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Intelligent Transformation of Financial Management Decision Making Powered by Artificial Intelligence

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SUMMARY: *The implementation of smart algorithms to support financial planning is increasingly widespread in corporate activities. As presented in this paper, the Metric-Based Decision Tree (MBDT) algorithm is introduced to measure the information gain rate of financial data on solvency, operational efficiency, profitability, and growth potential. This process enables data attribute segmentation and node classification. Based on a backtracking corporate financial decision tree, the algorithm achieves financial crisis early warning and decision support. The MBDT algorithm achieves a maximum financial data classification accuracy of 92.125%, with a goodness-of-fit error not exceeding 5.815%. In practical applications, it can analyze and forecast a company's financial data spanning the past 10 years and the next 10 years. Setting the critical threshold to 0.60 yields the highest precision in financial crisis early warning.*

KEYWORDS: *measurement method; MBDT; node classification; information gain rate; intelligent financial decision-making*

1 Introduction

The accelerated growth of technology has seen the use of artificial intelligence becoming prevalent in many industries, and it is now regarded as one of the most significant forces behind both social advancement and industry change [1, 2]. With the business world responding to the transition to digital intellect, big data and AI are now essential to the financial management system to enhance the competitiveness of organizations. Not only does this integration enable the automation of management accounting, but it also improves the quality of the decisions made. Through an in-depth examination of big data to determine financial trends, organizations will be able to make more data-driven and well-informed decisions[3, 4].Leveraging multi-layered encryption methods, AI technology enhances the security of data storage and transmission. The implementation of intelligent financial systems enables enterprises to deliver more personalized financial services[5]. Simultaneously, it ensures seamless integration of software functionalities with business operations, significantly boosting financial management efficiency while laying the foundation for enterprises' digital and intelligent transformation[6]. Artificial intelligence impacts corporate financial management in the following four dimensions:

1) Enhancing Efficient Data Processing

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Under the conditions of an ongoing corporate change-over and modernization, the theoretical framework and implementation of financial management have developed with it. Accounting information systems are continually updated and upgraded, and the shift is slowly being made to a model of financial management that embraces specialization in management [7, 8]. It indicates the growing extent of business-finance integration. In the course of this shift, companies implement more advanced technologies and practices to use big data, cloud computing, AI, etc., to achieve full-scale transformations in financial management. In particular, the use of big data and AI has seen financial management systems become even more streamlined and improved, with full integration and automatic financial data handling. Smart financial systems can automatically receive various data sources, such as ERP system data, e-commerce platform transaction records, and third-party payment platform data, then apply big data analytics to automatically extract and cleanse them. It increases data accuracy and completeness to a considerable degree, which will greatly enhance the efficiency of processing financial data [9].

2) Enhancing Capital Utilization Efficiency

The financial administration aspect that concerns capital management is a vital part of financial administration. The financing and investment management are both directly related to daily operations. Financing activities can lead to lower financing expenses as well as easier access to corporate funding through the use of big data and AI technologies[10, 11]. Investing activities can be controlled too much by using digital and intelligent technologies since they provide decision makers with full analytical information and information about the market in detail, allowing them to make their investment choices based on science. Specifically in cross-regional investments, the analysis of big data shows regional investment patterns, facilitates internal synergy, and optimizes multi-location investment approaches.

3) Achieving Cost Reduction and Efficiency Goals

The application of big data and AI can automate the process of financial accounting such as journal entry consolidation, generation of vouchers, and smart bank statement import to save a lot on labor costs and eliminate human errors and improve the overall efficiency of operations[12, 13]. Furthermore, online computing engines of intelligent financial systems always update the transaction information, which improves the precision of financial reports.The use of digital and smart technologies optimizes financial management, which contributes to improving business performance. In addition to reducing the cost of operations, this strategy also increases the effectiveness in using human resources and thus supports technological innovation more favorably.

4) Strengthening Risk Control Capabilities

By leveraging digital and intelligent technologies, enterprises can build intelligent financial systems to further elevate the informatization level of financial oversight. In practical management processes, big data technology enables end-to-end business-finance integration, clarifying specific requirements for financial management. Treating financial processes as a thread not only provides preemptive alerts but also offers greater support for in-process control. This effectively enhances internal control quality, curbs earnings management, and resolves issues like information asymmetry. Against this backdrop, enterprises continuously improve their risk assessment and identification capabilities. Analyzing big data will allow them to create scientifically valid approaches to risk prevention and management and thus help to enhance the effectiveness of risk management in financial operations. [14, 15].

The financial data analysis system created by Reference [16] combines data fusion, artificial intelligence and machine learning algorithm. This system has allowed the fast and correct analysis of financial data with a rate of analysis accuracy of 99.85% as well as balancing effectiveness of financial data analysis with security of financial data. Machine learning was applied by Reference [17] to mine and analyse a set of financial and accounting data of a company to find out that the most recent rates of asset returns (-11.2%) and net equity profits (-44.5%) and business profit margins (-12.1) indicated the risk of bankruptcy. Financial data analysis methods based on AI are more scientific, reliable, and precise and can be used as a basis to prevent corporate risks. Reference[18] states that AI algorithms that have been trained on yearly financial reports can be taught to recognize fraudulent activities in companies finances, which is highly applicable in determining credit risks associated with partner companies. Also, Reference [19]] uses an AI model to assess corporate financial risk and also applies principal component analysis to determine the major risk indicators. The suggested AI model correctly forecasts possible financial risks, which makes it possible to avoid problems with corporate financing at the right time.

One of the elements that lead to cost savings and efficiency gains in corporate financial systems and the acceleration of the financial management decision-making process through digitization is the application of artificial intelligence. The citation[20] refers to the role of AI technology in enhancing financial performance at engineering firms. Financial management makes use of intelligent systems to automate the operations of corporate finances, reduce the costs of tax administration, remove errors caused by humans and increase overall financial efficiency. The AI model developed in [21] has proven efficient in the optimization of the corporate financial accounting and auditing processes, which have high levels of accuracy (98.621%) and precision (99.517) and high recall (99.612). As per reference [22], an AI-based financial management system has reduced financial expenditure by 12-18 percent and operational efficiency has also gone up by 23-31 percent, indicating the possibility of AI-based systems to minimize spending and maximize efficiency. Reference [23] investigated the combined impact of AI and blockchain on cost-reduction and enhancement in quality of service in fiscal departments. The study of the data using SPSS confirmed that the combined use of AI and blockchain contributed to the improvement of credit underwriting, loan services, and real estate insurance in the fiscal departments. Source [24] looks at the impact of AI-based digital financial technology on the corporate green economy efficiency. With the consideration of the key constraints in the regression model, it was found out that the correlation between digital finance and corporate green economy efficiency coefficient was 0.2243 meaning that there is significant positive relationship.

