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Science and Technology Innovation Drives the Upgrading of Enterprise Financial Management System and the Enhancement of the Efficiency of Funds Utilization

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SUMMARY: *In the era of the swift advancement of information technology, it is extremely urgent for enterprise financial management systems to undergo digital upgrading. This research devises a comprehensive enterprise financial management system founded on big - data technology. This system incorporates two crucial subsystems: financial decision - making support and financial risk early - warning.Regarding financial decision - making support, through the utilization of FP - growth association rules and clustering algorithms, the indicators that influence the financial standing of enterprises are investigated and classified. For financial risk early - warning, a model is put forward, which is based on the optimization of a BP neural network by the particle swarm algorithm (PSO). The particle swarm algorithm is employed to search for the optimal initial weights and thresholds of the BP neural network.Moreover, the DEA - Malmquist approach is utilized to examine the impact on the enhancement of capital efficiency after the implementation of the digital financial management system in enterprises. The findings of the empirical research indicate that the overall prediction accuracy of the model attains 89.23%, suggesting that the model presented in this paper holds considerable practical worth.From 2019 to 2020, the efficiency of fund utilization has been increased by 13.06%. This reveals the substantial positive influence of digital transformation on improving the efficiency of fund utilization, and offers theoretical backing and methodological strategies for the digital transformation of the financial management of relevant enterprises.*

KEYWORDS: *financial risk early warning; financial decision support; PSO-BP; DEA-Malmquist method; fund use effectiveness; digital financial management*

1 Introduction

Modern enterprise operation is faced with internal and external complex environment, especially in the past two years by the new crown pneumonia epidemic, the economic recovery is weak, the enterprise must strengthen the internal management, improve the management effectiveness, to acquire the impetus for sustained operation [1, 2]. In this context, the functions of financial management continue to broaden, the traditional financial management model gradually exposed the low effectiveness of the use of funds, the response is not flexible enough and other issues, meeting the requirements of the swift growth of contemporary businesses has proven to be a challenging task.[3, 4]. In the current context of science and technology innovation-driven, financial management system upgrading and capital utilization efficiency is

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particularly important, This is not just an essential method for elevating the quality of corporate financial management; it is also an unavoidable option to keep pace with the digital economy era [5-7].

Over the past few years, there has been a swift advancement in information technology. Specifically, novel technologies like large - scale data analytics, machine intelligence, and cloud - based computing have been extensively utilized, has provided a new impetus for the change of financial management [8, 9]. By leveraging information technology, businesses are able to achieve automated gathering, instantaneous processing, and in - depth analysis of financial data. As a result, this enhances the transparency of financial management and the precision of decision - making [10, 11]. This conversion not only aids in minimizing the potential risks associated with financial operations but also streamlines the distribution of resources and boosts the overall operational effectiveness of the company [12]. Especially in the current complex and changing economic situation, rapid response to market changes and internal management needs has become an urgent problem for enterprises.

In the context of enterprise financial management systems, the utilization of information technology can be considered, the literature [13] introduces the low cost, high reliability, good scalability and other characteristics of cloud computing technology.Moreover, it elaborates on its utilization within the enterprise financial management system. This application not only facilitates the development of enterprise financial digitalization but also boosts the return on digitalization investment, along with enhancing flexibility and adaptability. Reference [14] delineates the drawbacks of the conventional enterprise financial management system. It then presents an enterprise financial management system founded on information technology. Subsequently, it validates the system's efficacy and worth via practical examples.Reference [15] conducts an analysis of the design of an enterprise financial management platform relying on multi - system data linkage. The aim is to enhance the coherence of multi - system data and the promptness of data updates in financial management. The experimental outcomes demonstrate the effectiveness of this design.Reference [16] presents a design approach for an Internet - based enterprise financial management system. The purpose is to enhance the accuracy and exactness of the information within the enterprise financial management system. By taking power enterprises as a case study, it elaborates on the system's design concepts and optimization. Reference [17] devises an enterprise financial management system based on the cloud platform. This system can notably facilitate the seamless flow of enterprise financial information, achieve refined management, and drive the informatization, digitization, and intelligence of enterprise financial management.Reference [18] introduces the two central aspects of financial management. One is to guarantee favorable cash flow and value - added processing, and the other is to implement risk prevention and control. It also emphasizes the significance of computers in the financial management process and explores the application of computer technology in enterprise financial management.Reference [19] systematically assesses the influence of the information age on enterprise financial management. It posits that the application of information technology can reinforce the continuous transformation and innovation of enterprise financial management, meet the development requirements of enterprises, and enhance the utilization of funds. It also puts forward specific strategies for enterprise financial management.Reference [20] analyzes the construction of financial management in the context of informatization. The goal is to offer better suggestions for enterprise development. It contends that the informatization of enterprise financial management can effectively address the issues in enterprise fund supervision, improve the fund utilization rate, reduce the enterprise operation risk, and enhance enterprise competitiveness.Consequently, enterprises should further augment their investment in informatization construction. With the aid of advanced technological means, they should continuously elevate the intelligent level of financial management to adapt to the ever - changing market environment and regulatory requirements [21-23]. Simultaneously, they should consistently monitor the system's application effect and user feedback, and make timely adjustments and optimizations to ensure that the information technology system can genuinely meet the actual needs of enterprises and provide robust support for the sustainable development of enterprises [24, 25].

This research centers around scientific and technological innovation as the primary impetus. It builds a decision - support sub - system within the financial management system by leveraging data mining algorithms. To achieve in - depth exploration of an enterprise's financial status, it employs association rules, clustering algorithms, and decision tree algorithms.The PSO algorithm is utilized to refine the BP neural network, which boosts the accuracy and reliability of financial risk alerts. Subsequently, adopting the DEA - Malmquist approach, this paper selects the financial data of small and medium - sized enterprises (SMEs) spanning from 2019 to 2024 as the data source. It evaluates the enhancement effect of fund - utilization efficiency during the digital transformation of the enterprise's financial management system from both static and dynamic viewpoints. Moreover, it delves into the practicality of this system.

2 Development of an enterprise financial management system leveraging big data

2.1 Comprehensive Technical Architecture Blueprint

The system's overall architectural design is segmented into three distinct tiers: the big - data parallel analysis tier, the big - data parallel processing tier, and the data storage tier. The big - data parallel processing tier addresses the needs for rapidity and real - time responsiveness. The big - data analysis tier conducts an in - depth examination of the data to uncover its latent value. Meanwhile, the data storage tier is responsible for housing the vast and diverse assortment of data. The comprehensive technical layout is depicted in Figure 1.

