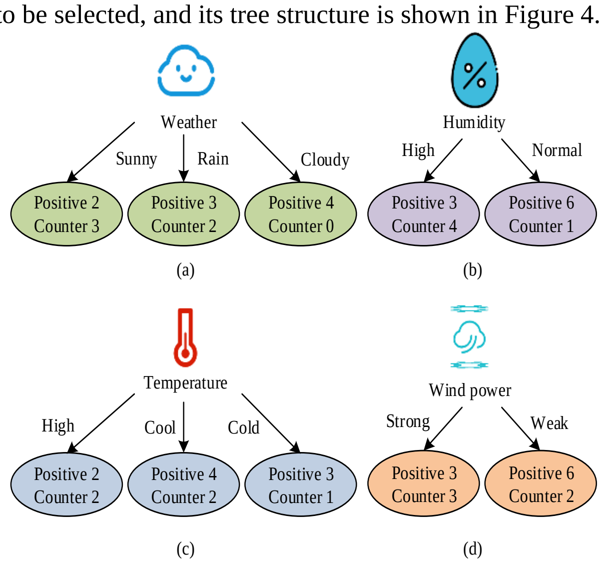

Figure 4: The initial split tree structure.

In Figure 4(a), the split attribute is weather, and the corresponding number of positive and negative instances of leaf nodes are (2, 3), (3, 2), and (4, 0), respectively. When the weather is "sunny", the positive and negative examples are (2, 3), and the information entropy is calculated as shown in Equation (5).

$$I(2,3) = -\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5} = 0.9710\text{bits} \tag{5}$$

When the weather is "rain", the positive and negative examples are (3, 2), and the information entropy is calculated as shown in Equation (6).

$$I(3,2) = -\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5} = 0.9710\text{bits} \tag{6}$$

When the weather is "cloudy", the positive and negative examples are (4, 0), and the information entropy is calculated as shown in Equation (7).

$$I(4,0) = 0\text{bits} \tag{7}$$

The splitting attribute of Figure 4(b) is humidity, and when the humidity is high, the positive and negative examples are (3, 4), and the information entropy is calculated as shown in Equation (8).

$$I(3,4) = -\frac{3}{7}\log_2\frac{3}{7} - \frac{4}{7}\log_2\frac{4}{7} = 0.9852\text{bits} \tag{8}$$

When the humidity is normal, the positive and negative examples are (6, 1) and the information entropy is calculated as shown in Equation (9).

$$I(6,1) = -\frac{6}{7}\log_2\frac{6}{7} - \frac{1}{7}\log_2\frac{1}{7} = 0.5917\text{bits} \tag{9}$$

The splitting property of Figure 4(c) is temperature, and when the temperature is "hot", the positive and negative examples are (2, 2), and the information entropy is shown in Equation (10).

$$I(2,2) = 1\text{bits} \tag{10}$$

When the temperature is "cool", the positive and negative examples are (4, 2), and the information entropy is shown in Equation (11).

$$I(4,2) = -\frac{4}{6}\log_2\frac{4}{6} - \frac{2}{6}\log_2\frac{2}{6} = 0.9183\text{bits} \tag{11}$$

When the temperature is "cold", the positive and negative examples are (3, 1), and the information entropy is shown in Equation (12).

$$I(3,1) = -\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4} = 0.8113\text{bits} \tag{12}$$

The splitting property of Figure 4(d) is wind force, and the information entropy is shown in Equation (13) when the wind force is strong.

$$I(3,3) = 1\text{bits} \tag{13}$$

When the wind is weak, the information entropy is shown in Equation (14).

$$I(6,2) = -\frac{6}{8}\log_2\frac{6}{8} - \frac{2}{8}\log_2\frac{2}{8} = 0.8113\text{bits} \tag{14}$$

Through calculation, the study selects "weather" as the root node, and humidity and wind as the split nodes, and then constructs a decision tree. The decision tree classification model based on ID3 algorithm is shown in Figure 5.