Artificial intelligence deep learning functions may also develop risk prediction models based on past financial risk scenarios allowing businesses to determine and address possible financial risks [25, 26]. The reference[27] utilizes big data and AI technologies to experiment with corporate information security management and risk assessment. This study shows that these technologies have the ability to efficiently examine internal and external financial data, provide important information regarding risk assessment and provide correct results of risk assessment. Literature [28] examines financial data on mobile payment companies using AI, which shows that about half of those companies demonstrate risky financial management in the market, giving valuable insight into the application of AI in assessing corporate financial risk. Literature[29]uses structural equation modeling with case studies to examine how AI can be used to improve the capability of corporate financial risk management. The results indicate that AI has greatly enhanced these capabilities by reducing the level of financial risk by 35-45 percent. Literature [30] develops a financial risk evaluation index system of enterprises and then applies AI-based data mining algorithms to identify and classify risk indicators. The validation of this approach is based on the tests of enterprise financial risk assessment. In order to increase the precision of SME financing risk assessment, and make the risk control efficient, [31] suggested an SME risk assessment and control algorithm. Performance testing showed that this algorithm had more than 70% risk optimization control efficiency and more than 95% risk assessment rate of accuracy, which highlights the benefits of AI algorithms in the assessment of enterprise risks.

The reference [32] develops an enterprise risk assessment approach based on deep learning. It examines in detail the information on both internal and external reasons that lead to enterprise risks. When used with case studies, it shows the effectiveness of this approach in assessing enterprise risks. Reference [33]combines various AI algorithms to assess the corporate financial management and risk early warning system. The identification of trends in the risk indicators, including the total asset turnover ratio is done with precision, and this highlights how valuable AI algorithms are to apply in financial management and risk evaluation. The BP neural network algorithm developed in Reference[34] has more than 95 percent accuracy in financial risk early warning simulation tests, which can effectively control and anticipate corporate risk factors and is highly adaptable. The financial data of several companies were mined using the reference [35], trained and learned using a machine-learning-based financial risk assessment model. This strategy minimized the rate of corporate default by 20%, improved the uniformity and scalability of financial decision-making, and improved corporate risk management.

The use of artificial intelligence in financial management is in line with modern tendencies, infusing the sector with a new dynamism alongside opportunities and challenges[36]. According to research [37], AI-based corporate financial management systems have benefits including effective solutions to make decisions and lower operational expenses but still, there are issues in some aspects including security of data and complexity of integration. Conventional financial management structures are typically characterized by inadequate data processing capacity and obsolete financial systems [38]. As per earlier studies, AI technology can facilitate holistic financial management, online financial data retrieval, accurate analysis, and successful prediction of the direction of the market and financial risks. It offers better reasons behind the operational choices made by companies, contributing to steady and long-term business growth [39, 40].

The present research computes information entropy, information gain as well as information gain rates in four types of financial indicator data. Due to the close resemblance between financial data, the Mahalanobis distance, and three metric methods are used in the Metric-Based Decision Tree (MBDT) algorithm to measure distances between similar data in a more objective manner. Computational results are used to determine the information content in the financial data. The sample data have been classified by various information levels after which classification training is done to develop a financial management decision tree. Four aspects are used to evaluate the possibility of a financial crisis happening in an enterprise through the branching results of the decision tree, which include; the external environment, moral hazard, availability of corporate cash reserves, and the sufficiency of the financing available. It serves as a basis of making decisions by the managers.

2 Financial Management Decision Model Supported by Metric-Based Decision Tree Algorithms

2.1 Information Entropy and Measurement-Based Detection Technique (MBDT) Analysis

2.1.1 Information Entropy

Entropy, as used in thermodynamics, is a measure of the extent of disorder. Information theory considers it as a measure of uncertainty. The decision tree algorithms are based on the concept of information theory proposed by Shannon whereby the test attributes are chosen using the information entropy criterion. The algorithms learn entity classes to classify them and build a decision tree to predict how the test attributes may be applied to divide the data space. In this step, entropy maximizing attributes need to be selected by dividing the data. Entropy is at its lowest when a node has a uniform distribution of classes, but it is at its highest when the distribution is skewed.

Shannon's entropy formula is defined as:

$$Entropy\left(p_1, p_2 \ldots, p_n\right) = p_{1\log_2 p_1} - p_{2\log_2 p_2} - \ldots - p_{n\log_2 p_n} \tag{1}$$

In equation (1), the minus sign is due to the logarithmic fraction $p_1, p_2, \ldots p_n$ being negative, although entropy itself is positive. Generally, entropy represents disorder in a system.

$$\text{Info}\left\{\left[C_1, C_2, \ldots, C_n\right]\right\} = entropy\left[E_s\right] \tag{2}$$

Group each training set E_s and utilize property A. The entropy $\left(E_s\right)$ will decrease. Define the new expected information content:

$$new\_entropy\left(E_s, A\right) = \sum_{i \in value_{(A)}} \left[\left|E_{s_i}\right| / \left|E_s\right|\right] entropy\left[E_s\right] \tag{3}$$

The amount by which $entropy\left[E_s\right]$ decreases represents the information gain $Gain[E_s, A]$ of A relative to E_s. A larger information gain indicates greater advantage for the training set:

$$Gain\left[E_s, A\right] = entropy\left[E_s\right] - new\_entropy\left(E_{s_i}, A\right) \tag{4}$$

Information entropy is the average amount of information after removing redundancy, representing the degree of disorder in information. The formula for calculating information entropy is:

$$I\left(S_1, S_2, \ldots S_m\right) = -\sum_{i=1}^{m} p_{i\log_2\left(p_i\right)} \tag{5}$$

S is the set of samples, defined with m distinct classes $C_i (i = 1, 2, \ldots, m)$, S_i is the number of samples in the C_i class, and P_i is the probability that any sample belongs to C_i: S_i / S.

