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Machine learning in corporate M&A valuation: an empirical study based on big data

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ABSTRACT
Machine learning provides new perspectives and methods for company M&A valuation due to its powerful data processing and prediction capabilities. This paper analyzes the prediction steps based on the decision tree algorithm, i.e., decision tree generation, attribute selection, decision tree construction, and accuracy metrics, and obtains the relevant data of AB after merger and acquisition through data mining. The model and SHAP framework are utilized to predict the financial risk, financial performance, and enterprise value of the two post-merger companies. The precision, recall, and F1 scores of this paper's model range from 91.25 to 93.81, which has a good performance of company M&A valuation. This paper's model predicts that in 2024, the key indicator of AB's financial crisis is Gross margin, which has an importance of 0.297, and the possibility of AB's financial crisis increases when the value of Gross margin is between -0.0279 and -0.0014. The accuracy of the financial performance prediction of this paper's model is more than 0.97, which can accurately value the company's performance. The model in this paper predicts the enterprise value of AB in 2024 to be 52.14yuan/share, respectively.

Keywords: machine learning, decision tree, data mining, SHAP framework, M&A valuation

1. Introduction

Mergers and acquisitions (M&A) is an important way and mode of development strategy for enterprises, belonging to the exogenous growth of the company, which is relative to the endogenous growth of enterprises relying on their own operations. The earliest mergers and acquisitions can be traced back to the second industrial revolution, and the developed capitalist economy has experienced five major waves of mergers and acquisitions in its history [1-3]. From the transaction level, the success of an M&A transaction depends on the expected price match between the two parties, and the price of the transaction stems from the valuation of the subject of the merger and acquisition between

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the two parties, especially the buyer's valuation of the subject of the merger and acquisition, because the seller can often make a profit and close the transaction, transferring the assets and transferring the future risk to the buyer. Therefore, the buyer often need to comprehensively and objectively analyze the value of the subject of the merger and acquisition, the buyer in the valuation model is usually used in the discounted future cash flow method for valuation [4-7]. This valuation method is simple and easy to understand, the free cash flow of a business according to different risk factors to discount the net present value of the expected investment project. However, with the continuous development of the economy, the uncertainty of the future of each investment and acquisition, including gains and losses, is increasingly difficult to estimate. This brings a great challenge for valuation, and also forms a certain obstacle for the conclusion of M&A transactions [8-10]. With the maturity and perfection of the capital market and the encouragement and support of national policies, more and more enterprises in China also carry out M&A valuation to promote enterprise development. Since the concept of machine learning was put forward in the last century, it has experienced more than 70 years of tortuous development, and in recent years, it has begun to be emphasized by academics and research applications in various industries [11-12]. Its algorithms and applications have also made important breakthroughs, resulting in algorithms such as decision trees, support vector machines, neural networks, random forests, etc., which have been widely used in the fields of stock market analysis, data mining, credit rating, biometric identification, medical diagnosis, etc [13-15].

The result of value assessment in the M&A process depends on the choice of approach, and the choice of valuation method for value assessment is one of the core elements in the M&A and reorganization work of enterprises. Literature [16] tries to use machine learning method to analyze the M&A activities of enterprises, and the feasibility of this method is verified by empirical analysis with high accuracy.This proposed method helps to predict counterfactual scenarios and answer policy questions in M&A valuation, and may have different applications ranging from detecting fraud to better deals. Literature [17] constructs a predictive model for corporate M&A decisions from the perspective of ecosystems and sustainability and utilizes machine learning techniques to measure cross-border M&A decisions, and the results show that there are differences in the predictive characteristics of corporate M&A with different sustainability characteristics, and this finding is instructive for corporate strategy design. Literature [18] compares the effectiveness of six machine learning models, namely k-nearest neighbor, decision tree, support vector regression, artificial neural network, AdaBoost, and random forest, in predicting the value of oil companies and electric power companies, and takes nearly 5000 mergers and acquisitions as the experimental data, and the results of the experiment point out that the artificial neural network model has the best prediction performance, which can be widely used in the enterprise's merger and acquisition decision-making and value assessment. . Literature [19] compared the performance of logistic regression, random forest classifier, Adaboost classifier and multilayer perceptron classifier in predicting the possibility of acquirer's mandatory delisting due to performance reasons after the deal closure, and the results showed that random forest classifier and Adaboost classifier have the optimal prediction performance, and also found out that the company's size, leverage, and profitability are the most important factors in predicting performance most informative features in the models that lead to the likelihood of delisting. Literature [20] focuses on analyzing the existing theoretical foundations behind M&A prediction and the current state of the art of M&A prediction methods, finding that the correctness of these theories may depend on the context, and stating that M&A prediction methods should take into account and reflect the goals of the M&A transaction and the additional motivations of the buyer, and always include context. Literature [21] uses data on M&A of Chinese firms listed in Shanghai and Shenzhen as a source of experimental data, and utilizes a machine learning approach to explore the determinants of success or failure of M&A deals.The experiment side by side validates the superior performance of machine learning models in predicting the success of M&A deals, and points out that deal characteristics, especially the use of share-based payments, are key determinants of the outcome of mergers and acquisitions (M&As) in China's capital market.