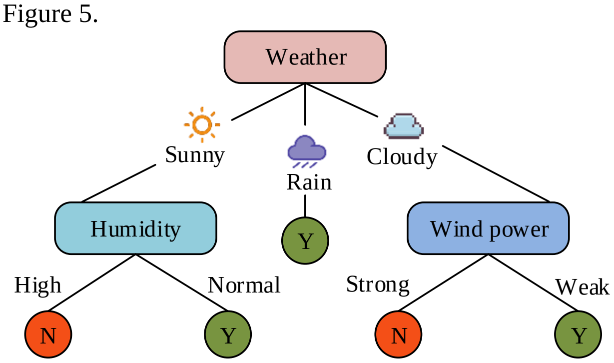

Figure 5: Decision tree classification model based on ID3 algorithm.

The traditional ID3 algorithm is computationally intensive and has a large number of repetitive operations. Since the algorithm formulae contain logarithmic functions, the function library needs to be called each time a logarithmic operation is performed, thus increasing the computation time [20]. To address this problem, the study introduces the decision coordination degree to optimise the ID3 algorithm in order to reduce the computational cost and improve the speed of tree building. Decision coordination degree occupies an important position in rough set theory, which reflects the coordination probability between conditions by randomly extracting specific rules in the decision-making system and evaluating the degree of consistency between the antecedent and antecedent conditions of such rules. Through the coordination probability, the degree of dependence of specific condition attributes can be inferred. Therefore, the degree of decision coordination is an important consideration in the split attribute selection process when performing decision tree construction. Suppose a decision system contains ordered quaternions, which are represented as shown in Equation (15).

$$S = (U, A, V, f) \tag{15}$$

In Equation (15), U denotes the full domain; A denotes the set of attributes, and V denotes the set of attribute values. f denotes the information function. The attribute values are equivalent to the intersection of the condition and category attribute sets, which are represented as shown in Equation (16).

$$A = C \cup D \tag{16}$$

In Equation (16), C is a conditional tree set and D is a set of category attributes. The □ notation $X \subseteq C$ is a subset of attributes and $IND(X) \subseteq U \times U$ is a conditional attribute, then the representation of decision coordination is shown in Equation (17).

$$CON(X \to D) \subseteq |X \cup U| / |X| \tag{17}$$

In Equation (17), $|X|$ denotes the base of the condition attribute, and $|X \cup U| / |X|$ denotes the probability of taking out two rules from the decision system with the same antecedent and subsequent conditions, which reflects the dependence of D on X. The higher the value, the higher the probability that D is predicted by X. $CON(X \to D)$ denotes the coordination degree of any subset $X \to D$ in C. The larger the value, the greater the dependence of D on X, and the greater the probability that D is predicted from X. After the introduction of decision coordination degree in ID3 algorithm, then the split attribute selection can be carried out through the decision coordination degree, and the specific process is shown in Figure 6.

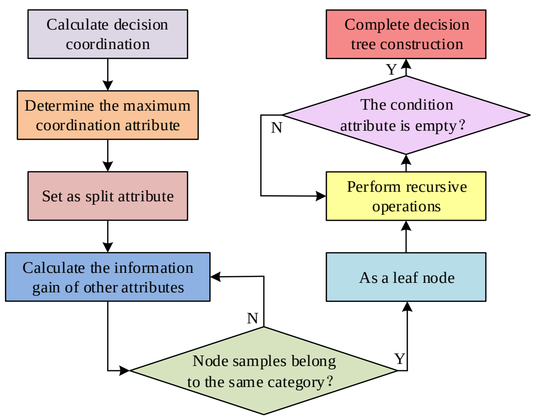

Figure 6: Improved ID3 algorithm process based on decision coordination degree.

After introducing the concept of decision coordination in the ID3 algorithm, split attributes can be selected based on decision coordination, and the specific operation process calculates the decision coordination of all attributes in the sample dataset. If the maximum value differs significantly from other values in the calculated decision coordination degree, and the attribute corresponding to the maximum value is unique, then the attribute with the highest coordination degree is selected as the splitting attribute. Due to the presence of many attributes in the sample dataset, it is inevitable that the two or more values with the highest calculated decision coordination degree may be extremely close or even equal. In this case, relying solely on decision coordination degree is no longer sufficient to select splitting attributes. At this point, it is necessary to separately calculate the information gain of these attributes whose decision coordination is close to the maximum value, and select the attribute with the highest information gain as the splitting attribute. If the samples in each split node belong to the same category, they can be used as leaf nodes and the decision tree construction is completed. Otherwise, recursive operations are used until the set of conditional attributes is empty, or until all samples in any node are of the same class, and finally a decision tree is constructed. The research adopts the ID3 algorithm based on decision trees to construct decision trees, and calculates the decision coordination degree of various conditional attributes. Taking the attribute "weather" as an example, the calculation is shown in Equation (18).