2.1.2 Information gain

The information gain size is used to evaluate the amount of information represented by each attribute during the classification process. This measurement will assist in identifying the most pertinent node to choose at the stage of building the decision tree. Higher information gain means that the attribute adds more value to the classification compared to lower gain which means that the attribute has less value. Information entropy is calculated per single attributes but information gain is used to find the best classification attribute. The information gain obtained after branching is as follows:

$$Gain(A) = I\left(s_1, s_2, \ldots, s_m\right) - E(A) \tag{6}$$

where $I\left(s_1, s_2, \ldots s_m\right)$ is the desired information entropy for a given sample S, and $E(A)$ is calculated as follows:

$$E(A) = \sum_{j=1}^{v} \frac{s_{1j} + \cdots + s_{mj}}{s} I\left(s_{1j} + \cdots + s_{mj}\right) \tag{7}$$

Let attribute A take distinct values $\left\{a_1, a_2, \ldots, a_v\right\}$, where attribute A partitions the sample S into subsets $\left\{s_1, s_2, \ldots, s_v\right\}$. In each subset s_j represents the number of samples belonging to class C_i.

2.1.3 Information gain rate

The amount of information gain depends on how many values an attribute can take; the size of information gain has a direct relationship with the number of attribute values. Nevertheless, such a solution might not be meaningful at all times. An example is the fact that an ID number is simply an attribute that acts as a unique identifier to a sub set of data. With increasing size of the dataset, the information gain of the ID attribute also increases, but it is apparent that the ID attribute does not play any significant role in the classification process.

One of the key steps in the construction of a decision tree is dividing nodes. The node division in the C4.5 algorithm is based on the information gain rate that is determined as the information gain divided by information entropy. It compares quantity of information per unit of an attribute, not the overall quantity of information. Information gain tends to be biased because it depends on the values of variables when the dataset is broken down into smaller datasets. To solve this bias, the formula of information gain rate is used.

$$SplitInfo(S, v) = \sum_{i=1}^{m} \frac{\left|S_i\right|}{|S|} \times \log_2 \frac{\left|S_i\right|}{|S|} \tag{8}$$

From this, the gain rate can be obtained:

$$GrainRatio = \frac{Grain(S, v)}{SplitInfo(S, v)} \tag{9}$$

2.2 Metric Based Decision Tree (MBDT) Algorithm Improvement

2.2.1 MBDT metrics

Euclidean distance, Chebyshev's distance, checkerboard distance and Mahal's distance are all linear methods for multiple measures of data similarity. The more distinctive of all the linear methods is the Mahalanobis distance measure, which has the invariance of the scale transformation. Let $y = Ax$, then the vectors x_1, x_2 and m_x, whose transformed distances are y_1, y_2 and m_y, are completely different from the pre-transformation distances, which sometimes occurs as follows :

That is, $\left\|x_1 - m_x\right\|_G > \left\|x_2 - m_x\right\|_G$, but $\left\|y_1 - m_y\right\|_G < \left\|y_2 - m_y\right\|_G$. Where G denotes a certain paradigm.

This situation produces a degree of similarity between the data that is not objective and cannot be measured. The use of the Mahalanobis distance overcomes this difficulty and maintains the distance scale properties even when the scale is changed.

The Mahalanobis distance is:

$$\|x-m\|_M = (x-m)^T C^{-1}(x-m) \tag{10}$$

To adjust the classifier, first select an appropriate covariance matrix that clusters the samples into any form of hyperellipsoid. On the Mahalanobis distance scale, this method provides the foundation for distance assessment.

2.2.2 MBDT Algorithm

The MBDT algorithm is a recursive algorithm. It employs the interval method as its branching criterion. Let $T=\{t_i\},1\le i\le c$ denote the sample set, where c is the number of sample categories. Let $A=\{a_i\},1\le i\le m$ denote the feature space, where m is the number of attributes. Then $B=\{b\mid b\in A\}$ is the power space of A. Let β_e denote the misclassification rate and β_c denote the cross-misclassification rate.

1) For a superset $C\in T,C$ containing samples from several categories. $b\in B$ belongs to an attribute set. If a sample in C has attribute values $x=\left(x_1,\cdots,x_n\right),x_i\in b,n=|b|$ and achieves the minimum value with one class label in the typical Mahalanobis distance, assign the sample to that class. Then select a target attribute set $b_{best}\in B$ such that most samples in C are correctly classified. If the proportion of samples from class t_i misclassified into class t_j exceeds β_c, then t_i and t_j are grouped into the same class and held for classification at the next layer.

2) Selecting the optimal scenario for classification is the method adopted when no attribute set satisfying condition 1) is found.

3) The process concludes when all samples are classified or further classification becomes impossible. This algorithm introduces the concept of a metric method when calculating information gain, serving as a reference for classification selection. Figure 1 illustrates the flowchart of the improved algorithm.

The A and B components divide the experimental data into two parts. Training and validation are performed on these two data sets, yielding four classification results: A validation, A training B validation, B training A validation, and B training B validation. Each validated result is represented as a matrix. The number of correctly classified samples is indicated by the diagonal elements of the matrix. The number of samples misclassified from class i to class j is represented by the matrix element $[i,j](i\ne j)$.

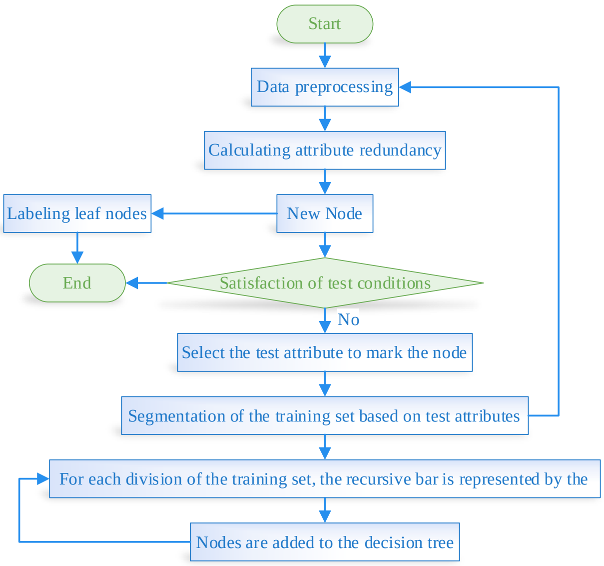

Figure 1: Flowchart of the Improved Algorithm

2.3 Building a Financial Intelligence Analysis and Decision-Making System

The financial analysis and decision-making process is an economic management practice that makes use of financial statements and other relevant data. The process entails using specialized analysis techniques to judge the profitability, operational efficiency, debt repayment capability, and growth potential of the organization. The analysis includes the previous and current financing, investment, operational, and distribution operations in the economic entities like companies. It provides essential information that investors, creditors, managers, and other stakeholders need to comprehend the history of the enterprise, its current situation, predict what will happen with it in the future, and make rational decisions.