In this study, the focus is on analyzing the motives of corporate mergers and acquisitions as well as the traditional company valuation methods, including the cost method, the market method, the income method, and the real option method. By analyzing the M&A and restructuring cases of companies A and B, relevant financial information is collected by combining data mining techniques. A machine learning model based on the decision tree algorithm is constructed, and the SHAP interpretation framework is introduced in detail to provide a theoretical foundation for the subsequent application of company M&A valuation using machine learning models.

2. Study of the motives for mergers and acquisitions of companies and traditional valuation methods

2.1. Analysis of the motives for mergers and acquisitions

2.1.1. Operational synergies:

1) Expansion of scale to reduce costs. Through the implementation of mergers and acquisitions, on the one hand, it makes the company directly obtain the shares of Zhongyi through cash payment. On the other hand, through mergers and acquisitions to expand the production scale of enterprises, so that the unit of product burdened by depreciation and amortization costs gradually decline, and improve the marginal returns on products.

2) Reduction of agency costs. In the merger and acquisition of Zhongyi shares, in order to avoid Zhongyi shares being controlled by the original controlling shareholders after the merger and acquisition, the company adopts the method of acquiring the original controlling shareholders together, so as to reduce the agency cost, avoid the agency risk, and safeguard the integration effect after the merger and acquisition, so as to obtain the operational synergy effect.

2.1.2. Financial synergies. For companies with sufficient cash flow and abundant capital pools, mergers and acquisitions are conducive to revitalizing the company's idle funds and improving the efficiency of capital use. At the same time, after the completion of the merger and acquisition, through the implementation of financial centralized management of the merger and acquisition of the target, financial centralized integration, is conducive to reducing the company's cost of capital, to obtain financial synergies.

2.1.3**.** Management system effects. A corporate merger can achieve complete control over production and operations. A merger not only offsets cumbersome related transactions in management, but also facilitates the reduction of competition in the same industry and the realization of management synergies through a proven management model.

2.2. Traditional valuation methods for companies

2.2.1. Cost approach. The basic principle of the cost approach is to determine the value of the asset under appraisal on the basis of the cost of the investment required, with the central idea being the principle of substitution, i.e., that the value of the asset should be equal to the cost of purchasing or reconstructing the asset. The relevant mathematical model is shown below:

$$V = RC - FD - TD - ED \tag{1}$$

In the above formula, V represents the current appraised value of the appraised company, RC represents the rehabilitation cost of the company, FD represents the appraised functional depreciation, TD represents the physical depreciation and ED represents the economic depreciation.

2.2.2. Market approach. The basic principle of the market approach to valuation is to infer the value of the asset or company to be valued by analyzing the prices at which similar assets or companies are traded in the market. The relevant mathematical model is shown below:

$$V = V'\prod_{i=1}^{n}\left(\frac{p^{i}}{p_i'}\right)^{m_i} \tag{2}$$

where V is the value of the asset or company. V' is the actual value of similar assets or companies in the trading market. p^i is the comparable adjustment parameter for the asset under appraisal. p_i' is the comparable adjustment parameter for the same or similar assets. m is the size adjustment parameter.

2.2.3. The revenue approach. The core idea of the income approach is to calculate the value of an asset or company by estimating the expected future cash flows and capitalization rate of the asset or company. The mathematical model is as follows:

$$V = \sum_{t=1}^{n}\frac{CF_t}{(1+r)^t} \tag{3}$$

where V is the value of the company. n is the life cycle of the firm. CF_t is the cash flow generated by the firm at the t moment. r is the discount rate that reflects the expected cash flows.

2.2.4. Real options method. This method allows for the timing of the investment in the target company to be divided into stages, with a reasonable assessment of each stage and finally an overall assessment. The method for evaluating the determination of the investment environment is the discounted cash flow method, while the method for evaluating the feasibility of investing in a project in a high-risk or uncertain environment is the real options method.

2.3. Case Study of M&A and Reorganization of Companies A and B

Mergers and acquisitions is a collective term for inter-company mergers and acquisitions. Merger refers to the merger of two or more companies into a single company through merger and acquisition activities, and the other companies involved in the merger and acquisition lose their independent nature of operation. Acquisition means that the acquiring company obtains ownership or control of all or one of the assets of the acqured company.

2.3.1. Overview of Company A. Established in June 2000, Company A is a comprehensive power group mainly engaged in power generation, in addition to its business scope covers coal, new energy, power generation equipment, science and technology, environmental protection, engineering construction, technical services and high-tech and many other fields, with its industries spreading over 31 provinces, municipalities and autonomous regions in China. Compared with Company B, Company A has more listed operating platforms.

2.3.2. Overview of Company B. Company B is a mega state-owned energy company based on coal industry, integrating electric power, coal chemical industry, coal-to-oil production, ports, shipping and railroad transportation. Company A has realized the value-added rate of state-owned assets as well as total annual profits that have always ranked at the forefront of the industry, and has steadily ranked first in the national coal industry in terms of the company's economic contribution rate, and as of June

2023, the total assets of Company A exceeded 2 trillion yuan. Prior to its merger and reorganization with Company B, Company A had a total of 30 wholly owned or controlled subsidiaries.