$$CON(R_1 \to D) = \frac{2^2+4^2+3^2+3^2+2^2}{5^2+4^2+5^2} = 0.6364 \quad (18)$$

In Equation (18), R_1 represents weather, and the denominators represent the square of the number of samples when the attribute "weather" has values of "sunny", "cloudy", and "rainy". The numerator represents the square of the number of samples for each classification corresponding to each attribute value. The calculation results of the decision coordination degree for the other three conditional attributes are shown in Equation (19).

$$\begin{cases} CON(R_2 \to D) = 0.6327 \\ CON(R_3 \to D) = 0.5589 \\ CON(R_4 \to D) = 0.58 \end{cases} \quad (19)$$

From the results, it can be seen that the decision coordination between attributes "weather" and "humidity" is the highest, and the difference is less than 0.01. Therefore, we will continue to compare the information gain of these two attributes. Due to the greater information gain of weather, "weather" is selected as the splitting attribute. Next, recursive operations are performed on each branch node based on an improved algorithm to construct a complete decision tree.

4 Analysis of financial performance measurement based on improved ID3 algorithm

The study takes a manufacturing company as an example of financial performance measurement. Firstly, variance-inflated factor analysis is used to derive 19 measurement variables. Then the building performance of the improved ID3 algorithm is analysed. Finally, four common classification models are used to compare the measurement performance with the proposed improved model of the study, and the measurement performance advantages of the improved ID3 model are investigated.

4.1 Performance analysis of the improved ID3 model

The data used for the study are financial statements of a manufacturing industry collected by a commercial bank between 2020 and 2022, totalling 528. These financial statements went through a rigorous auditing process and were unqualified. After screening and elimination, the study removed irrelevant variables with 0 values or null values that accounted for more than or equal to 9% of the original sample data, and finally retained 41 key candidate variables. For the null values in the remaining data, a mean-filling strategy was adopted to ensure data integrity. Meanwhile, in order to further eliminate the discrepancies between data direction and magnitude, the study adopted the Z-score normalisation method. In the training and testing phase of the model, the experiment strictly follows the ten-fold cross-validation method to ensure the objectivity and accuracy of the experimental results. The study began with a stepwise analysis using variance inflation factors, where each of the 41 variables was used as the dependent variable and the rest as independent variables, and the process was repeated in a circular manner until all variables were tested. By using SPSS 19.0 software, the final results obtained are shown in Table 1. From Table 1, it can be seen that the VIF values of all 18 variables are less than 5 and the tolerance is greater than 0. For further validation, the study repeated the test using 1 of the variables as the independent variable and the remaining variables as the dependent variable. The result of the test shows that the VIF value of the variable total assets growth rate is always greater than 0 and less than 5 with a tolerance close to 1. Therefore, the variable is retained.

Table 1: Results of variance inflation factor analysis.

Final variable	Tolerance	VIF
Accounts receivable to current assets ratio	0.624	1.527
Leverage ratio	0.983	1.025
Monetary capital to current assets ratio	0.627	1.482

Long term asset to long-term capital ratio	0.897	1.105
Accounts payable to current liabilities ratio	0.875	1.158
Inventory to current assets ratio	0.753	1.276
Current liabilities to current assets ratio	0.527	1.865
Short term debt to total debt ratio	0.746	1.127
Ratio of fixed assets to non current assets	0.887	1.138
Operating liabilities to operating assets ratio	0.869	1.169
Cash ratio	0.536	1.769
Current ratio	0.968	1.057
Operating cash to net flow income ratio	0.956	1.068
Cost cash flow ratio	0.262	3.983
Revenue growth rate	0.269	4.124
Rate of capital accumulation	0.946	1.017
Main business income	0.769	1.327
Operating profit growth rate	0.473	1.628
Total asset growth rate	Dependent variable	