Traditional financial analysis methods primarily examine a company's financial condition and operating results from four perspectives: solvency, operational efficiency, profitability, and growth potential. Subsequently, comprehensive financial analysis methods such as the DuPont Analysis System are employed to conduct a holistic assessment of the company's operational status. The Financial Intelligence Analysis and Decision Support System also selects indicators adhering to traditional financial analysis metrics. Building upon this foundation, it integrates with the company's management information system and utilizes data mining techniques like the Metric-Based Decision Support Technology (MBDT) algorithm to perform dynamic analysis and forecasting.

2.3.1 Solvency Ratios

Solvency is the capacity of an enterprise to satisfy its debt obligations, which are principal as well as interest payments. Solvency analysis requires evaluating short-term and long-term capabilities to repay the loans.

1) Short-Term Solvency Analysis

The short-term solvency of a company is its ability to pay off its current liabilities with the help of its current assets. It acts as one of the most important indicators of a companys short term finances especially on the liquidity of the current assets. The measure of short-term solvency is subdivided into two; stock ratios and flow ratios. Working capital, the current ratio, quick ratio, and the cash ratio are included in the stock ratios. Cash-to-current liabilities ratio is represented by the flow ratios.

2) Long-Term Debt Repayment Capacity Analysis

Debt repayment capacity is a long-term indicator that measures the capability of the enterprise to meet its long-term liabilities. Indicators which are used to determine this may be divided into stock and flow indicators. The stock indicators are; debt-to-asset ratio, equity ratio, equity multiplier, long-term capital debt ratio, and interest-bearing debt ratio. The flow indicators are; interest coverage ratio, cash flow interest coverage ratio, and cash flow debt ratio.

2.3.2 Operational Capability Analysis

Operating capability is the ability of a company to achieve its financial targets through efficient usage of the internal human resource and production factors, as well as operating in the context of the external market environment. Operational capability analysis is defined as assessing the effectiveness of the human resources and the production factors.

1) Human Resource Operational Capacity Analysis

As the primary drivers of productivity and the original creators of corporate wealth, the quality and caliber of human resources play a decisive role in shaping an enterprise's operational capacity. The focus of analyzing and evaluating human resource operational capacity lies in how to fully mobilize workers' initiative and motivation, thereby enhancing their operational efficiency. Human resource operational capacity is typically analyzed using labor efficiency indicators.

2) Production Resource Operational Capacity Analysis

The modes of production are of different asset types, regardless of ownership or control by an enterprise. Hence, the operational capability of production resources indicates how efficient a company uses its overall resources and its parts. The rate of asset operations is highly influenced by how fast the assets turn over. This turnover rate is often estimated through turnover rates and turnover periods. The analysis may be analyzed in terms of various perspectives such as current asset turnover, non-current asset turnover, and total asset turnover.

2.3.3 Profitability Analysis

Profitability is a measure of a companys capacity to produce returns on its investment, which is usually expressed using the magnitude and stability of its profits. The analysis of profitability requires looking at the analysis of operating profitability, the analysis of asset profitability, the analysis of capital profitability, and the quality of earnings.

1) Operating Profitability Analysis

The analysis looks at earnings potential of the company on the basis of the connection between production output and consumption and profits. The major indicators to be used in the analysis are gross profit margin, operating profit margin, net profit margin and cost-to-profit ratio.

2) Asset Profitability Analysis

Asset profitability measures the ability of a company’s economic resources to generate income. The primary metrics for this analysis include return on total assets (ROA), total asset utilization rate, and net return on total assets.

3) Capital Profitability Analysis

The term capital profitability is used to describe the capacity of an enterprise investor to make profits by investing in the business in terms of capital. In this field, the most important indicators are such as the return on equity (ROE), the return on capital employed (ROCE), earnings per share (EPS), and the price-to-earnings (P/E) ratio.

4) Earnings Quality Analysis

Earnings quality refers to the structure and stability of an enterprise's profits. The primary indicator for evaluating earnings quality is the cash coverage ratio.

2.3.4 Development Capability Analysis

Development capacity represents a company's potential to expand its scale and strengthen its capabilities beyond mere survival. Analysis of development capacity encompasses the following dimensions: profit growth analysis, asset growth analysis, capital growth analysis, and technological investment growth analysis.

1) Profit Growth Analysis

The value of a company is largely determined by its ability to generate profits and sustain growth. As such, the growth of profits is a critical measure of a company's development potential. Important indicators to assess this growth include the rates of operating revenue growth, operating profit growth, net profit growth, and the three-year average growth rate of operating revenue.

2) Asset Growth Analysis

Asset growth is a vital aspect of corporate development and a key means of increasing enterprise value. The primary metric is the total asset growth rate.

3) Capital Growth Analysis

Capital growth signifies a company's strength and serves as the source for expanded reproduction. It demonstrates the company's development level and is a crucial aspect for evaluating its growth potential. Key metrics include capital accumulation rate, capital preservation and appreciation rate, and the three-year average capital growth rate.

4) Analysis of Technology Investment Growth

Technology investment growth reflects the company's emphasis on and commitment to research, development, and technological innovation. It is a vital aspect for evaluating the company's growth potential. The primary metric is the technology investment ratio.

2.4 Decision Tree-Based Financial Crisis Early Warning and Risk Control Analysis

A decision tree is a hierarchical graph that is composed of nodes and directed edges, usually having three kinds of nodes:

(1)The root node is a node that does not have any incoming edges, but may have one or more outgoing edges.

(2)Internal node: The node has one incoming edge and at least two outgoing edges.

(3)Leaf node (terminal node): It has only one incoming edge and no outgoing edges.

The procedure starts at the root node and involves using test conditions to assess the records. Depending on the outcome of the test, the corresponding branch is chosen. Evaluation goes down the branch and can lead to another internal node (to which a new test is applied) or a leaf node. When a leaf node is attained, then the associated class label of that leaf is applied to the evaluated record.