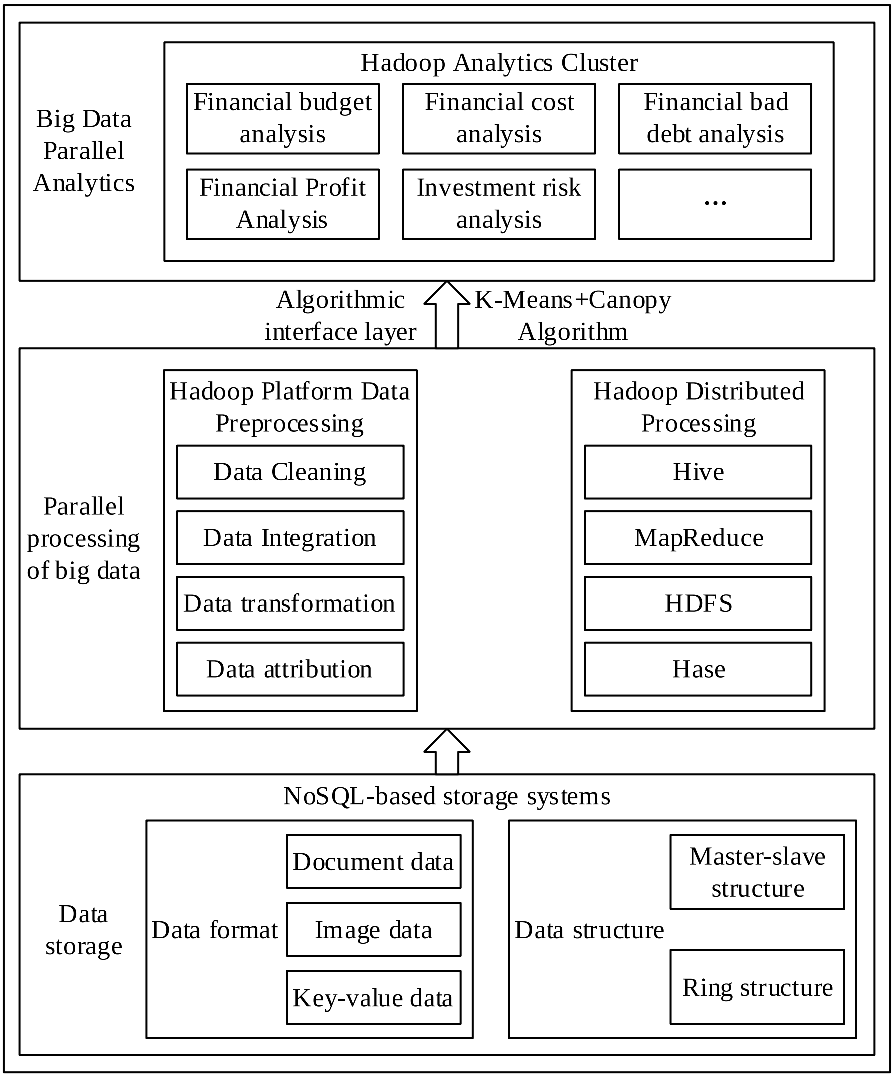

Figure 1: Overall technical architecture

2.2 Enterprise financial decision support subsystem design

The design is founded on the structural framework of "data collection stratum - data storage stratum - financial analysis stratum - decision support stratum". To begin with, relying on the internal financial system, external systems, and other relevant websites, data from internal departments, suppliers, customers, products, and other enterprises within the same industry are gathered. Subsequently, the collected raw data undergo processing and are stored in the data warehouse. Next, the processed data are analyzed and explored using big - data technology analysis approaches. Based on the outcomes of the financial analysis, the most optimal financial decision - making scheme is devised. Finally, the output results are presented in a visual format. Overall, the structural design framework of the enterprise financial decision support platform leveraging big - data technology is depicted in Figure 2.

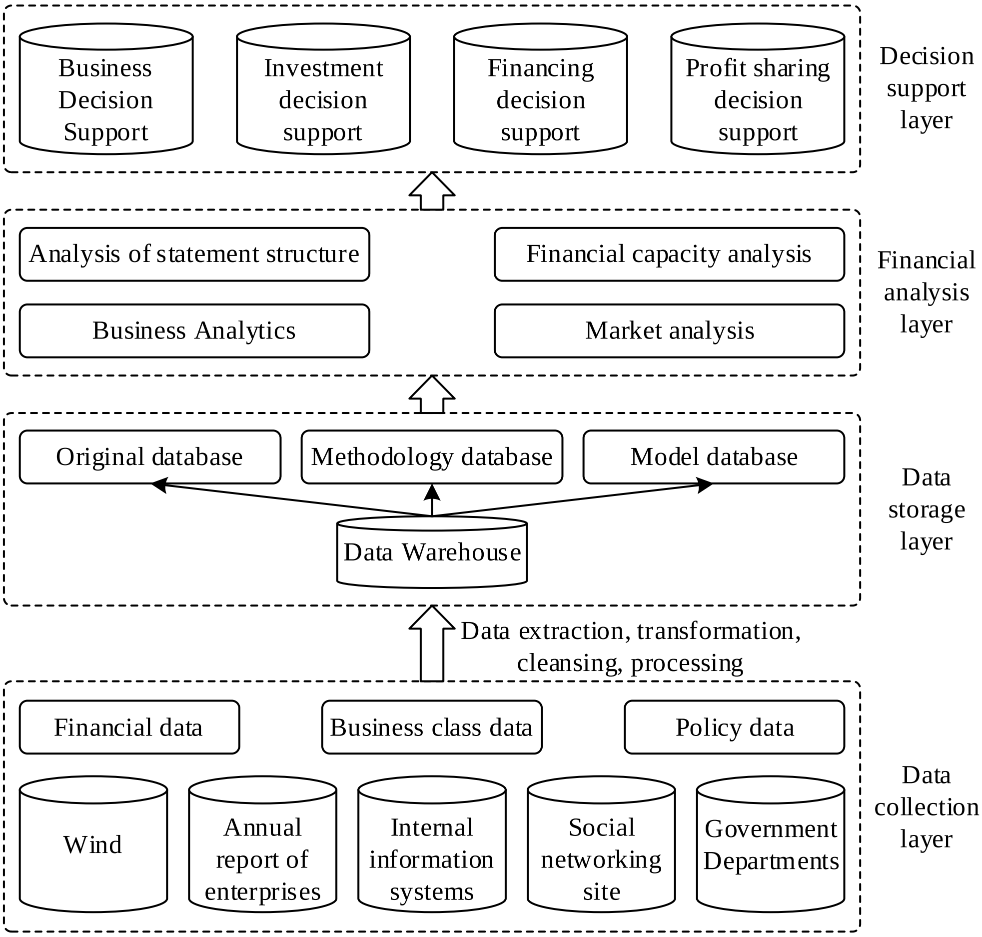

Figure 2: Enterprise financial decision support platform structure

2.2.1 Financial decision support subsystem hierarchy design

Enterprise managers rely on data as the foundation for making decisions. The application of big data technology addresses the issue of the scattered and outdated nature of traditional enterprise financial data. By integrating and updating in real - time the comprehensive accounting data and business data of enterprises, it strengthens the data foundation for decision - making by enterprise personnel.The primary raw data acquired through big data technology can be classified into three main types. Firstly, there is financial data. Secondly, business data is included. Thirdly, policy data forms the third category.Regarding the data sources, with the assistance of big data technology, enterprises are not limited to obtaining financial or business data from internal databases, OA office systems, and financial databases. They can also use web crawlers to gather policy - related data such as text data and macroeconomic data from external websites and social media networks in the external environment.

Given that financial data are publicly available and easily retrievable in financial databases, pertinent financial data reports and financial capability indicator data can be directly extracted from the database. Subsequently, these data can be fed into the enterprise financial decision - making support platform via the connection interface. In contrast, when it comes to business data and policy data, direct importation into the platform poses challenges. To address this, it is essential to leverage big - data technologies, such as Hadoop technology. These technologies enable the effective storage of data that are hard to store in traditional databases.

Through the extraction and examination of data from the original data repository using diverse financial assessment models in the model data repository, the outcomes of the analysis offer pertinent financial decision - making support to corporate managers. Corporate financial assessment leveraging big - data technology relies on the data in the original data repository. It employs the technical approaches and models in the method data repository and model data repository to conduct an analysis and evaluation of the enterprise's past and current operational and financial conditions. This process also furnishes a foundation for corporate managers to formulate precise and efficient financial decision - making plans.

Typically, the commercial choices made by companies encompass decisions related to production, sales, and inventory.

The implementation of big data technology in enterprise investment decision - making analysis generally consists of four main steps.First, in alignment with the short - term objectives and long - term strategies of enterprise development, it is necessary to identify the target that the enterprise most urgently needs to invest in during its current development phase.Second, by integrating the macro - economic environment data related to both internal and external investments stored in the data warehouse, industry trend data, and market information about competitors in the same industry, and leveraging the analytical models in the model database, an in - depth analysis of the investment risks and costs of the enterprise project can be carried out. The aim is to minimize these risks and costs to the greatest extent possible.Third, taking into account the time - value factor, relevant financial indicators such as net present value and present - value index from the data warehouse are used to estimate the investment returns of the project.Fourth, the existing investment decision plans are evaluated against the historical implementation of corporate investment decisions documented in the methodology database. From these evaluations, the most optimal investment decision plan is selected.

2.2.2 Clustering algorithms

In data mining, cluster analysis is the division of data based on certain attributes of the data, so that the similarity of the attributes of the data divided into the same cluster is as large as possible, and the similarity of the attributes of the data divided between different clusters is as small as possible. Due to the different ways of data processing, clustering algorithms are divided into five types: based on division, based on density, based on hierarchy, based on model, and based on grid.

(1) Among the clustering models founded on the principle of division, the K - means algorithm stands as the most classic one. The specific operational steps of the K - means algorithm are as follows:

First, arbitrarily select k sample points $\{\mu_1, \mu_2, \ldots, \mu_k\}$ in the dataset as the initial clustering centers, and calculate the Euclidean distance from each sample point to each clustering center:

$$Dist(x_i, \mu_i) = \sqrt{\sum_{i=1}^{k} (x_i - \mu_i)^2} \tag{1}$$

Each clustering center corresponds to a class, Compute the Euclidean distance from every sample point to each cluster center;

Then, for each class division of a sample point, it is necessary to recalculate the clustering center of this class, at this time, the new clustering center of this class is the center of mass of all sample points in this class:

$$\mu_i = \frac{1}{|c_i|} \sum_{x \in c_i} x \tag{2}$$

The objective function computes the sum of squares of the Euclidean distances from each sample point to the clustering center of the class to which it belongs, and the algorithm iteration is stopped when the objective function converges to a minimum value.

$$E = \sum_{i=1}^{k} \sum_{x \in c_i} \left\| x - \mu_i \right\|_2^2 \tag{3}$$

In Generally speaking, the fundamental principle of the K - means algorithm is relatively straightforward. Its specific implementation is relatively effortless, and the rate of convergence is relatively rapid. but the anti-interference ability is not strong, the clustering effect is not good in the face of data imbalance samples, and the clustering effect is greatly affected by the number of clusters.