The study then proceeded to evaluate the proposed model by using the unimproved ID3 model and Classification and Regression Tree (CART) model with which the tree building time was compared. Among them, CART model is a decision tree learning algorithm that is applicable to both classification and regression problems. It mainly uses Gini coefficient to select features for node splitting, or uses square error minimization to select split features. To ensure the accuracy of the experiments, the study divided all the financial statement samples into 5 groups with sample sizes of 100, 200, 300, 400, and 500 each group was run 20 times and the average was taken as the final result. The building time of each algorithm is shown in Figure 7. From Figure 7, it can be seen that the tree building time of each model increases gradually as the number of samples increases. At the same time, it can be seen that the tree building times of the proposed models are lower than the remaining two algorithms. Among them, when the number of samples is 300, the tree building time of the improved ID3 model is 120ms, which is reduced by 105 ms and 43 ms compared with the unimproved ID3 model and the CART model, respectively, indicating that the improved ID3 model effectively reduces the computational cost and improves the tree building speed.

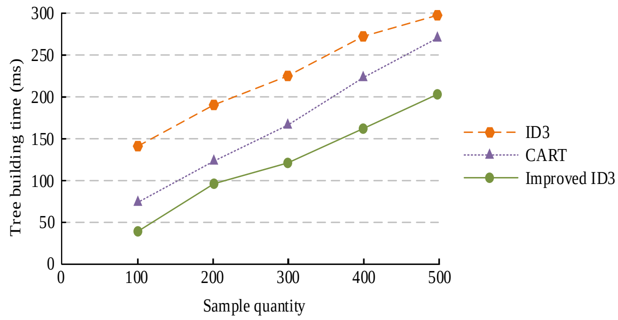

Figure 7: Tree building time for each algorithm.

4.2 Analysis of the results of financial performance measurement for each indicator

The study takes profitability, solvency, and operating capacity indicators of financial performance measurement as dependent variables, and 19 variables as independent variables, and constructs a classification model through the improved ID3 algorithm. The evaluation indexes of the model include accuracy rate and Area Under Curve (AUC) index. Accuracy is the ratio of the number of correctly predicted samples by a classification model to the total number of samples. AUC is an indicator used to evaluate the performance of binary classification models, with values ranging from 0 to 1. The closer it is to 1, the better the model performance and the better it can distinguish between positive and negative samples. The test results of the improved ID3 algorithm on profitability, solvency, and operating capacity indicators are shown in Figure as can be seen from Figure 8(a), out of the 50 financial statements, only 7 financial statements with "poor" profitability are misclassified as "excellent", and the rest of the statements are correctly classified. From Figure 8(b), only 6 statements with "poor" solvency were misclassified. From Figure 8(c), only 8 statements with "poor" operating ability are misclassified as "excellent", and the overall classification accuracy of the model is as high as 86%. Figure 8(d) shows that the AUC values of each index are as high as 0.8439, 0.8697, and 0.8384, indicating that the classification model based on the improved ID3 algorithm has an excellent classification effect.

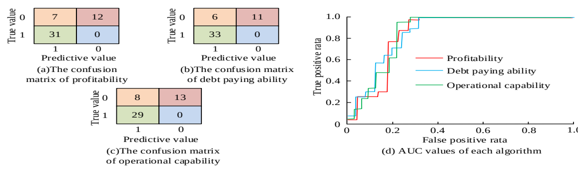

Figure 8: Confusion matrix of various indicators and AUC test results.

Further conduct 8 financial performance evaluations on 50 financial statements and perform statistical tests on the evaluation results. The statistical significance analysis results of the accuracy and misjudgment rates of different financial performance indicators are shown in Table 2. According to Table 2, the differences in accuracy and misjudgment rates of profitability, debt paying ability, and operational ability indicators are statistically significant (P < 0.001).

Table 2: Statistical significance analysis results of accuracy and misjudgment rates of different financial performance indicators.