The MBDT algorithm forms the foundation for several decision tree methods, including ID3, C4.5, and CART. In this approach, a decision tree is built by recursively partitioning the training records into increasingly homogeneous subsets. Let D_t represent the training records associated with node t, and $y=\{y_1, y_2, \cdots, y_n\}$ denote the class labels. The recursive definition of the MBDT algorithm is outlined below:

1) If all records in D_t belong to the same class y_t, then node ttt becomes a leaf node labeled with y_t.

2) If D_t contains records from multiple classes, choose an attribute test condition to divide the records into smaller subsets. For each outcome of the test condition, create a child node and

distribute the records from D_t to the child nodes based on the result of the test. The algorithm is then applied recursively to each child node.

2.4.1 Trigger Conditions for Corporate Financial Crisis Early Warning

The assessment of whether a company is in a state of financial crisis primarily involves evaluating four dimensions: the external business environment, moral hazard, the adequacy of corporate cash reserves, and whether sufficient financing has been secured. The trigger conditions for corporate financial crisis early warning will be incorporated into the model as attribute testing criteria and nodes.

1) Based on the previously constructed analytical decision model comprising four financial indicators—debt-paying capacity, operational capability, profitability, and growth potential—the initial consideration focuses on the impact of the external environment on the company's status:

a) Favorable state (probability p_{H}). External environmental factors are highly favorable; the project will succeed regardless of the entrepreneur's effort.

b) Unfavorable state (probability p_{L}). External environmental factors are highly unfavorable; the project will fail even with maximum entrepreneurial effort.

c) Intermediate State (probability $\Delta p = p_{\mathrm{H}} - p_{\mathrm{L}}$). Success is neither guaranteed nor inevitable; the project may succeed if the entrepreneur exerts effort.

When the external state shifts to the adverse state, the financial crisis warning is triggered. Here, $p_{\mathrm{H}}, p_{\mathrm{L}}$ are derived from data mining across numerous enterprises.

2) At the moral hazard level, the financial crisis warning is triggered upon detecting entrepreneurial shirking.

3) At the cash flow and liquidity risk level, the financial crisis warning is triggered when the enterprise's cash holdings fall below the critical threshold $\bar{A}$.

4) At the financing level, the financial crisis warning is triggered when the funds raised fall below the critical threshold ρ^*; the π function is derived from data mining across numerous enterprises.

2.4.2 Decision Tree-Based Financial Crisis Early Warning and Risk Control Model

There are two main types of variables used in decision trees:

1) Numeric variables (NC): These are either integer or floating-point numbers. The symbols "$>=$" "$>$", "$<$", and "$<=$" are used as segmentation conditions (after sorting, this helps optimize the time complexity of the segmentation algorithm by leveraging existing segmentations).

2) Name type (NI): This is similar to the enumeration type in programming languages, where values must be selected from a limited set of options. The "=" symbol is used to denote selection.

The basic steps of decision tree construction are as follows:

1)Start by treating all records as a single node.

2)Test each split for every variable to find the best division.

3)Split the node into two branches, t_1 and t_2.

4)Repeat steps 2-3 for nodes t_1 and t_2 until the node is "pure" enough to be optimally divided.

Let $k(i \mid t)$ represent the proportion of a given node t that belongs to class i, and denote this proportion as k_i. In a two-class problem, the class distribution of any node can be written as $\left(k_0, k_1\right)$, where $k_1 = 1 - k_0$. The metric used to determine the best division is typically based on the level of impurity in the child nodes after the split. The lower the impurity, the more the class distribution is skewed. Common measures of impurity include:

$$\text{Entropy}(t) = -\sum_{i=0}^{n-1} k(i \mid t) \log_2 k(i \mid t) \tag{11}$$

$$\text{Gini}(t) = 1 - [k(i \mid t)]^2 \tag{12}$$

$$\text{Classification error}(t) = 1 - \max_i [k(i \mid t)] \tag{13}$$

Formulas (11)-(13) are used to specify three popular metrics: larger numbers are associated with higher purity, whereas smaller numbers represent lower purity, or a better partition. The available literature shows that the application of these formulas in defining splits does not influence the ultimate classification accuracy significantly. In order to measure the usefulness of a test condition, you should check the degree of impurity of the parent node prior to splitting with the degree of impurity of the child node after the split. More difference between the parent and child nodes implies a more effective test condition.

MBDT algorithm incorporates decision tree elements (TreeNode), and it is intended to make sure that the user focuses on branch attribute choice strategies that do not overfit. It is done by using the bootstrap approach to evaluate models.

Employing the bootstrap method for model evaluation:

Training records utilize sampling with replacement, meaning that records chosen for training are returned to the original dataset, giving them an equal chance of being selected again. If the original dataset contains NNN records, the probability of a record being selected by bootstrap sampling is given by $1-(1-1/N)^N$. As N becomes large, this probability approaches $1-\mathrm{e}^{-1}$. Records not selected for training automatically form part of the test set. By applying the model trained on the training set to this test set, an estimate of the bootstrap sample accuracy (ε_j) is obtained. This sampling process is repeated bbb times, generating bbb bootstrap samples.

Thus, the overall accuracy ($\left(acc_{boot}\right)$) is derived from the accuracy ($\left(acc_s\right)$) calculated using the complete training set of labeled samples:

$$acc_{boot} = \frac{1}{b}\sum_{1}^{b}\left(0.632 * \varepsilon_j + 0.368 * acc_s\right) \tag{14}$$

Once a company is identified as being a financial crisis and the reasons are established using a decision tree model, what should be done with the risk controls? In what way can the preservation of value theory be integrated into this risk control model? Decision-making strategies must be developed to forecast the occurrence of a financial crisis on four factors, including the external environment of the company, moral hazard, the availability of corporate cash reserves, and the availability of sufficient financing. Using such criteria, a decision tree model can be constructed as follows:

1 In case the crisis is caused by the company external environment, apply the value preservation strategies like hedging.

2) If entrepreneurship is to blame, enhance incentives, enhance control, or replace the entrepreneur.

3) If the issue stems from cash flow problems, aim to adjust A to the critical threshold $\bar{A}$. If this cannot be achieved, terminate the project to cut losses promptly.

4) If the issue stems from insufficient financing, aim to adjust the financing amount ρ to $\rho^*(\tau)$—for example, by increasing τ—and if this cannot be achieved, terminate the project to cut losses promptly.