(2) In the density-based clustering model, the Mean Shift algorithm is more representative. The core of its algorithm is to use the mean shift vector to find a region with the highest local density, and consider all sample points in the search process as a class, first, randomly select a sample point as the center point, set a radius, draw a circular sliding window, and calculate the sum of the vectors from the center point to all the sample points in the region, and the direction of this vector represents the direction of the data with higher density:

$$M_h(x) = \frac{1}{k} \sum_{x_i \in S_h} \left(x_i - x \right) \tag{4}$$

(3) Apart from the Mean Shift algorithm, the DBSCAN algorithm is another frequently utilized algorithm in density - based clustering models. In contrast to the K - means algorithm, the K - means approach requires users to pre - determine the number of clusters. Conversely, the DBSCAN algorithm does not have this requirement; instead, it will automatically categorize the data.

The specific steps of the DBSCAN algorithm are as follows: first, arbitrarily select a sample point, according to the given radius of the domain and the minimum number of points to determine whether it is a core point, if it is a core point, it and its density accessible to all the sample points will be divided into a class cluster, and they are marked as processed, if it is not a core point, select another sample point to carry out the above operation; and then keep repeating the above steps until all the sample points are processed, and finally the data are divided into different class clusters, and the sample points in the class clusters are all density connected.

(4) The above clustering algorithms also have certain limitations, DBSCAN it is necessary to set the domain radius and the minimum number of points of the two parameters in advance, and it is more difficult to quickly adjust to the appropriate value, to address this issue, the concept of hierarchical clustering is incorporated into the DBSCAN algorithm to develop the HDBSCAN algorithm.

HDBSCAN algorithm is a variant based on the DBSCAN algorithm, compared to DBSCAN, HDBSCAN does not need to set the domain radius and the minimum number of points artificially, but only needs to set the minimum number of samples for generating the class clusters, and the algorithm can recommend the optimal clustering results automatically.

Specifically, HDBSCAN introduces a novel distance metric that can more effectively mirror the density of data points. The corresponding formula is presented as follows:

$$d_{mrearch-k}(a,b) = \max\left\{ core_k(a), core_k(b), d(a,b) \right\} \tag{5}$$

where $d_{mrearch-k}(a,b)$ is the mutually reachable distance between the point a and the point b, $core_k(a)$ is the furthest distance containing k points centered on the point a, and $d(a,b)$ is the Euclidean distance between the point a and b the Euclidean distance between them.

2.2.3 Association Rule Algorithm

Association rule analysis stands as one of the most frequently employed research techniques in data mining. Its objective is to uncover the latent relationships between diverse data. Among the commonly utilized algorithms are the Apriori algorithm, the FP - growth algorithm, and others.

In the process of association rule analysis, to evaluate the efficacy of the mined rules, it is necessary to compute the support and confidence of each rule.

The support is determined as the probability of the simultaneous occurrence of event A and event B. Here, support_count$(A \cap B)$ represents the number of transactions that encompass both event A and event B, while total_count refers to the number of all transactions.

$$support(A => B) = P(A \cup B) = \frac{\sup port\_count(A \cap B)}{total\_count} \tag{6}$$

Confidence is computed as the quotient of the likelihood of events A and B happening concurrently and the likelihood of event A taking place. Here, support_count(A) represents the total number of all transactions that include event A.

$$confidence(A => B) = P(B \mid A) = \frac{\sup port\_count(A \cap B)}{\sup port\_count(A)} \tag{7}$$

Prior to conducting rule mining, a threshold is typically established for support and confidence, referred to as the minimum support and minimum confidence.

As can be discerned from the aforementioned steps, the Apriori algorithm necessitates multiple scans of the database. Simultaneously, it generates a substantial quantity of candidate item sets, which elevates the algorithm's time expenditure. Given that the drawbacks of the Apriori algorithm cannot be evaded, numerous improvement algorithms have been put forward by researchers. Among them, the FP - growth algorithm curtails the number of database scans and does not require the generation of candidate item sets, thereby enhancing the operational efficacy. The specific steps are presented as follows:

Building an FP tree involves a series of well - defined steps. To begin with, conduct an initial scan of the database. During this scan, calculate the occurrence frequency of each item. Next, establish a minimum support threshold. Then, arrange all items in a descending order based on their respective frequencies. Items with a frequency lower than the minimum support threshold are removed. This process results in the creation of a set of frequent items.After obtaining the frequent item set, perform a second scan of the database. For each transaction in the database, filter and re - order the items in the transaction in descending order, following the sequence of the frequent item set determined earlier.The final step is to construct the FP tree. Start by creating a root node labeled as null. Then, for each transaction, insert its items as nodes into the FP tree one by one. If all the items in a transaction are already present in an existing branch of the tree, increment the count value of the corresponding branch nodes. In cases where some or all of the items in a transaction do not exist in any existing branch, create a new branch. Keep repeating this process until all transactions have been incorporated into the FP tree.

(2) Extracting frequent item sets from the FP tree. Initially, acquire the conditional pattern base associated with each item in the FP tree. This conditional pattern base refers to the collection of paths that terminate with that specific item. Subsequently, build a conditional FP tree using the conditional pattern base. The construction principle of this conditional FP tree is consistent with the principle for constructing the FP tree mentioned earlier. Screen out the items within the conditional pattern base whose count values are less than the minimum support. Then, add the processed conditional pattern base to the conditional FP tree one - by - one and adjust the count value of each node to match the count value of the leaf nodes. Eventually, merge the items with the count values of the corresponding branch nodes. If this is not feasible, create a new branch. Continue this process until all transactions have been inserted into the FP tree.

2.2.4 C5 Decision Tree Classification Algorithm

Classification is to find out what a set of data objects in a data set have in common and to classify the data into different categories according to a certain pattern, it aims to map the data elements in a data set into a given certain category by means of a certain classification model, it is generally used in application classification, trend prediction, etc. There are many kinds of data classification algorithms, but among all the classification methods available today, none is more popular than the decision tree classification method.

C4.5 decision tree algorithm is a data classification algorithm with an extremely wide range of applications, while C5 is a decision tree generation algorithm developed on the basis of C4.5, which uses the attributes of the samples as the nodes of the tree, the values of the attributes as the branching of the tree structure, and is generated by using the principles of information theory and the attributes of a large number of data samples to analyze and generalize. For the selection of attributes, the parameters that can be used as metrics are: information gain rate, Gini index, distance and so on.

C5 adopts the information gain rate as the metric parameter for attribute selection, and its calculation method is as follows:

Suppose that there is a dataset T with categories categorized into $\left[C_1, C_2, \ldots, C_k\right]$. Choose a data attribute V that will T be divided into subsets. Let V have mutually non-overlapping n values $\left[V_1, V_2, \ldots, V_n\right]$, then the dataset T will be divided into n subsets, $\left[T_1, T_2, \ldots, T_n\right]$ when all instances in T_i are V_i.

Let: $|T|$ be the number of examples in the dataset T; $\left|T_i\right|$ be the number of examples in $V = V_i$; $\left|C_i\right| = freq\left(C_i, T\right)$ be the number of examples in class C_j; $\left|C_j V\right|$ is the number of $V = V_i$ examples with class C_j.

Then there are:

(1) The probability that category C_j occurs:

$$P\left(C_i\right) = \frac{\left|C_i\right|}{|T|} = freq \frac{\left(C_i, T\right)}{|T|} \tag{8}$$

(2) Probability of property $V = V_i$:

$$P\left(V_i\right) = \frac{\left|T_i\right|}{|T|} \tag{9}$$

(3) Example of property $V = V_i$ with conditional probability of category C_j:

$$P\left(\frac{C_j}{V_i}\right) = \frac{|C_j V|}{|T_i|} \tag{10}$$

(4) Information entropy of categories:

$$\begin{aligned} -H(C) &= \sum_J P(C_J)\log_2\left(P(C_J)\right) \\ &= \sum_J \frac{freq(C_J, T)}{|T|} \times \log_2\left(\frac{freq(C_J, T)}{|T|}\right) = info(T) \end{aligned} \tag{11}$$

(5) Conditional entropy of category:
Partitioning T according to the attribute V, the category conditional entropy is:

$$H\left(\frac{C}{V}\right) - \sum P(C_i)\sum\left(\frac{C_j}{V_i}\right)\log_2\left(\frac{P_j}{V_i}\right) = \sum_{i=1}^{n}\frac{|T_i|}{T}\times info(T_i) = infov(T) \tag{12}$$

(6) Information gain:

$$I\left(\frac{C}{V}\right) = H(C) - H\left(\frac{C}{V}\right) = info(T)infov(T) = gain(V) \tag{13}$$

(7) Information entropy of property V:

$$H(V) = \sum_i P(V_i)\log 2\left(P(V_i)\right) = \sum_{i=1}^{n}\frac{T_i}{T}\times\log 2\left(\frac{T_i}{T}\right) = split\_info(V) \tag{14}$$

(8) Information gain rate:

$$gain\_ratio = I\,\frac{(C,V)}{H(V)} = \frac{gain(V)}{split\_info(V)} \tag{15}$$

The maximum information gain rate serves as the standard for attribute selection and sample partitioning. It outperforms the ID3 algorithm, which utilizes the information - gain approach. This superiority mainly stems from the fact that it addresses the drawback of the ID3 algorithm, where the algorithm has a bias towards attributes with a greater number of values; however, no matter which decision tree algorithms, the establishment of which generally need to include the growth of the decision tree and pruning of the two processes.