2.3.3. Merger and Acquisition Program. The merger between Company A and Company B is a large-scale reorganization of energy companies led and promoted by the government, and as such, it has a number of differences from ordinary mergers and acquisitions between companies. The specifics are as follows:

1) Mode of integration. Company A and Company B respectively merged their respective subordinate thermal power companies' equity and assets to form a new joint venture company, and the control of the joint venture company was enjoyed by Company B.

2) Both sides contribute the subject assets. The subject assets contributed by Company A include the equity interests of 28 companies in which it has a controlling or controlling stake, as well as installed capacity under construction and in operation, with an installed capacity of 44.27 million kWh, valued at 89.159 billion yuan in total. The subject assets contributed by Company B include the equity interests of 22 companies in which it has a controlling or controlling stake, as well as installed capacity under construction and in operation of 63.15 million kW, valued at 103.189 billion yuan in total.

3) Transaction consideration and shareholding ratio. According to the appraisal, the value of the subject assets of Company A is 69.804 billion yuan and the value of shareholders' equity is 32.619 billion yuan, while the value of the subject assets of Company B is 89.146 billion yuan and the value of shareholders' equity is 49.161 billion yuan. After negotiation between the two parties, the agreement stipulates that after the establishment of the joint venture company, its registered capital will be 10 billion yuan, the shareholding ratio of Company B will be 58%, and the shareholding ratio of Company A will be 42%.

4) Name and shareholding structure of the joint venture company. This time, Company A and Company B joint venture company full name AB Mergers and Acquisitions Limited, according to the material described earlier, organize and produce to get AB Mergers and Acquisitions Limited shareholding structure as shown in Figure 1.

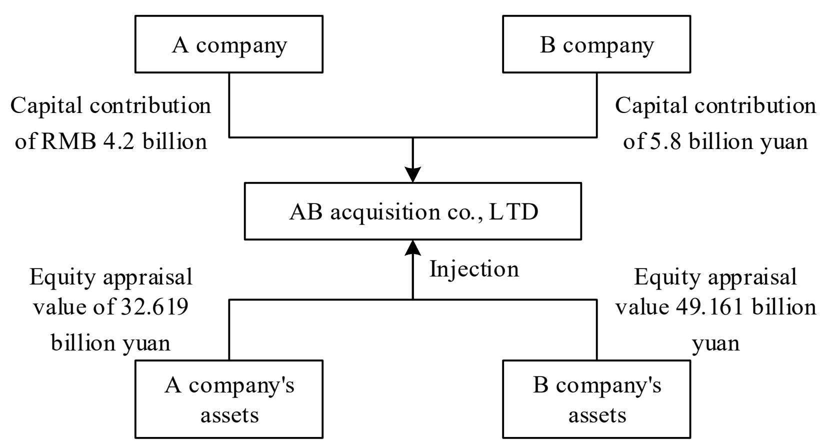

Fig. 1. Shareholding structure diagram of AB acquisition co., LTD

3. Predictive model for valuation of mergers and acquisitions of companies based on the decision tree algorithm

3.1. Data mining

The flowchart of data mining is shown in Fig. 2. It is mainly divided into the following steps: data cleaning, data integration, data selection, data transformation, data mining, pattern evaluation, and knowledge representation [22].