3 Construction and Application of Financial Intelligence Analysis and Decision-Making Models Supported by MBDT

3.1 Analysis of Precise Financial Decision-Making Requirements

Company T is a leading enterprise in a certain industry with substantial mineral resources. For the purpose of industrial transformation and upgrading, it seeks to select outstanding ferrous metal smelting enterprises from downstream companies for substantial investment. Company T needs to verify the financial statement data of downstream enterprises interested in participation, extract data supporting investment decisions, and screen out an enterprise demonstrating excellent comprehensive capabilities.

The analysis is carried out based on financial information of 10 ferrous metal smelting companies that are available to invest. The balance sheets, income statements, cash flow statements and industry classification tables are analyzed and correlated with data in four sources. Four important financial indicators are selected as the screening criteria: debt-to-asset ratio, total asset turnover, operating profit margin, and capital accumulation rate. These respectively represent the enterprises' debt-paying ability, operational efficiency, profitability, and growth potential. Using the measurement of financial data in an overall manner, and classification of nodes, the enterprise having the best financial statement performance was initially identified. Following that, there was a thorough financial analysis of such an enterprise.

The classification results of the four types of financial statement data of the ten enterprises are shown in Table 1. The classification results of these ten enterprises are presented on Figure 2. Of the four kinds of data, balance sheet, income statement, and cash flow statement, as well as industry classification, Company H has the largest information content, at 25.208, 20.893, and 23.363 respectively, and it is the only one in two categories. Between the 10 companies aggressively pursuing investments, Company H is the most successful in the area of balance sheet structure, profitability, cash flow, and industry positioning.

Table 1: Classification of Four Types of Report Data from 10 Enterprises

Enterprise number	Balance Sheet	Income Sheet	Cash Flow Sheet	Industry Classification Sheet
A	6.307	6.757	6.044	0
B	8.212	6.223	6.286	0
C	6.497	4.603	5.246	0
D	8.952	4.556	6.139	0
E	10.784	6.481	7.155	1
F	9.062	8.199	6.945	1
G	10.559	5.735	6.564	1
H	**25.208**	**20.893**	**23.363**	**2**
I	13.164	6.968	10.378	3
J	14.548	6.763	11.388	3

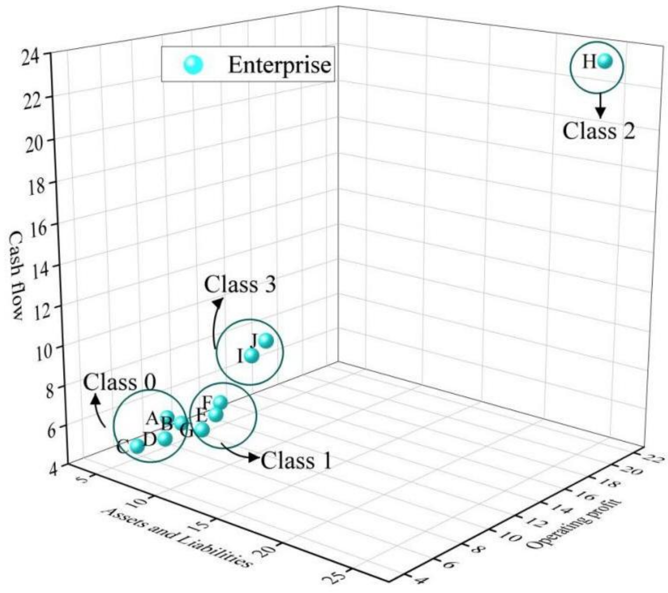

Figure 2: Visualization of 10 enterprise classification results

Through the process of filtering out significant information based on financial statements in relation to four essential indicators (debt-to-asset ratio, total asset turnover, operating profit margin, and capital accumulation rate) and comparing them in totality, we can determine which enterprise has the best operational performance. The comparison of the operational performance of the 10 enterprises is shown in Figure 3. Enterprise H has a debt-to-asset ratio of merely 5.017 percent, and its total asset turnover, operating profit margin, and capital accumulation rate are 12.946, 18.236, and 19.286, respectively. According to the comparison of the four capability measures, it can be concluded that the operational performance of Enterprise H is higher than that of other enterprises. Thus, Enterprise H is chosen as a high-quality investment objective of in-depth financial data analysis.

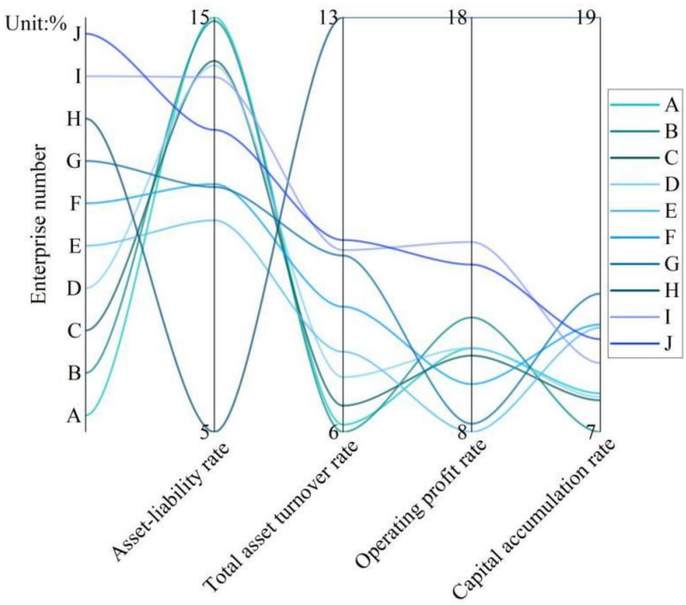

Figure 3: Comparison of the operating conditions of 10 enterprises

3.2 Algorithm Performance Simulation Experiments

The effectiveness of the improved MBDT algorithm was assessed through a simulation platform that will be used to analyze the financial situation of the company and make decisions related to it using the MATLAB 8.5 environment. The information in the experiment came out of four kinds of financial reports in the case of Company H, which included 2015-2024: balance sheets, income statements, cash flow statements, and industry classification tables. Test set - randomly selected 70 percent of the sample data, training set - other 30 percent. The Support Vector Machine (SVM) algorithm was selected to compare the algorithm performances. The experiment comprised of two stages: the first stage was assessing the performance of the algorithm on the basis of classification accuracy as a subjective measure, whereas the second stage relied on goodness-of-fit as an objective measure to determine the pros and cons of each algorithm in terms of corporate financial analysis and decision-making.