1) The growth of the decision tree:

a.Each division of it is based on the most significant features;

b.The sample space of the data being analyzed is called the root, and the algorithm has to select one of the most significant features from all of them and use this feature to partition the sample space into a number of subspaces;

c.Repeat the second process until all the data below the class branches belong to the same class, such a branch can then be identified as a node of a leaf, and the tree stops growing after all the data in all the subspaces have become of a uniform class.

2) Decision tree pruning method:

a.In the decision data establishment, if built too deep, it will easily lead to overfitting the data, that is to say, all the number of classification results are basically the same, and therefore lack of representativeness;

b.For decision trees pruning is usually done top-down, each time to identify the branch in the training data that contributes the least to the prediction accuracy and cut it off, i.e., put the corresponding two categorical data together;

c. Simply put, it is necessary to let the decision tree grow freely first, after growing to a certain extent, slowly through pruning is the decision tree back to contraction, as for the contraction of how much, it is usually necessary to according to the decision tree itself in the object dataset on the performance of repeated attempts.

The current mainstream decision tree algorithms are ID3, C4.5, C5 three, they are similar in the basic principles, but there are some differences, the following advantages and disadvantages of various algorithms for in-depth analysis:

ID3 algorithm uses the information gain maximization method for node selection, compared with C4.5, C5, ID3 algorithm's shortcomings are more obvious, it only considers a single attribute in the branch node, and only considers the parameter belongs to the discrete attribute variables.

C4.5 algorithm in the node selection is used in the information gain rate maximization method, in C4.5 algorithm attribute variables can be continuous, simultaneously, during the construction of the decision tree, the pessimistic pruning approach can be employed to prune using the training set. This enables the algorithm to skip the separate pruning step. However, it also suffers from two significant drawbacks. Firstly, throughout the decision - tree construction process, the dataset has to be scanned and sorted sequentially multiple times. This, to a certain degree, reduces the algorithm's efficiency. Secondly, it is only applicable for constructing decision trees on datasets cached in memory. Therefore, when the training set is too large to fit entirely in memory, this algorithm cannot be used for decision - tree construction.

The C5 decision - tree algorithm addresses the aforementioned drawbacks. It employs the Boosting approach during node selection to enhance the model's accuracy. Moreover, it boasts a faster computational speed and requires less memory space, in addition to the following four important breakthroughs: 1. It improves the execution efficiency and memory usage, and therefore is more suitable for the classification of large datasets; 2. When faced with the dataset More robust performance when faced with datasets with missing data or too many fields; 3. Higher classification accuracy; 4. Compared to other models, it is easier to understand and has a very intuitive explanation of the exit rules.

2.2.5 Results of data analysis of corporate financial decision-making

In this research paper, we will employ the traditional FP - growth algorithm, a component of the association rule analysis algorithms, to conduct an analysis of nine food production companies. We have performed an analysis using the traditional FP - growth algorithm on these nine food production companies, denoted as A = {A1, A2, A3, A4, A5, A6, A7, A8, A9}. Through this analysis, we have obtained the outcomes of the traditional FP - growth algorithm analysis, which are presented in Table 1. In this table, B1 to B11 respectively stand for net assets per share (in yuan), net capital reserve per share (in yuan), undistributed profit per share (in yuan), net assets ratio (in %), long - term liabilities ratio (in %), cash ratio (in %), inventory ratio (in %), net assets growth rate (in %), total assets growth rate (in %), return on investment growth rate (in %), and current assets ratio (in %).The FP - growth algorithm has identified certain crucial factors that influence the production and operation of these enterprises. Subsequently, we will use the decisive clustering algorithm to appropriately categorize the aforementioned nine enterprises.

Table 1: Classical FP-growth algorithm analysis results

	A1	A2	A3	A4	A5	A6	A7	A8	A9
B1	8.79	7.93	8.15	7.81	7.93	8.26	8.29	7.82	8.33
B2	0.68	0.76	0.76	0.75	0.72	0.81	0.78	0.77	0.74
B3	1.30	1.45	1.37	1.39	1.36	1.38	1.45	1.37	1.34
B4	28.35	29.21	28.95	28.96	28.84	28.81	28.10	28.95	28.74
B5	1.29	1.34	1.28	1.32	1.34	1.38	1.30	1.39	1.35
B6	88.31	88.19	82.50	81.08	83.21	84.32	86.25	87.34	85.56
B7	16.24	18.34	24.51	35.25	29.31	37.41	29.98	32.82	40.11
B8	34.17	16.37	32.85	17.86	28.46	15.22	7.31	36.74	8.95
B9	5.44	6.11	4.16	4.95	6.11	3.28	6.36	5.23	6.48
B10	31.18	21.60	22.32	19.81	30.12	28.41	19.30	19.59	18.43
B11	50.15	49.40	49.05	53.34	55.20	50.09	48.32	48.80	47.41

In the analysis of the clustering algorithm, this research will conduct a clustering - based analysis on the financial data of the aforementioned nine food - manufacturing enterprises. Generally speaking, the financial situation of enterprises can typically be classified into four categories: excellent financial standing (A), relatively good financial standing (B), mediocre financial standing (C), and subpar financial standing (D).During the cluster analysis in this section, the distribution clustering utility within the MATLAB software was employed to carry out the financial cluster analysis of grain enterprises. By programming with the MATLAB software and obtaining the operation results, this paper directly converts the data into graphical representations. The outcomes of the cluster analysis are presented in Figure 3. Here, the yellow - colored, blue - colored, orange - colored, and gray - colored enterprises represent those with financial standings of class A, B, C, and D respectively.

Based on the outcomes of the cluster analysis, among these nine food - producing enterprises, one enterprise has a sound financial standing and is classified as a top - notch Class A enterprise. That enterprise is A8. There are a total of three enterprises with a good financial status, falling into the Class B category. These enterprises are A1, A3, and A5. Another three enterprises have an average financial situation and are classified as Class C. They are A2, A4, and A6. The financial condition of enterprises A7 and A9 is relatively poor, and they belong to the D category.Next, the decision - tree algorithm will be employed to assist business leaders and venture capitalists in determining the investment direction and key areas for the next phase.

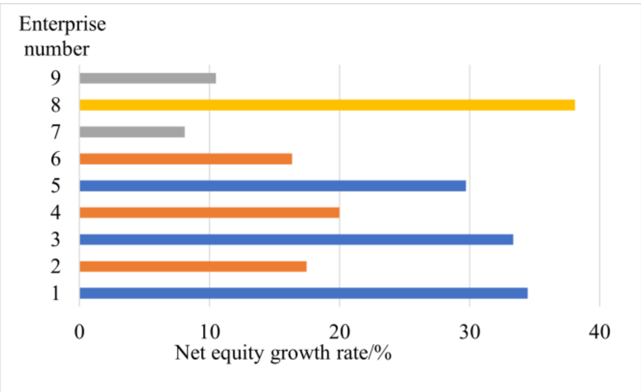

Figure 3: Cluster analysis results

Previously, through association rules and clustering analysis, we've identified the indicators that influence an enterprise's financial standing and classified the enterprise's financial operational status. In this section, we'll employ the C4.5 decision - tree algorithm to forecast the enterprise's financial development status. The indicators that impact the enterprise's financial condition, presented in Table 1, will serve as the classification criteria for the decision - tree analysis in this part.These indicators are as follows: undistributed earnings per share (in yuan), net assets ratio (in percentage), long - term debt ratio (in percentage), cash ratio (in percentage), inventory ratio (in percentage), current assets ratio (in percentage), current ratio (in percentage), growth rate of net assets (in percentage), growth rate of total assets (in percentage), and growth rate of return on investment (in percentage).The fluctuations in the values of these indicators significantly affect the enterprise's financial data. Next, we'll use the decision - tree analysis approach to construct a decision - tree analysis of these indicators.