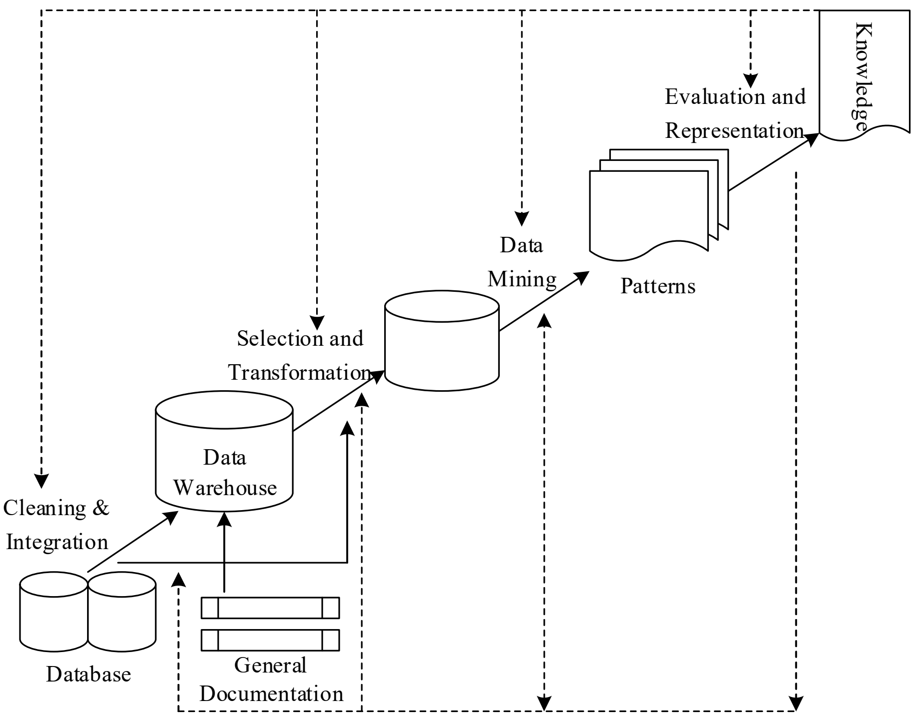

Fig. 2. The basic steps of data mining

3.2. Steps of Decision Tree Algorithm Prediction

Figure 3 shows a simplified schematic of a decision tree. A decision tree [23-24] consists of a root node, a series of non-leaf nodes, and leaf nodes. The topmost node of the tree is the root node, and each non-leaf node consists of a parent node and one or several child nodes. A node is a leaf node if it has only parent nodes and no children. Each non-leaf node represents a test on an attribute, each branch corresponds to an output test, and each leaf node is a representation of a categorical category.

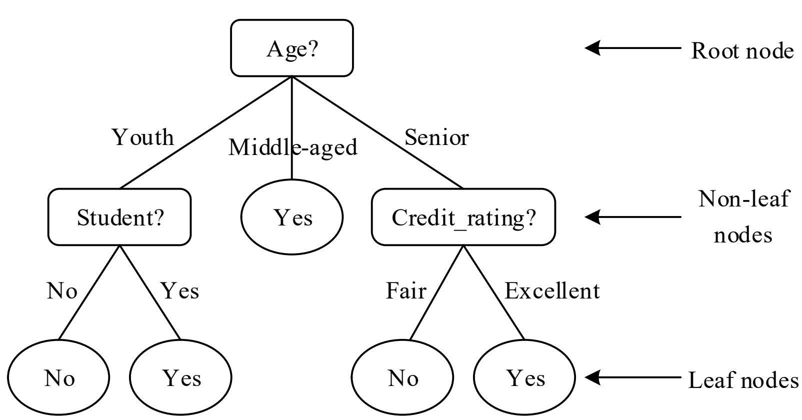

Fig. 3. Illustrating figure of a simplified deision

The ID3 algorithm is to test all the candidate attributes, select the attribute with the largest information gain as the best split attribute, and use this split attribute as the root node of the decision tree, construct branches through different values of this attribute, and then repeat the above method for the subset of each branch, and construct other branches of the decision tree node in turn, and so on, until all the subset includes only the same kind of training sample set. The resulting ID3 decision tree model can then be used to classify and predict new data sample sets.

3.2.1. Decision Tree Generation. The basic strategy of the decision tree algorithm is as follows:
1) The root of the tree starts from a single node representing the training sample set.
2) Nodes belonging to the same class of the training sample set are leaves of the tree and the class is labeled.
3) Otherwise, using the information gain metric as the splitting criterion, the attribute that can achieve the best sample classification is selected as the splitting attribute for that node.
4) Create a branch for each known value of the split attribute and divide the sample set on this basis.
5) Use the same process as above to recursively form a sample decision tree for each division.

3.2.2. Metrics for attribute selection:

1) Information gain. Let data division T be a training sample set that includes t data samples, and the class labeling attribute can be selected with n different values, defining n different classes G_i, $i \in \{1,2,3,\cdots,n\}$. Assume that $G_{i,T}$ is the set of training sample sets in G_i classes in T, and $|G_{i,T}|$ and $|T|$ are the number of training sample sets in $G_{i,T}$ and T, respectively. Then the expected information obtained by classifying the given set of training samples is:

$$Info(T) = -\sum_{i=1}^{n} P_i \log(P_i) \tag{4}$$

where P_i is the probability that any training sample set in T belongs to class G_i and is estimated using $|G_{i,T}|/|T|$. $Info(T)$ is also referred to as the entropy of data partitioning T and is the average amount of information required to recognize the class labeling of the set of training samples in T.

It is assumed that attribute R takes u different data values $\{r_1,r_2,\cdots,r_u\}$ which correspond exactly to the u output of the test on R if R they are discrete values. Using attribute R the set of training samples T can be divided into u different subsets $\{T_1,T_2,\ldots,T_u\}$ of training samples, where T_j contains the set of data samples for which attribute R takes r_j values in the data division T, and if attribute R is selected as the test attribute for classifying the current set of samples, and assuming that T_{ij} is the set of training samples belonging to the category G_i in subset T_j, the information entropy required for dividing the current training sample using attribute R set requires an information entropy of:

$$Info_R(T) = \sum_{j=1}^{u} \frac{T_{1j} + T_{2j} + \ldots + T_{nj}}{T} Info(T_{1j}, T_{2j} \ldots T_{nj}) \tag{5}$$

where $\frac{T_{1j} + T_{2j} + \ldots + T_{nj}}{T}$ is the weight of the j nd division. $Info_A(T)$ is the expected value required for classification based on dividing the sample set T by attribute R. The information gain obtained by dividing the current branch node using attribute R is:

$$Gain(R) = Info(T) - Info_R(T) \tag{6}$$

2) Gain rate. Let data division T be a training sample set including t data samples, and the class labeling attribute can be selected with n different values to define n different classes $G_i, i \in \{1,2,3,\cdots,n\}$. Suppose $G_{i,T}$ is the set of training sample sets in G_i classes in T, and $\left|G_{i,T}\right|$ and $|T$ are the number of training sample sets in $G_{i,T}$ and T, respectively. Then the split information is similar to $Info(T)$ and can be defined as follows:

$$SplitInfo_R(T) = -\sum_{j=1}^{n} \frac{|T_j|}{|T|} \times \log_2\left(\frac{|T_j|}{|T|}\right) \tag{7}$$