3.2.1 Comparison of Classification Accuracy Among Different Algorithms

It was performed as an experiment to check the quality of classification of the developed enhanced version of the MBDT algorithm in the context of corporate financial analysis and decision-making. The comparison of the level of data classification accuracy of the two algorithms is shown in Figure 4. The MBDT algorithm had a classification accuracy of between 70.363 percent and 92.125 percent, whilst the SVM algorithm had an accuracy of between 50.993 percent and 58.650 percent only. The MBDT algorithm performed better than the SVM algorithm when it came to classification accuracy as its performance proved to be superior in the classification of the node features of financial data. This benefit is due to the fact that the MBDT algorithm employs three classification methods to operate on financial data, ensuring that the system can achieve the classification accuracy standards required by intelligent enterprise financial analysis and decision-making.

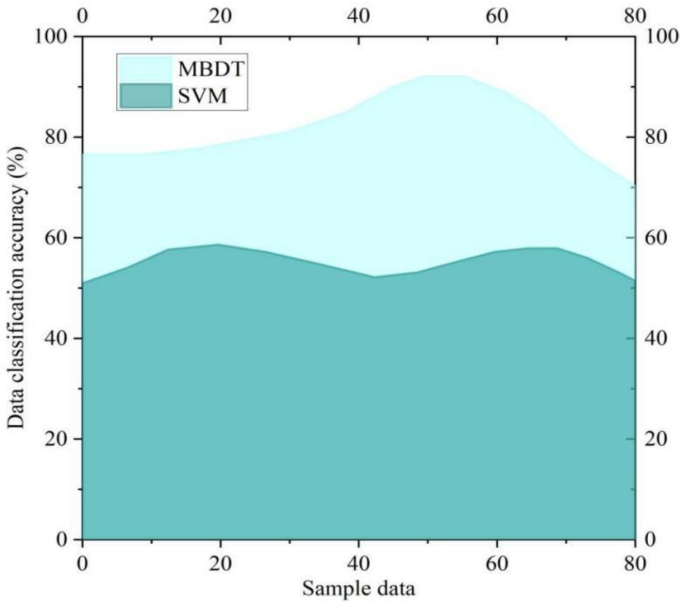

Figure 4: Comparison of data classification accuracy of the two algorithms

3.2.2 Comparison of Goodness-of-Fit Among Different Algorithms

Figure 5 compares the goodness-of-fit between the two algorithms and actual financial data during corporate financial analysis decision-making. The MBDT algorithm exhibits a maximum goodness-of-fit error of only 5.815% against actual financial data, with most data points showing minimal goodness-of-fit errors. In contrast, the SVM algorithm reaches a maximum goodness-of-fit error of 38.213%, with most data points exceeding 10% error. The metrology-based MBDT decision tree algorithm sets classification thresholds and refines sample data at each decision tree layer. Consequently, the decision tree-based financial crisis early warning model ensures comprehensive corporate financial analysis and decision-making capabilities.

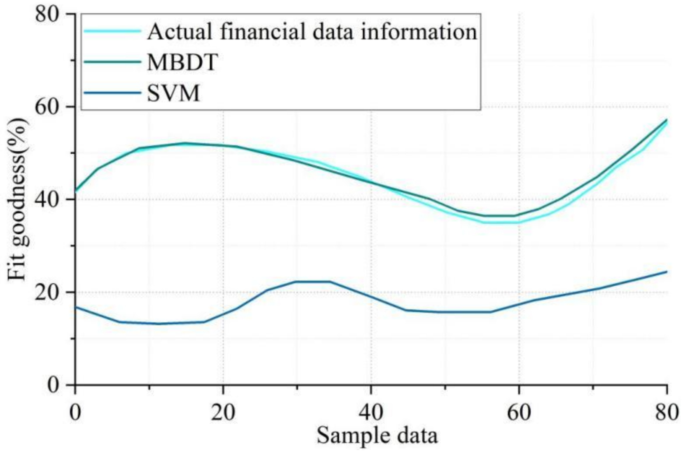

Figure 5: The goodness of fit of the two algorithms

3.3 Application of Financial Intelligence Analysis and Decision-Making Systems

3.3.1 Analysis of Debt-to-Asset Ratio

The improved MBDT decision tree algorithm has been incorporated in the financial intelligence analysis and decision-making system that was subsequently used to evaluate the debt-to-asset ratios of Company H over different years. After comparing these findings with real data, we investigated the quality of the system in terms of its accuracy in assessing the debt-to-asset ratio. Figure 6 depicts the comparison between the analyzed and real debt-to-asset ratios. The analysis of debt-to-asset ratio of H Company by the system between 2014 and 2024 reveals a minimal difference of about 0.529 percentage lower compared to the real ones. This error is regarded as insignificant in the scope of practical intelligent financial analysis and decision-making. To sum up, the financial intelligence analysis and decision-making system based on the MBDT decision tree algorithm can effectively help to analyze the past performance of a company in terms of finances.

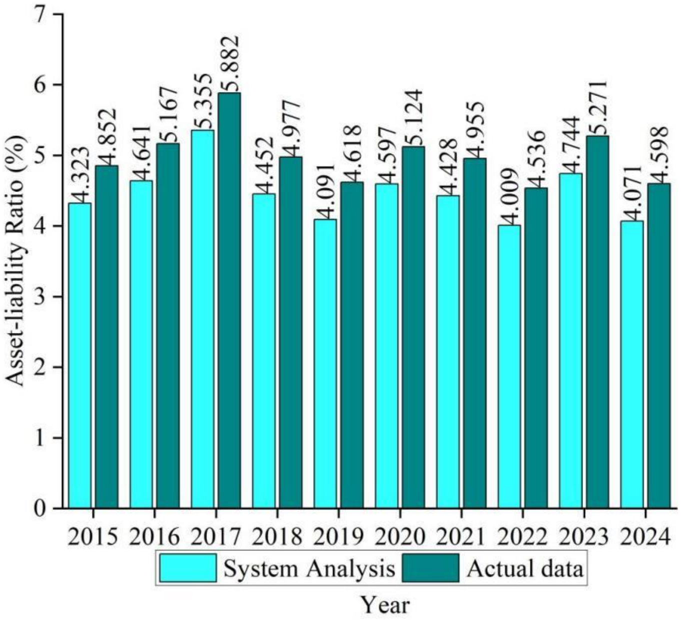

Figure 6: System analysis and comparison with actual asset-liability ratio

3.3.2 Budget Completion Rate Analysis

The application system makes budgetary decisions for the company's debt repayment, reserves, and profit/loss over the next decade, evaluating operational capability using budget fulfillment rates as an indicator. Higher fulfillment rates indicate stronger business prospects, leading to higher investment returns and greater feasibility for corresponding financial decisions. Figure 7 shows the system's analysis of Company H's projected budget fulfillment rates for the next ten years. The system analysis shows that the rates of debt repayment, reserves, and profit/loss budget fulfillment of H Company over the next decade are higher than 95 percent, which is a very good level of corporate performance. It is consistent with the evaluation of H Company performance during the last decade as excellent, which means that it has a very high credibility.