In this research paper, the financial operations of the enterprise are designated as the predictive metric for the study, and the relevant metric training set is created. Table 2 presents the features of the financial conditions of nine food - manufacturing enterprises. Among them, the risk assessment level of A7 and A9 enterprises is high risk, they have a higher degree of potential risk, which is not suitable for investors to make a large number of investments,the financial operating condition is better is A8, the recommendation index is higher.

Table 2: Attributes of the Financial Standing of Food - Producing Enterprises

Enterprise number	Financial status category	Degree of risk	Recommendation index	Evaluation level
A1	B	★★	●●●	Lower risk
A2	C	★★★★	●	High risk
A3	B	★★	●●●	Lower risk
A4	C	★★★★	●	High risk
A5	B	★★	●●●	Lower risk
A6	C	★★★★	●	High risk
A7	D	★★★★★		The risk is very high
A8	A	★	●●●●●	The risk is very low
A9	D	★★★★★		The risk is very high

2.3 PSO-BP based enterprise financial risk prediction subsystem

2.3.1 Selection of indicators for financial risk evaluation

The financial risks of an enterprise predominantly emerge during the company's operational process. The company's debt - paying ability, operational efficiency, profit - making capacity, and growth potential significantly influence the manifestation of the enterprise's financial risks, which are reflected via various financial metrics.Taking into account the current actual financial state of the enterprise and fully factoring in the accessibility of relevant data, we have chosen 14 indicators from five aspects: short - term debt - paying ability, long - term debt - paying ability, operational capacity, profit - making capacity, and growth capacity, to assess the enterprise's financial risks. The financial risk assessment indicators of the enterprise are presented in Figure 4. We will utilize the above - selected indicators as the input for the neural network to conduct a study on risk assessment.

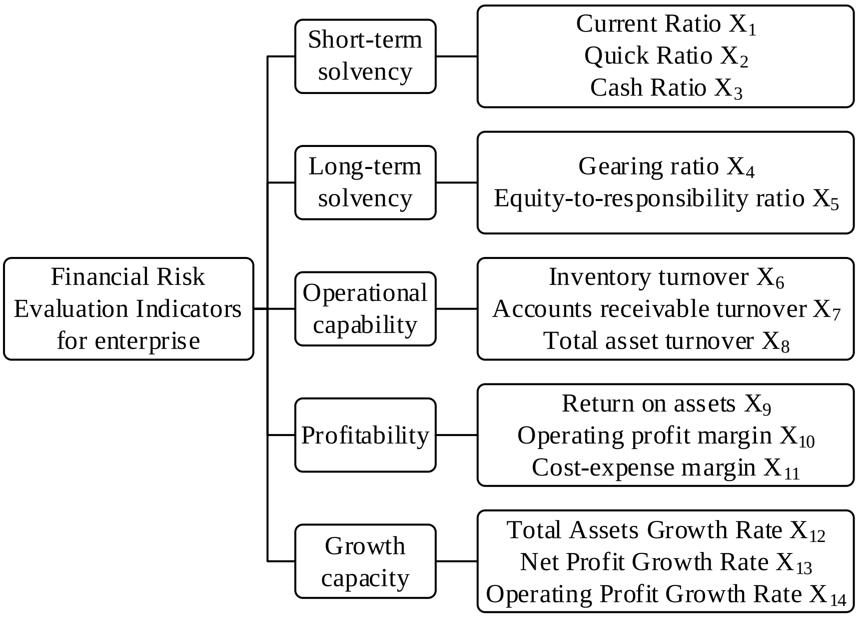

Figure 4: The evaluation index for the financial risk of the enterprise

2.3.2 BP Neural Networks

The Backpropagation (BP) neural network model is a multi - layer feed - forward neural network. It achieves non - linear mapping from the input to the output. By optimizing the connection weights of the hidden layers within the network, it enhances the learning capacity of the entire model. The BP neural network is characterized by parallel processing, distributed storage, self - learning, and self - adaptation.The primary learning procedure of the BP neural network consists of signal forward propagation and error back - propagation. During forward propagation, sample data enters from the input layer and is transferred to the output layer via the hidden layer. If there is a discrepancy between the output of the output layer and the expected output, the process shifts to reverse propagation. The error signal is then adjusted successively from the output layer through the hidden layer to modify the connection weights and thresholds. This adjustment aims to make the network's predicted output approximate the expected output. This cycle continues until the error is reduced to a pre - determined level of accuracy or the number of cycles reaches the pre - set maximum number of learning iterations.

The algorithm of the BP neural network is defined as follows:

(1) Let the input vector be:

$$X = \left(x_1, x_2, \ldots, x_n\right)^T \tag{16}$$

Then the output vector is:

$$Y = \left(\mathrm{y}_1, y_2, \ldots, y_m\right)^T \tag{17}$$

(2) Let the input to each neuron in the hidden layer be:

$$b_j = \sum_{i=1}^{n} W_{ij} - \theta_j \tag{18}$$

$j = 1, 2, \ldots, k, w_{ij}$ is the weights from the input layer to the hidden layer, θ_j is the threshold of the hidden layer, and k is the number of neurons in the hidden layer.

(3) If the transfer function here is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{19}$$

Subsequently, the output of the unit within the implicit layer is:

$$S_j = \frac{1}{1+\exp\left(-\sum_{i=1}^{n} W_{ij} + \theta_j\right.} \tag{20}$$

The input to each output layer neuron is:

$$C_t = \sum_{j=1}^{q} V_{jt} S_j - \lambda_t \tag{21}$$

The output of each output layer neuron is:

$$L_t = \frac{1}{1+\exp\left(-\sum_{j=1}^{q} V_{jt} S_j + \lambda_t\right)} \tag{22}$$

The weights spanning from the implicit layer to the output layer are denoted as $t = 1, 2, \ldots, p, V_{jt}$, and the threshold applicable to the output layer is represented by the symbol λ_t (presumably the missing symbol in the original).

(4) In error backpropagation, the individual sample error E_k is:

$$E_k = \frac{\sum_{t=1}^{p} \left(y_t^k - L_t^k\right)^2}{2} \tag{23}$$

The total system error E is:

$$E = \sum_{k=1}^{m} E_k \tag{24}$$

(5) If both E_k and E satisfy the predetermined accuracy, the training is complete, otherwise the output error of each node is calculated and the network weights and readings are corrected one by one. In order to keep E_k decreasing, then:

$$\Delta V_{jt} = -\alpha \partial E_k / \partial V_{jt} \tag{25}$$

The weights of the output layer are corrected by:

$$\Delta V_{jt} = \alpha d_t^k b_j \tag{26}$$

α is the learning rate, $t = 1, 2, \ldots, q, \ j = 1, 2, \ldots, p$, $k = 1, 2, \ldots, m$.

$$d_t^k = \left(y_j^k - L_j^{k)} t \left(1 - L_t^k \right) \tag{27}$$

The amount of threshold adjustment for the output layer is:

$$\Delta \lambda = \alpha d_t^k \tag{28}$$

Similarly, the weights of the implicit layer are modified by:

$$\Delta W_{ij} = \beta e_j^k x_i \tag{29}$$

The threshold correction for the hidden layer is:

$$\Delta \theta_j = \beta e_j^k \tag{30}$$

$i = 1, 2, \ldots, q, \ j = 1, 2, \ldots, p$, $k = 1, 2, \ldots, m$,

$$e_j^k = \left(\sum_{t=1}^{q} d_t^k v_{jt} \right) S_j \left(1 - S_j \right) \tag{31}$$

Based on the aforementioned computations, modify the weights and thresholds of the entire network to finalize one round of training. Repeat the above steps until the error reaches the preset conditions.

The starting values of the weights and thresholds within the network are produced randomly, even if there is an error as a judgment condition, it will lead to different implicit layer transfer function and output results, so that the results are very easy to fall into the local optimum, not be able to train the best network, which further affects the prediction results using the trained neural network, and makes the decision maker to make unfavorable judgments. In order to eliminate this possible disadvantage, In this research paper, the particle swarm optimization algorithm is employed to refine the BP neural network.

2.3.3 Financial Risk Prediction Model for PSO Optimized BP Networks

Inspired by the behavioral model of biological populations and its simulation results, the particle swarm algorithm (PSO) is proposed for solving optimization problems. Distinguished from intelligent evolutionary algorithms such as genetic algorithms, the PSO algorithm assumes an individual to be a particle flying at a certain speed and direction with no weight and volume, and each particle represents a potential possible solution to the actual problem.Moreover, the particles conduct a search within the n - dimensional search space to find the optimum.