This value represents the information generated by dividing the training dataset T categorization into u categorical divisions corresponding to the u outputs of the attribute R test. The gain rate can be defined as:

$$GainRation(R) = \frac{Gain(R)}{SplitInfo(R)} \tag{8}$$

3) GINI indicator. The GINI indicator classifies the impurity of data division T, defined as:

$$Gini(T) = 1 - \sum_{i=1}^{n} p_i^2 \tag{9}$$

where p_i is the probability that the sample set in T belongs to class G_i.

Assume that attribute R is discrete and that there are u different values $\{r_1, r_2, \cdots, r_u\}$ appearing in T. To determine which data values on attribute R are the best binary divisions, test all possible subsets formed by all attribute values of attribute R. Assuming that attribute R divides T into T_1 and T_2, the GINI metric for a given division is:

$$Gini_R(T) = \frac{|T_1|}{|T|} Gini(T_1) + \frac{|T_2|}{|T|} Gini(T_2) \tag{10}$$

4) χ^2-statistic. The core idea is to perform automatic judgmental grouping of multivariate listings based on the given target variables and the explanatory variables that have been 1 selected according to the significance of the χ^2 test. Each explanatory variable is cross-classified with the target variable to form N two-dimensional cross-classification tables (N being the number of explanatory variables), and the χ^2 statistics in each table are calculated separately:

$$\chi^2 = \sum_i \sum_j \frac{\left(F_{ij} - \hat{F}_{ij}\right)^2}{\hat{F}_{ij}} \tag{11}$$

where $\hat{F}_{ij} = \dfrac{\left(F_i \cdot F_j\right)^2}{\sum_i \sum_j F_{ij}}$, F_{ij} are the actual observations for each cell. The magnitudes of the N χ^2 statistics are compared and the largest χ^2 statistic is selected as the best classification method.The CHAID algorithm uses an attribute selection metric based on independent statistical χ^2 tests.

3.2.3. Construction of decision trees. Commonly used pruning methods are pruning first and pruning later, and in this paper the pruning first method is used. The first pruning method constructs the tree by stopping it early and pruning it. Once the construction process is stopped, the node also becomes a leaf node and may have the most frequent class among all the subset sample sets. Attribute selection metrics such as information gain, GINI metrics, or information gain rate can be utilized when constructing a decision tree to evaluate the merit status of branch generation. If the classification of the training sample set of a division node falls below a pre-defined threshold, further splitting of that subset is immediately terminated.

3.2.4. Classification Model Accuracy Metrics. k -fold cross validation method: the initial data sample set is first randomly divided into k disjoint "folds" of basically the same size $\{T_1, T_2, \cdots, T_k\}$. The classification model is trained and tested k times in total, with $k-1$ folds of the sample set being used as the training set for each classification model, and then the test is performed on a subset of the remaining data, with the average of all the error rates taken as the evaluated error rate.

3.3. SHAP Interpretation Framework

The SHAP framework [25], is an interpretation framework for complex machine learning models. Model interpretation is performed by calculating the contribution of each feature when it is added to the model. Each feature is considered as a contributor, and the final prediction of the model is derived by calculating its specific contribution value and summing the contributions of all features. For each sample, the final prediction of the sample is equal to the sum of the average prediction and the SHAP value of each feature of the sample. In addition, traditional feature importance only indicates which feature is important, but it is not clear how that feature affects the prediction. SHAP, on the other hand, can reflect the influence of each feature and the positivity or negativity of the influence, revealing how the feature affects the prediction results.

4. Empirical analysis of corporate M&A valuation based on big data

4.1. Machine Learning M&A Valuation Performance Evaluation

In this section, the dataset is divided into a training set and a test set with a ratio of 8:2, i.e., 100 M&A companies are tested, and the following is a comparative analysis of the test results. CatBoost, K nearest neighbor, logistic regression, neural network, random forest are selected as comparison models as well as models in this paper, a total of six groups of machine learning models, which are recorded as models 1-6 in order, to compare the prediction performance of the valuation prediction effect of the company's mergers and acquisitions. The models are all experimented based on the dataset after adding Benford factors and balancing the sample data using the ADASYN algorithm. The performance evaluation metrics include precision (P), recall (R), and F1 score. Figure 4 shows the comparison of test results of different models.

As can be seen from the figure, from the evaluation index accuracy, in order from high to low: this paper's model, logistic regression, K nearest neighbor, CatBoost, neural network, random forest. And comprehensively, the best classification effect is this paper's model, the main parameters are higher than other classification algorithms, which can be better used in the valuation of company mergers and acquisitions, and its precision rate, recall rate, and F1 scores are 92.76, 93.81, and 91.25, respectively.