/	Profitability	Debt paying ability	Operational capability
Accuracy rate	85.29±1.33	86.31±1.41	86.02±1.68
Misjudgment rate	14.63±1.62	13.85±1.32	15.33±1.28
t	238.3764	265.2771	236.6664
P value	0.0000	0.0000	0.0000

To further validate the effectiveness of the improved ID3 model, the study further used Logitic regression model, Support Vector Machine (SVM) model, the basic ID3 model, and the plain Bayesian model with which to compare the performance. Logistic regression is a classic statistical method used to solve binary classification problems. It maps the linear combination of input features to a probability value between 0 and 1 through a logical function, and then performs classification. SVM is a powerful supervised learning algorithm used for classification and regression analysis. It classifies by searching for hyperplanes that can maximize the boundaries between categories. Naive Bayes is a classification algorithm based on Bayes' theorem and independent assumption of feature conditions, which performs well in handling multi classification problems. A total of 10 tests were conducted to ensure that the results were enhanced and convincing. In the test of profitability metrics, the accuracy and AUC values of different models are shown in Figure 9. From Figure 9(a), it can be seen that the classification accuracy of the improved ID3 model is higher than 85% in all 10 tests, and its mean value is as high as 87.57%. The classification accuracy of the plain Bayesian model ranks second, and its average classification accuracy is 80.43%. And the accuracy mean values of ID3 model, SVM model and Logitic regression model are significantly inferior to the improved ID3 model. As can be seen from Figure 9(b), the Improved ID3 model has the highest AUC value, which is as high as 0.8369 on average. Meanwhile, the SVM model corresponds to a lower AUC value, which indicates that the model is less sensitive to the sample categories. The Logistic regression model, on the other hand, has the lowest AUC value and is the worst in classifying profitability indicators. The effectiveness of the improved ID3 model is illustrated.

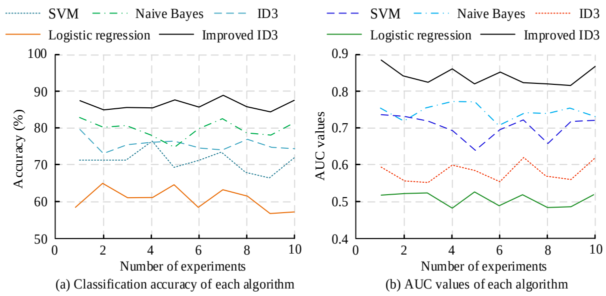

Figure 9: The accuracy and AUC value of profitability indicators.

In the test of solvency index, the accuracy and AUC values of different models are shown in Figure 10. From Figure 10(a), it can be seen that the mean value of the classification accuracy of the improved ID3 model in the solvency indicator is as high as 84.21%, which is significantly better than the rest of the models. the mean value of the accuracy of the SVM model is only 75.64%, while the Logitic regression model has the lowest accuracy of 63.41%. From Figure 10(b), the mean value of the AUC value of the improved ID3 model is as high as 0.8814, which is an increase of 0.1274 compared with the plain Bayesian model. it shows that the improved ID3 model is able to accurately measure the debt servicing capacity.

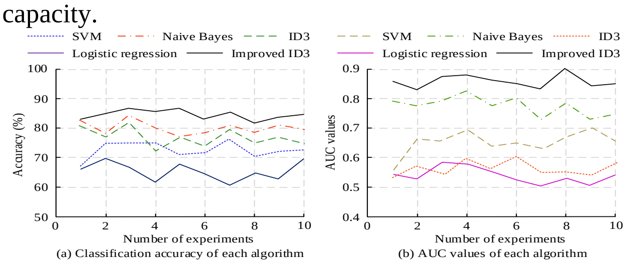

Figure 10: The accuracy and AUC value of debt paying ability indicators.

The accuracy and AUC values of each model in the test of operating capacity indicators are shown in Figure 11. As can be seen from Figure 11(a), the mean accuracy of the classification of the improved ID3 model in the operational capacity indicator is as high as 85.16%, and the highest accuracy reaches 88.01%. Compared with the unimproved ID3 model, its average accuracy rate is improved by 6.28%. Figure 11(b) shows that compared with the other four models, the improved ID3 model has the highest AUC value of 0.8514, the plain Bayesian model has the second highest AUC value of 0.7349, and the logistic regression model has the lowest AUC value of 0.5639, which demonstrates that the improved ID3 model is able to accurately determine the operating capacity of enterprises.