In recent years, the research heat of intelligent evolutionary algorithms has been increasing, and many scholars have begun to take advantage of the characteristics of the particle swarm algorithm's stronger global convergence ability To enhance the stability and resilience during the training of the artificial neural network model, a strategy is adopted that capitalizes on the complementary strengths and mitigates the weaknesses of the particle swarm algorithm and the neural network. This approach aims to boost the overall performance of the artificial neural network.The Particle Swarm Optimization (PSO) algorithm is employed to train the initial parameters of the Back - Propagation (BP) neural network. In this process, all the connection weights and thresholds within the BP network are represented as distinct individuals. These individuals have a one - to - one correspondence with the particles in the PSO algorithm. The fitness value of each particle is computed using the particle's fitness function, which is equivalent to the training error of the BP network.As the speed and position of the particles are continuously updated, at each iteration, the individual extreme values and population extreme values are compared to identify the global optimum. This means that the optimal initial weights and thresholds for the BP network are determined. Subsequently, the BP network with optimized weights and thresholds is trained. Based on this, an enterprise financial risk prediction model founded on the PSO - BP neural network is constructed to forecast the financial condition of the enterprise. The flowchart of the PSO - BP algorithm is presented in Figure 5.

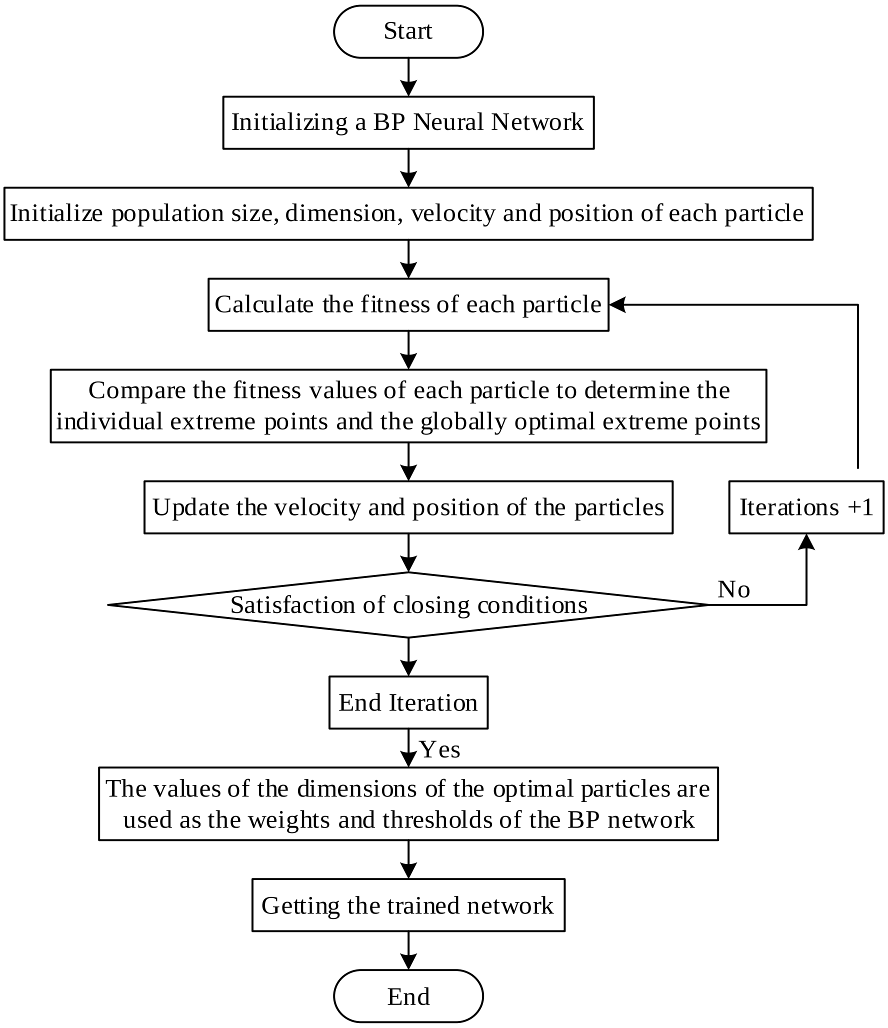

Figure 5: PSO-BP algorithm process

2.3.4 Results of financial risk prediction simulation experiments

A total of 130 enterprises in the electronic information sector were chosen as the objects of study. The data were sourced from the CSMAR and Wind databases. Regarding the selection of the research sample period, numerous scholars designate the year when a warning is issued as the T year. Subsequently, they opt for the data from the T - 1 year, T - 2 year, or T - 3 year to conduct research on financial risks. Since the annual report of the enterprise is out in April of the second year, the information has a lag, so the T-1 year data is not able to take timely measures to save the financial crisis for the managers. Many scholars believe that the financial data of T-2 years can produce more accurate prediction results, so the data of enterprises' T-2 years are chosen to conduct the experiment. Sixty-five enterprises a set of enterprises is chosen at random to serve as training specimens, and the remaining businesses are employed as prediction specimens.

In this research paper, the MATLAB R²019a software is employed to conduct a simulation of the financial risk early - warning model founded on the PSO - BP neural network for the purpose of experimentation. According to the divided test samples and prediction samples, the data are imported into MATLAB R²019a for training. The following is the process and results of one training simulation experiment of PSO-BP neural network.

Figure 6 shows the training error variation curve. In this graph, the x - axis denotes the quantity of training sessions, while the y - axis represents the error precision. The blue line depicts the error fluctuations of the training data set, the orange line shows the error variations of the validation data set, and the gray line indicates the error changes of the prediction data set. From the graph, it is evident that the error attains the desired precision after the neural network has been executed 32 times.

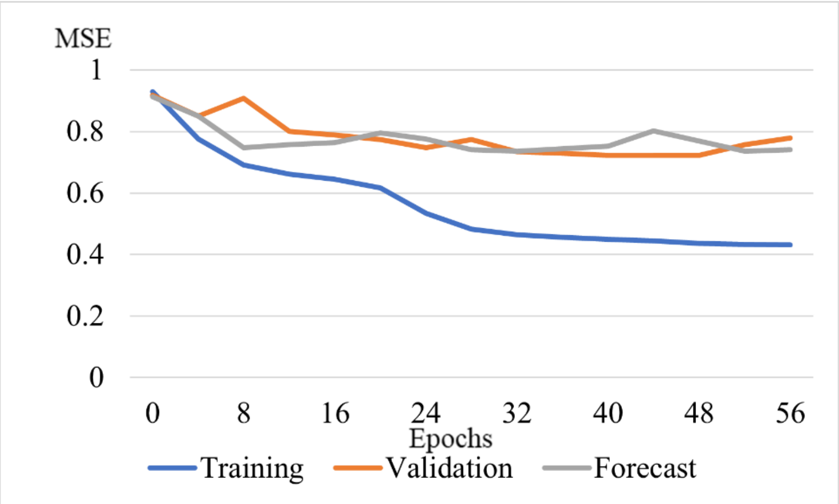

Figure 6: Training error curve

Figure 7 shows the fit between the outputs of the TRAINING training sample data, VALIDATION validation sample data, and TEST test sample dataset and the desired output. Generally an R^2 value greater than 0.85 indicates a better network performance. From the figure, it can be seen that the R^2 value is basically greater than 0.85 and the network has higher accuracy in predicting the results.