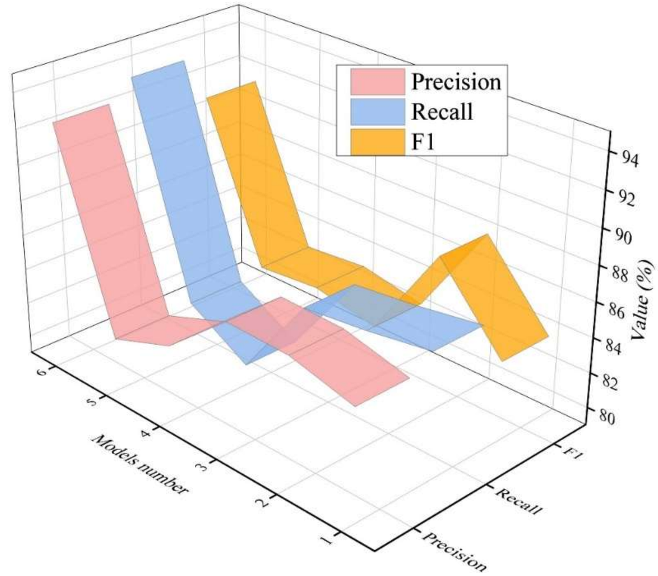

Fig. 4. Comparison of test results of different models

4.2. Financial Risk Assessment of Corporate M&A Based on SHAP Methodology

This section collects the financial data of AB after merger and acquisition as described above, and carries out the financial risk prediction of AB as well as the subsequent related research.

To address the issue of financial crisis early warning in corporate mergers and acquisitions, in this paper we utilize the Shapley value in the SHAP method to measure the marginal contribution of the model input features to the prediction results, which is able to be used as a metric to measure the impact of the features on the prediction results.

Therefore, in this paper we also calculate the average of the absolute values of the Shapley values of each financial indicator as a measure of importance to extract the key features in performing financial crisis early warning. Figure 5 demonstrates the results of this paper's model for predicting the importance of features under different time window periods from 2020-2024.

As can be seen from the figure, the importance of the key indicators of financial crisis changes every year for AB after M&A. In 2020, the key financial indicator that has an impact on the company's financial crisis warning results is Return on equity, which is a measure of the company's profitability, which has an importance of 0.262. By 2024, this paper's model is useful in predicting the key indicators of AB's financial crisis as Gross margin, the importance degree is 0.297. It shows that the characteristic importance of financial indicators will change with the time of approaching financial crisis.

Based on the above analysis, we can conclude that the model in this paper can predict the importance of key indicators of financial crisis, and by comparing and analyzing the changes in the characteristic importance of the same indicators at different times, it can provide key indicators for market regulators, company management, and market investors to pay attention to in the actual early warning of the company's financial crisis, and can be used to determine the company's financial crisis by observing the changes in these key indicators at different times. By observing the changes of these key indicators in different periods, we can judge the possibility of the company's financial crisis, so as to formulate corresponding preventive, control and management measures in advance.

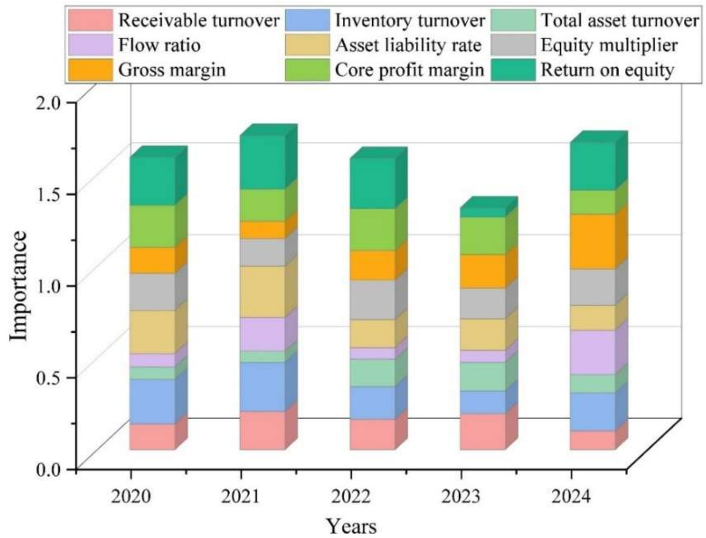

Fig. 5. The characteristics of the characteristics of different times are predicted

The key features are extracted by the SHAP-based method described above, but it is not possible to know the specific role of these key financial indicators in influencing the financial crisis. Therefore, in this section, we show the specific impact role of key financial indicators on financial crisis through visualization based on SHAP interpretation algorithm. Figure 6 shows the SHAP dependence results of key financial indicators of AB after merger and acquisition for 2020-2024, demonstrating the influence of the value of each feature on the results of the company's financial warning judgment.

The horizontal axis of the figure represents the value of the features, and the vertical axis is the SHAP value of each feature, when the SHAP value is negative, it means that the features have a negative contribution to the early warning results, on the contrary, when the SHAP value is positive, it means that the features have a positive contribution to the early warning results, and the larger the absolute value of the SHAP value is, the larger the marginal contribution is.