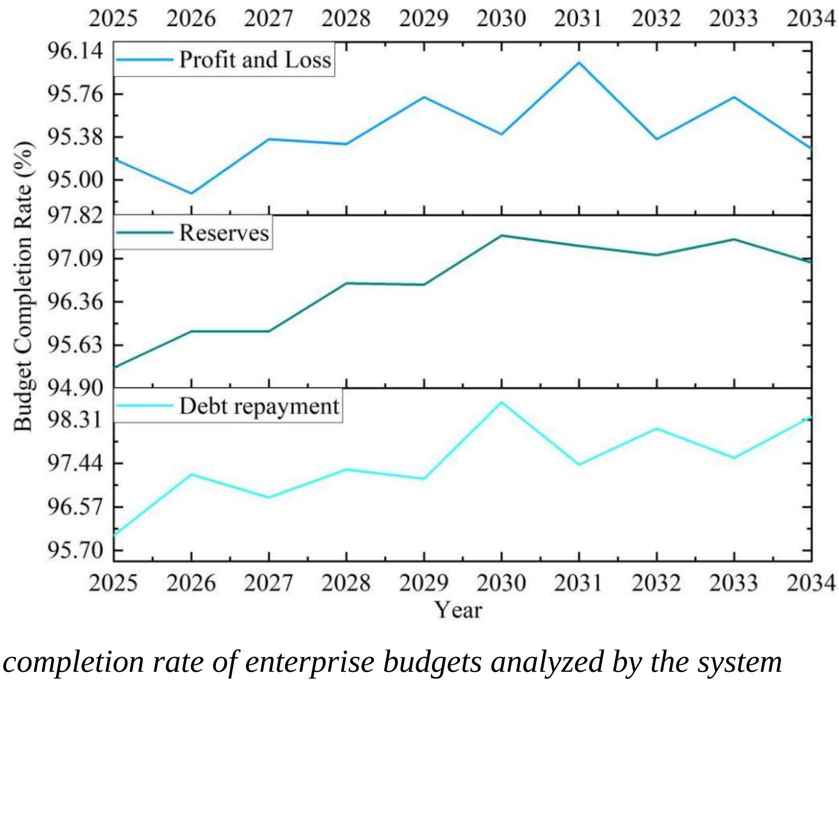

Figure 7: The completion rate of enterprise budgets analyzed by the system

3.4 Determination of Critical Thresholds

With the help of the MBDT decision tree algorithm and the financial intelligence analysis decision system, a financial crisis early warning model of the company has been developed. In order to make the model more accurate, so that Company T could predict possible financial crises in companies that need investment and thus minimize investment risks, this part defines the critical levels of two financial conditions, i.e. financial crisis and financial soundness. The development of sound critical thresholds will greatly enhance the accuracy of the early warning model.

Two types of errors may occur during prediction: Type I error refers to misclassifying financially sound companies as financially distressed, while Type II error involves misclassifying financially distressed companies as financially sound. To achieve optimal financial crisis early warning effectiveness, the threshold cannot be simplistically set at 0.50. Compared to Type I errors, model users prioritize minimizing Type II errors. Therefore, this study adopts the criterion of minimizing Type II errors while ensuring the lowest overall error rate. This study sets threshold points at intervals of 0.10 between 0.00 and 1.00. After processing the training set samples, they are fed back into the early warning model to calculate the Type I and Type II error rates and the overall error rate at different threshold values. Table 2 summarizes the Type I and Type II error rates at different critical thresholds. Among the nine tested thresholds, the lowest Type I error rate (28.215%) occurred at a threshold of 0.60. This threshold also yielded the lowest Type II error rate (1.047%), resulting in a total error rate of 29.262%—below the 30% threshold. Therefore, setting the critical threshold to 0.60 yields the most accurate financial crisis early warning results.

Table 2: The rates of two types of errors under different critical thresholds

Split point	I-class error rate (%)	II-class error rate (%)	Total error rate (%)
0.10	45.293	1.203	46.496
0.20	40.184	2.395	42.579
0.30	41.273	2.845	44.118
0.40	31.172	3.614	34.786
0.50	42.981	3.827	46.808
0.60	28.215	1.047	29.262
0.70	43.722	3.495	47.217
0.80	50.294	2.913	53.207
0.90	49.102	3.765	52.867

The financial data of 10 companies seeking investment were input into the financial crisis early warning model to evaluate its classification prediction performance. Table 3 presents the financial crisis early warning test results with a critical threshold of 0.60. No prediction errors occurred for either the 5 non-crisis enterprises or the 5 crisis enterprises, achieving 100% accuracy. This indicates that setting the critical threshold at 0.60 renders the constructed intelligent financial crisis early warning model highly reliable.

Table 3: Financial crisis warning test results of 0.60 critical threshold

Observed		Predicted		
		Non-financial crisis	Financial crisis	Correction percentage(%)
		0	0	
Non-financial crisis	0	5	0	100
Financial crisis	0	0	5	100
Total percentage(%)		-		100

4 Conclusion

The paper will present an enhanced version of the MBDT decision tree algorithm that can be used to analyze and model the corporate financial information and offer support with decision-making concerning forecasting of the corporate financial crisis. The accuracy rate of the MBDT decision tree algorithm is between 70.363% and 92.125, which is higher than the accuracy rate of the SVM algorithm (between 50.993 and 58.650%). In addition, in terms of goodness-of-fit to real financial data, the error of goodness-of-fit of the MBDT decision tree algorithm is within the range of ≤5.815%, which means very low error. In application to analysis of corporate debt-to-asset ratios, the algorithm had an error of about 0.529 percent. The predictions it made on budget completion rates were consistent with the results. At a critical level of 0.60 of the financial crisis early warning model, the overall error rate of both categories was 29.262 per cent, which is a very good indicator of crisis warning performance.

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