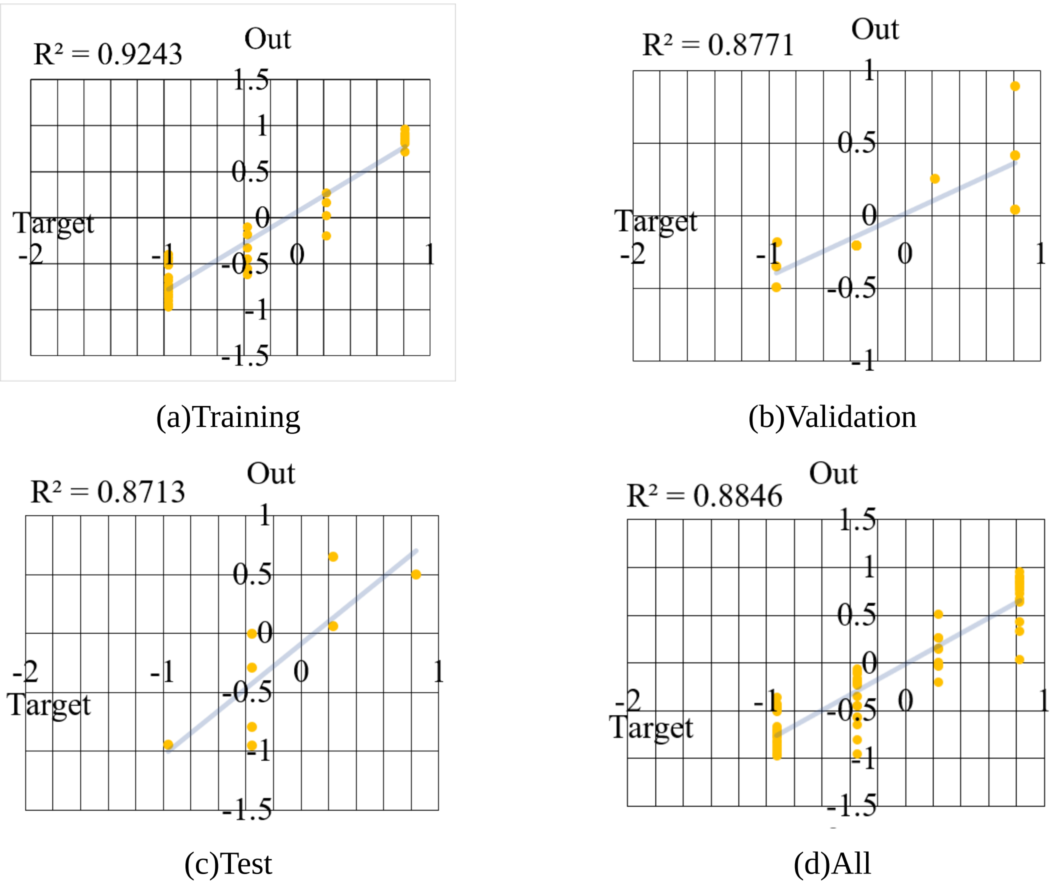

Figure 7: The network is a good situation

The prediction error of the PSO - BP network is presented in Figure 8. In this figure, the x - axis denotes the sample, while the y - axis indicates the disparity between the predicted value and the expected value. As can be observed from the figure, the network prediction error is relatively large for just 2 enterprises. For the remaining enterprises, the errors are smaller, and the error range lies between 0.5.

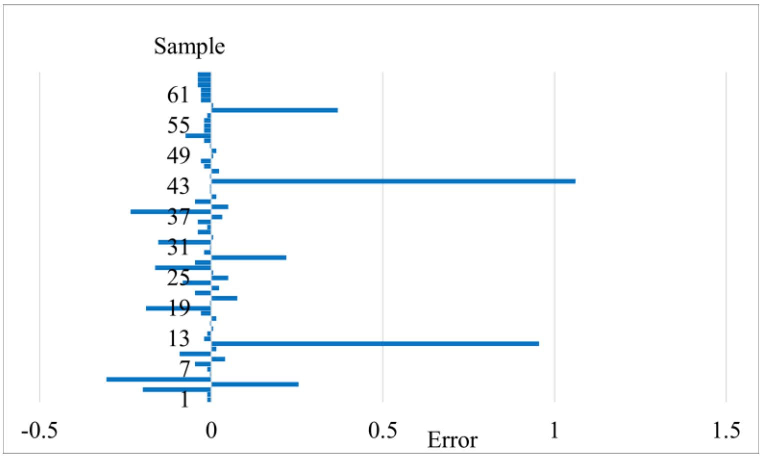

Figure 8: Network prediction error

The prediction outcomes of the prediction samples are presented in Table 3. Based on the data in the table, it can be seen that there are a total of 65 prediction samples. The correct rates of the firms with no risk, less risky firms, medium risky firms, and severe risky firms are

92.86%, 89.47%, 83.33%, and 83.33%, respectively. The combined correct rate of the model reached 89.23%.

From the results, the overall correct rate reaches more than 85%, indicating that the model predicts better results. As a whole, 47 enterprises are in the stage of no risk and less risk, and 18 enterprises are in the stage of medium risk and severe risk.

We should pay attention to the enterprises in medium risk and serious risk to avoid more serious financial crisis. For enterprises at serious risk, we need to take corrective measures in time to prevent the occurrence of major irreparable harm.

Table 3: Network prediction results

Warning grade	Enterprise quantity	Wrong number	Accuracy/%
Risk-free	28	2	92.86
Minor risk	19	2	89.47
Medium risk	6	1	83.33
Serious risk	12	2	83.33
Tot	65	7	89.23

Since the network training initialization are random, the weights and thresholds optimized by the particle swarm algorithm are all different, and the training results will be somewhat different. In order to reduce the chance of the experiment, the program is run several times, and the results of 12 times are selected to be summarized, The average correct rate is employed to substitute the accuracy of the PSO - BP neural network early warning model. Based on the analysis of statistical outcomes, the correct rate of the financial risk early warning model can attain 86.55% (see Table 4).

Table 4: 10 results of the network

Training frequency	Risk-free/%	Minor risk/%	Medium risk/%	Serious risk/%	Mean/%
1	89.58	85.05	75.01	84.67	83.58
2	93.09	85.04	75.01	84.65	84.45
3	93.13	90.03	50.00	93.25	81.60
4	93.07	80.03	75.00	93.31	85.35
5	86.14	84.92	99.97	84.60	88.91
6	89.63	84.93	74.92	93.38	85.72
7	86.22	85.02	98.45	93.34	90.76
8	89.60	79.96	99.96	84.54	88.52
9	93.11	90.08	74.96	84.61	85.69
10	93.10	84.94	75.05	93.35	86.61
11	90.71	85.02	80.01	89.01	86.19
12	86.22	84.90	99.98	93.32	91.11
Average accuracy/%	89.61	79.95	92.05	84.58	86.55

3 Research on improving the effectiveness of capital utilization based on the DEA-Malmquist method

3.1 DEA model

Data Envelopment Analysis (DEA), a commonly utilized linear programming approach, has its first model known as the CCR model. DEA serves as a powerful tool for evaluating the prioritization of numerous decision - making options within a multi - objective context. Its primary purpose is to create an efficiency metric for the set of technical efficiencies (Decision - Making Units, DMUs) that need to be evaluated. This is accomplished by measuring two or more indicators.By virtue of the input and output information, an efficiency frontier is formed, which is formed by the linear programming method. Data Envelopment Analysis (DEA) finds extensive application in gauging the relative effectiveness of decision - making entities across a diverse range of sectors. These sectors encompass manufacturing plants, governmental agencies, the financial industry, medical facilities, ports, airports, airline companies, and electric power utilities, among other decision - making units.

The planning formulation of the input-oriented CCR model is shown below. Assume a set of a total of n decision-making units with technical efficiency, denoted as $DMU_j(j=1,2,\cdots,n)$; each DMU has m inputs, denoted as $x_i(i=1,2,\cdots m)$; q , outputs, denoted as $y_r(r=1,2,\cdots,q)$; the weight of the output, denoted $u_r(r=1,2,\cdots,q)$; and the decision unit to be measured, denoted DMU_K . The relationship between outputs and inputs:

$$h_k=\frac{u_1y_{1k}+u_2y_{2k}+\cdots u_qy_{qk}}{v_1x_{1k}+v_2x_{2k}+\cdots+v_mx_{mk}}=\frac{\sum_{r=1}^{q}u_ry_{rk}}{\sum_{i=1}^{m}v_ix_{ik}}(v\geqslant 0;u\geqslant 0) \tag{32}$$

Subsequently, the condition is linked to the value of technical efficiency that is to be gauged, that is to say:

$$\frac{\sum_{r=1}^{q}u_ry_{rj}}{\sum_{i=1}^{m}v_ix_{ij}}\leqslant 1 \tag{33}$$

The initial model formulated by the group of Charnes and colleagues was founded on constant returns to scale.

$$\min\theta \tag{34}$$

$$\text{s.t.}\sum_{j=1}^{m}\lambda_jx_{ij}\leqslant\theta x_{ik} \tag{35}$$

$$\sum_{j=1}^{n}\lambda_jy_{rj}\geqslant y_{rk} \tag{36}$$

$$\lambda \geqslant 0 \tag{37}$$

where: $i = 1, 2, \cdots, m; r = 1, 2, \cdots, q; j = 1, 2, \cdots, n$. The λ represents the linear combination coefficients of the DMUs, and the optimal solution of the model represents the value of the efficiency of the decision unit, which takes the range of values $(0,1]$. The optimal solution of the model's objective function is $\theta^*, 1-\theta^*$ in the case of no change in the level of technology and the level of output remains unchanged, it can be seen that the assessed DMU_K the maximum limit of its inputs can be seen, the smaller the θ^* the more it can be significantly scaled back the inputs The smaller the θ^*, the more drastically the inputs can be scaled down. When $\theta^* = 1$ it means that the evaluated DMU is located on the efficiency frontier and is technically efficient in the sense that all its inputs cannot fall in the same proportion while output remains constant. $\theta^* < 1$ indicates that the DMU fails to reach the technically efficient state, and its various inputs can fall in the same proportion as $\left(1-\theta^*\right)$ while keeping output constant. The frontier determined by the above equation is a shaped envelope, which wraps around all DMUs, often referred to as the DEA envelope form, is a measure of the absence of efficiency to the extent that the various inputs can be scaled down in equal proportions while output is held constant, and is therefore referred to as an input-oriented CCR model.