From the figure, we can find that the model of this paper predicts that the key financial indicator of AB in 2020 is Return on equity, when Return on equity gradually decreases in the interval from -0.017 to -0.55, the SHAP value is positive and gradually increases, and as the value of gross profit margin continues to decrease, the positive contribution to the financial crisis is gradually increasing, and the possibility of the company's financial crisis is increasing. The likelihood of financial crisis of the company increases gradually. Similarly, the most important discriminative characteristic for predicting AB's financial crisis in 2024 is Gross margin, and the SHAP dependence plot based on this characteristic shows that when the value of Gross margin decreases gradually within the range of -0.0014 to -0.0279, the value of SHAP is positive and increases gradually, and the probability of the company's financial crisis increases gradually. The probability of the company having a financial crisis increases gradually.

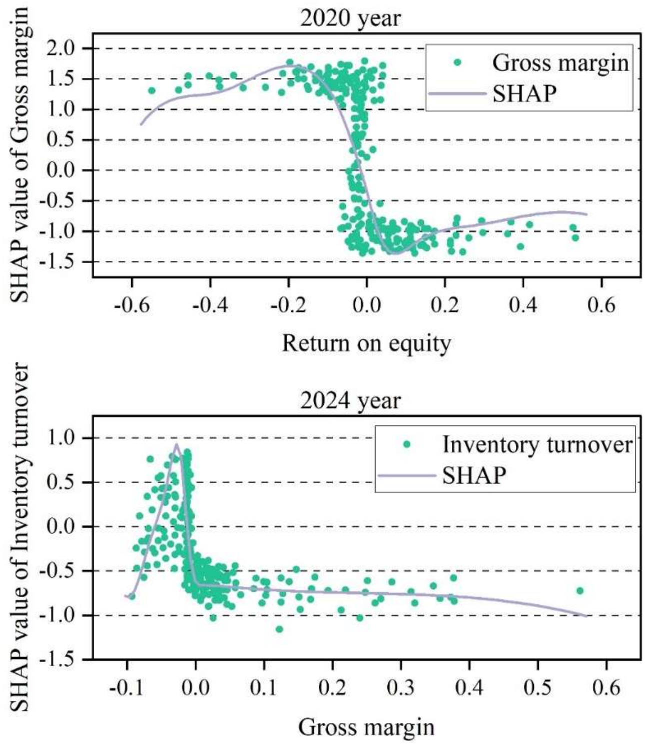

Fig. 6. Key financial indicators SHAP dependent results

4.3. Machine Learning Financial Performance Valuation

Financial Indicator Analysis (FIA) is an important method used to assess the financial status of a company.

In this section, the machine learning-based prediction model in this paper is used to predict the financial performance of AB after merger and acquisition for 2020-2023, and further predict the financial performance of the two companies for this year (2024) based on the accuracy of performance prediction for 2020-2023. This forecasting financial performance indicators are categorized into operational capacity indicators, debt service capacity indicators, and profitability indicators. Figure 7 shows the accuracy of this paper's model in predicting AB's financial performance from 2020-2023. Table 1-Table 3 shows the predicted results of financial performance indicators in 2020-2024.

As can be seen from the figure, the prediction accuracy of this paper's model for the two companies in 2020-2023, on each indicator is higher than 0.97, indicating that this paper's model can better capture the characteristics and laws in the financial data, with excellent predictive performance, ensuring the reliability of the prediction results of the performance indicators. Based on this, this paper's model values the financial performance in 2024, and taking AB's operational capacity indicators as an example, this paper's model calculates its Receivable turnover, Inventory turnover, and Total asset turnover in 2024 to be 53.52, 6.37, and 0.88, respectively.

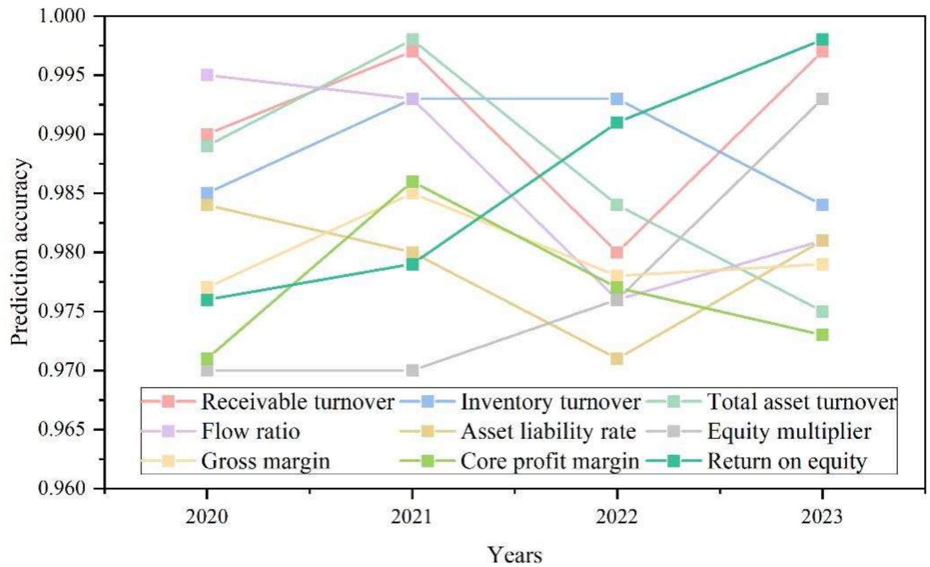

Fig. 7. Accuracy of financial performance prediction

Table 1. 2020-2024 AB company operating ability indicator forecast

Indicator/time	Receivable turnover	Inventory turnover	Total asset turnover
2020	28.01	4.42	0.67
2021	29.75	4.92	0.77
2022	38.51	5.41	0.76
2023	43.81	5.57	0.86
2024	53.52	6.37	0.88