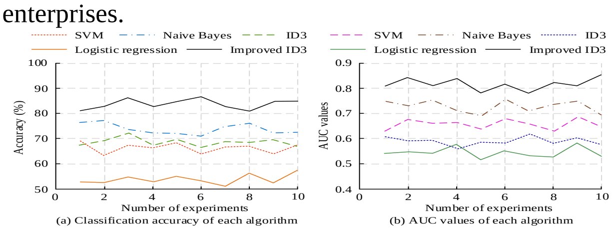

Figure 11: The accuracy and AUC value of operational capability indicators.

5 Discussion

Regarding the research, the ID3 algorithm based on decision coordination improvement is adopted for financial performance evaluation and analysis. The results showed that when the sample size was 300, the construction time of the improved ID3 model was 120ms, which was reduced by 105ms and 43ms respectively compared to the unimproved ID3 model and CART model. The improved ID3 model effectively reduces computational costs and enhances tree building speed. The reason is that traditional ID3 algorithms may face problems such as unreasonable or redundant selection of decision nodes when constructing decision trees, resulting in overly complex tree structures and high computational costs. The improved ID3 algorithm optimizes decision coordination, selects partition attributes and node order more effectively, reduces unnecessary decision node generation, and thus reduces the time consumption of building trees. At the same time, the classification accuracy of the improved ID3 model is higher than 85%, and its average is as high as 87.57%. The Naive Bayes model ranks second in classification accuracy, with an average classification accuracy of 80.43%. The average accuracy of ID3 model, SVM model, and Logistic regression model is significantly lower than that of the improved ID3 model. The AUC value of the improved ID3 model is the highest, with an average of 0.8369, significantly higher than other models. The reason is that compared to logistic regression and naive Bayes models, the improved ID3 algorithm can better handle nonlinear relationships and complex decision boundaries, which is particularly important in complex financial data. In addition, the ID3 algorithm itself has good interpretability, and the improved algorithm retains this advantage while further enhancing its understanding and interpretability of the decision-making process through improved decision coordination. However, traditional ID3 algorithms may be prone to overfitting when faced with a large number of features or imbalanced data, and are sensitive to noisy data. The Naive Bayes model assumes that features are independent of each other, which often does not hold true in actual financial data, resulting in lower classification accuracy. The SVM model takes a long time to train on large-scale datasets and is sensitive to parameter tuning and kernel function selection. The logistic regression model has poor modeling ability for nonlinear data. Liu C and other scholars proposed an improved ID3 algorithm based on variable precision neighborhood rough sets, and the results showed that the accuracy of this method was greatly improved compared to traditional ID3 algorithms, which is similar to the research results [21]. But the ID3 algorithm improved through decision coordination has higher accuracy.

6 Conclusion

Currently, the performance evaluation of enterprises has become the object of focus for the relevant stakeholders of enterprises. Based on this, the study introduces the ID3 model based on the degree of decision coordination and applies it to the measurement of corporate financial performance. The results show that the construction time of each model increases gradually with the increase of the sample size. At the same time, it can be seen that the building times of the proposed models under study are all lower than the remaining two algorithms. Out of 50 financial statements, only 6 statements with "poor" solvency were misclassified. Meanwhile, only 8 statements with "poor" operating capacity were misclassified as "excellent", giving the model an overall classification accuracy of 86%. The AUC values of the proposed model are as high as 0.8439, 0.8697, and 0.8384, respectively, and the classification accuracies of the improved ID3 model are higher than 85% in the profitability indexes, and the mean value is as high as 87.57%. The classification accuracy of the plain Bayesian model was ranked second, and its average classification accuracy was 80.43%. The mean accuracy of ID3 model, SVM model and Logitic regression model are significantly inferior to the improved ID3 model. In the measurement of solvency and operating capacity indicators, the mean values of AUC values of the improved ID3 model are as high as 0.8814 and 0.8514, respectively, which are significantly better than the remaining models. This indicates that the ID3 model based on decision coordination has significant classification performance and can effectively measure the financial performance of enterprises. However, there is still some room for improvement in the measurement accuracy of the classification model, and the Gaussian distribution can be subsequently considered to further improve the model.

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