3.2 Malmquist Indicator

The Malmquist productivity index was initially put forward by Malmquist. Researchers employ Data Envelopment Analysis (DEA) to compute the Malmquist index and break it down into two alterations: technical efficiency change (EC) and production technology change (TC). The connection among these three elements can be represented by the following equation:

$$\begin{aligned} MI &= EC \times TC \\ M_{\alpha c} &= \sqrt{\frac{E^t\left(x^t, y^t\right)}{E^{t+1}\left(x^t, y^t\right)} \frac{E^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E^t\left(x^{t+1}, y^{t+1}\right)}} \\ &= \frac{E^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E^t\left(x^t, y^t\right)} \sqrt{\frac{E^t\left(x^t, y^t\right)}{E^{t+1}\left(x^t, y^t\right)} \frac{E^t\left(x^{t+1}, y^{t+1}\right)}{E^{t+1}\left(x^{t+1}, y^{t+1}\right)}} \end{aligned} \tag{38}$$

Let and represent the values of the evaluated entity during the periods and respectively. Meanwhile, stands for the distance function within the period, that is, the gap between a single - period observation and the efficiency frontier in the period. If, it indicates that the total factor productivity of the representative decision - making unit has advanced from period to period. When, it means that the total factor productivity of the decision - making unit has remained constant from period to period. In the case where, the total factor productivity of the representative decision - making unit has decreased from period to period.

3.3 Data selection

At present, there exist three primary approaches for ascertaining DEA input - output indicators: the production approach, the intermediary approach, and the asset approach.

This piece of writing ascertains the input and output indicators for enterprise finance in accordance with the concept of the intermediary approach. When it comes to the selection of indicators, this study chooses "equity capital" and "deposits" as the investment - related indicators. Meanwhile, "gross profit" and "interest earnings" are selected as the output indicators.

This research focuses on the small and medium - sized enterprises that were listed on the New Third Board between 2019 and 2024. Data related to these enterprises during their listing year and the subsequent year were gathered from the WIND platform.

3.4 Results of the study on improving the effectiveness of the use of funds

3.4.1 Static analysis

The mean values of capital utilization efficiency for small and medium - sized enterprises (SMEs) from 2019 to 2024 are 0.697, 0.788, 0.805, 0.812, 0.844, and 0.856 respectively. There is an overall upward trajectory in these values. The most significant improvement in the mean value of capital utilization efficiency occurred between 2019 and 2020, with a remarkable 13.06% surge in efficiency. This suggests that after the system upgrade in 2019, the Science and Technology Innovation (STI) initiative has had a positive impact on enhancing the efficiency of self - built allocation. Table 5 presents the mean values of fund utilization for SMEs from 2019 to 2024.

In terms of specific years. in 2019~2020, the pilot program of upgrading the financial management system of enterprises driven by science and technology innovation was launched, and the top-level design has been continuously improved, creating a favorable policy environment for the company's sound development, which has positively promoted the improvement of the company's capital efficiency. In 2020, the comprehensive technical efficiency of SMEs' capital use was significantly improved by 13.06% compared with 2019. In the following years, enterprises, including SMEs, They have proactively modified their business development approach and gradually acclimated to the initiative of upgrading the corporate financial management system spurred by technological innovation. As a result, the overall technical efficiency has shown a stable improvement, attaining 0.812 in 2022 and 0.844 in 2023 respectively.

In terms of the number of organizations. 15 SMEs have a relatively efficient use of funds (comprehensive technical efficiency value of “1”) of 7, 11, 12, 12, 13 and 13 in 2019~2024, respectively. This means that most of the SMEs are in efficient use of funds during these 6 years.

Between 2019 and 2024, SMEs experienced diminishing returns to scale a total of 8 times. Diminishing returns to scale implies that considerable output cannot be obtained by continuing additional inputs.

Table 5: Company 2019~ 2024 use of mean

Year	CRSTE	VRSTE	SCALE	Dea validity	Economies of scale increasing	Economies of scale invariant	Scale economic decline
2019	0.697	0.820	0.870	7	8	1	6
2020	0.788	0.875	0.912	11	13	1	1
2021	0.805	0.889	0.918	12	13	1	1
2022	0.812	0.897	0.925	12	14	1	0
2023	0.844	0.905	0.931	13	14	1	0
2024	0.856	0.912	0.936	13	14	1	0

3.4.2 Dynamic analysis

According to the aforementioned theory, the changes in the capital utilization efficiency of the 15 SMEs in 2019~2024 can be measured by the Malmquist index, and Table 6 presents the detailed outcomes of the annual average statistics for the Malmquist index.

Overall, apart from the increase in the average total - factor productivity between 2019 and 2020, the average total - factor productivity (TFPCH) of the 15 small and medium - sized enterprises (SMEs) from 2020 to 2024 experiences less volatility and demonstrates a gradual upward trajectory. The mean value of the Malmquist index from 2019 to 2024 is 1.213. This implies that the total - factor productivity of the sampled SMEs is on the rise, with an average annual growth rate of 21.3%.Analyzing the average change from 2019 to 2024, the alteration in the Malmquist index is primarily determined by the comprehensive efficiency change index. Specifically, the pure technical efficiency change index and the scale efficiency change index are increasing by 15% and 18.4% respectively.During the development process, SMEs have intensified their efforts in scientific and technological innovation. This innovation drives the improvement of corporate financial management systems, enhances financial efficiency through technological means, and also emphasizes the recruitment and development of high - level professionals， which have pushed the SME industry's Comprehensive Technical Efficiency Change Index to continue to rise.

Analysis of the change of Malmquist index of each SME.From 2019 to 2024, 13 out of 15 sample SMEs are improving their capital use efficiency, i.e., the Malmquist index is greater than 1, reflecting the enhancement of the sustainable development ability of capital use efficiency of these SMEs.

In summary analysis, the overall efficiency of SMEs' capital use is high, and most SMEs' capital use is in a highly efficient state, which is greatly influenced by the environment of upgrading enterprise financial management system driven by science and technology innovation.The fluctuation of Malmquist index of the 15 sample SMEs is relatively small, and it shows a gradual upward trend. The overall capital utilization efficiency improvement is primarily influenced by the comprehensive efficiency change index. To some degree, the enhancement of pure technical efficiency and scale efficiency among small and medium - sized enterprises (SMEs) has contributed to the overall boost in capital utilization efficiency.

Table 6: presents the annual average statistics of the Malmquist index

Year	EFECH	TECH	PECH	SECH	TFPCH
2019~2020	1.025	0.545	0.865	0.783	0.812
2020~2021	1.274	1.611	1.138	1.215	1.295
2021~2022	1.365	1.658	1.211	1.284	1.301
2022~2023	1.375	1.663	1.245	1.316	1.312
2023~2024	1.389	1.671	1.289	1.322	1.345
2019~2024	1.286	1.030	1.150	1.184	1.213

4 Conclusion

Motivated by scientific and technological advancements, this research centers on the intelligent enhancement of the corporate financial management system. It builds an enterprise financial management system leveraging big data, integrates intelligent decision - making algorithms with financial risk prediction models, and achieves a comprehensive optimization of corporate financial decision - making and risk early - warning. Empirical analysis was conducted using the DEA - Malmquist approach to examine the impact of the enterprise financial management system application on improving the efficiency of the enterprise's capital utilization.

This paper integrates the FP - growth association rule algorithm, the clustering algorithm, and the decision - tree algorithm to conduct an analysis of the specific financial situations of various food production enterprises. It reveals the internal factors that influence the further development of these food production enterprises and pinpoints a high level of financial risk in Enterprises A7 and A9. As a result, it offers a scientifically sound and reliable basis for decision - making for enterprise leaders and risk investors.

In response to the limitations of the BP neural network in terms of training efficiency and training precision, this article selects the particle swarm algorithm to optimize the weights and thresholds of the BP neural network. The aim is to further enhance the prediction accuracy of the financial risk prediction model. The evaluation indicators are fed into the model. Subsequently, model training and prediction are conducted using MATLAB R^{2}019 software. The outcomes reveal that the overall correct prediction rate of the financial risk early - warning model based on the PSO - BP neural network reaches 89.23%. When the results of 12 trials are aggregated, the average correct rate of the financial risk early - warning model can achieve 86.55%. This indicates that the financial risk early - warning model constructed in this paper, which combines PSO and BP, can reach an accuracy rate of 86.55%. All in all, the financial risk early - warning model based on PSO and BP created in this study has significant practical value.

The findings of the research on enhancing the efficiency of capital utilization indicate that companies can effectively boost the efficiency of their capital use via digital transformation and technological innovation. As a result, by actively engaging in technological innovation, enterprises can achieve data interconnection and information sharing. They can augment the utilization of technologies such as artificial intelligence and big data in fund monitoring, forecasting, and financial meticulous management. This will strengthen the integration of information technology and financial management, drive the development of a smart financial ecosystem, offer a comprehensive array of financial data to enterprise managers, and ultimately contribute to the enhancement of fund efficiency.

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