Table 2. 2020-2024 AB company solvency index forecast

Indicator/time	Flow ratio (times)	Asset liability rate (%)	Equity multiplier (times)
2020	0.9	54.39	2.32
2021	1.08	49.77	2.08
2022	1.12	51.97	2.17
2023	1.16	53.05	2.28
2024	1.22	52.33	2.21

Table 3. 2020-2024 AB company profitability indicator forecast

Indicator/time	Gross margin	Core profit margin	Return on equity
2020	18.34	7.13	13.39
2021	18.02	7.06	17.71
2022	14.47	7.57	17.47
2023	13.77	7.75	18.18
2024	16.42	9.39	18.9

4.4. Post-merger forecast of AB's enterprise value

In this section, a variety of traditional valuation methods are used to assess and predict AB's post-merger enterprise value based on the anatomy of industry characteristics and in a post-merger based context. The comparison methods include, cost approach, market approach, income approach, and real option approach. Figure 8 shows the results of enterprise value prediction based on multiple methods.

In 2020-2023, the enterprise per share value of AB is shown in the figure, and based on the real value, the absolute error between the enterprise value predicted by this paper's method and the real value is measured to be 0.36~1.22 yuan/share, which is much lower than that of the traditional method, which is 2.42~12.68 yuan/share. Due to the traditional valuation method focuses on different factors, coupled with the lack of maturity of the stock market, there may be asymmetry of information, valuation between the valuation and the valuation and stock price, although there is a slight difference between the slight differences. The method of this paper, due to its unique set of features, breaks the limitations of data collection and information disclosure, etc., and ensures that the resulting enterprise value prediction has a reasonable reference value through its strong predictive ability, providing opinions and suggestions for the decision-making governance of the enterprise management. In this regard, the model in this paper predicts the enterprise value of AB in 2024, which is $52.14/share, respectively.

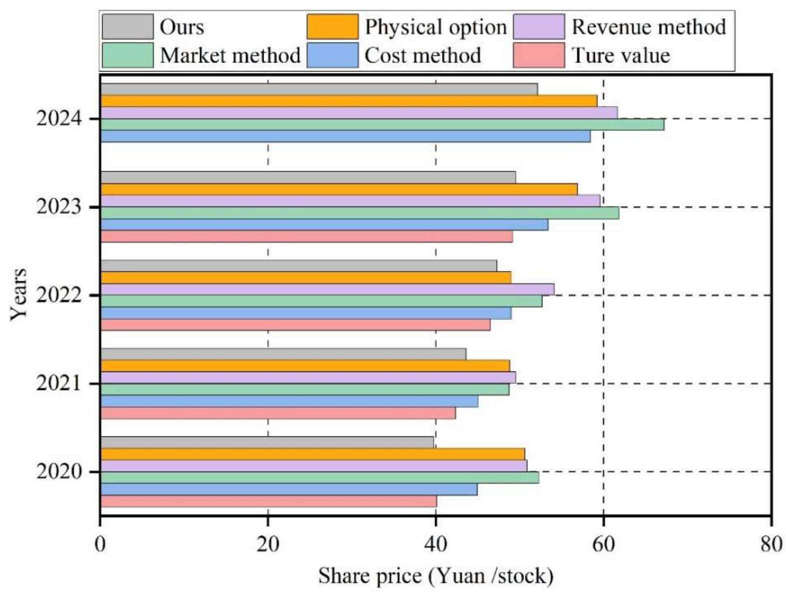

Fig. 8. The enterprise value prediction results based on multiple methods

5. Conclusion

This paper constructs a machine learning model based on the decision tree algorithm and applies it to the empirical study of M&A and reorganization cases of A and B companies. By collecting the financial related information of the two companies, the model of this paper is utilized to predict the financial risk, performance, and enterprise value of AB after merger and acquisition.

1) The precision rate, recall rate, and F1 score of this paper's model are improved by 7.41% to 17.02%% compared with the comparison model, showing better valuation effect.

2) This paper's model can predict the importance of financial indicators to identify the key indicators of financial crisis and measure the possibility of financial crisis by calculating the SHAP value.

3) This paper's model predicts that the operating capacity indicators Receivable turnover, Inventory turnover, and Total asset turnover of AB in 2024 are 53.52, 6.37, and 0.88, respectively.

4) The absolute error between the enterprise value predicted by the method of this paper and the true value is 0.36~1.22 yuan/share.

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