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Enterprise Financial Management Informatization Platform Based on Intelligent Decision Support System

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ABSTRACT

In response to the shortcomings of traditional enterprise financial management information platforms in data processing and analysis efficiency and decision support capabilities, this study introduces intelligent decision support systems to fundamentally improve these issues. In this study, we automated data collection through API (Application Programming Interface) technology, used ETL (Extract, Transform, Load) tool for data format conversion, and strictly performed data cleaning and standardization to ensure data quality. The article uses association rules and support vector machine machine learning algorithms for in-depth analysis and prediction of financial data, and optimizes decision-making scenarios based on multi-criteria decision analysis, Monte Carlo simulation and linear programming techniques. Evaluation results show that the system significantly improves the speed and accuracy of data processing, with an increase in processing efficiency of more than 70% and a decision-making accuracy rate of up to 95%. The intelligent decision support system effectively improves the informatization level of enterprise financial management and provides more scientific and reliable decision support for the enterprise leadership.

Keywords: Intelligent Decision Support System, Financial Management, Data Processing, Machine Learning Algorithms, Decision Support

1. Introduction

With the rapid development of information technology, many enterprises began to digitalization and networking direction. Financial management as an indispensable core part of the enterprise, but also in the digitalization and networking on the road forward, become an indispensable part [1]. The traditional manual financial management has been unable to meet the increasingly complex economic environment and enterprise management needs, and information construction has become an inevitable choice to improve the level and efficiency of enterprise financial management [2].

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Enterprise financial management informationization construction is conducive to improving the efficiency and accuracy of financial management. Traditional manual bookkeeping and financial processing is prone to human error, and through the construction of information technology systems, enterprises can realize the automated collection, processing and analysis of financial data, reducing the impact of human factors on financial management, and improving the accuracy and reliability of the data; at the same time, the construction of information technology can standardize and automate the cumbersome financial processes, reduce repetitive work, and improve the efficiency of work [3-6]. Informatization construction can strengthen the financial supervision and risk control ability of enterprises. Through the informationization system, the supervisory department can monitor the financial operation of the enterprise in real time, discover and solve the risks in time, such as abnormal capital flow, debt risk, etc., and carry out comprehensive control of the enterprise's business activities [7-9]. Informatization construction can also promote enterprise management decision-making and strategic planning. By analyzing and mining a large amount of financial data through the informatization system, the management can understand the business situation of the enterprise in a timely manner, make more targeted decisions, and improve the competitiveness of the enterprise and operational efficiency [10-13].

The research and application of financial management informatization is crucial to the financial management, risk control, decision-making support and economic efficiency of enterprises [14-15]. It refers to the use of modern technology, accounting, finance, funds management, taxation and other financial management operations for integration, unification, automation, standardization, standardization of processing of integrated management platform [16]. Its core functions include financial accounting, financial analysis, cost management, fund management, tax management, etc., and also need to have data interaction with other management systems, security and confidentiality functions [17-20]. In addition to the above advantages, compared with the traditional financial management, financial management information technology model also has many advantages. First of all, it realizes the computerization of finance, improves the work efficiency and reduces the error rate; secondly, the multi-dimensional data processing and analysis functions provide enterprises with more complete financial information and more real-time economic performance; in addition, the efficient cost management and capital management functions will help enterprises better control risks and optimize the management process; and accurate and timely financial information can help enterprises to better understand the inputs and outputs of the business. Accurate and timely financial information can help enterprises better understand the input and output of each business, so as to rationally allocate resources, improve the efficiency of resource utilization, and invest limited funds into the most valuable projects [21-24]. Nowadays, financial management informatization mode is widely used in enterprises, including manufacturing, finance, education, service industry, scientific research institutes, agriculture and other fields [25-26].

2. Overview

For the financial management system to achieve informatization, intelligence and data, some studies have contributed. Literature [27] developed a financial management cloud platform system combining the financial situation and management characteristics of local enterprises in the context of neural network models and Bayesian regularization algorithms, realizing enterprise financial informatization management. Literature [28] constructed an enterprise financial budget management cloud platform through artificial intelligence technology, and then with the budget decision-making part to machine learning, data mining, artificial intelligence and other intelligent algorithmic techniques and accounting actions are integrated to make decisions together. Literature [29] developed a financial management platform including, blockchain and supply chain fusion to achieve the automated flow of enterprise funds and settlement, model-view-controller to do the main framework of the unified modeling language, the platform is not only safe and effective, but also in the supply chain of enterprise financing to provide information reference. Literature [30] innovated a BF algorithm supported by multiple eigenvalue hash splitting to optimize the case of erroneous deletion of duplicate data in URLs, while designing a financial adjustment strategy for dynamic scenarios, and co-creating a financial management information system.

In addition, for the extremely important risk management in financial management, literature [31] constructed an enterprise financial shared management platform based on BP neural network algorithm, particle swarm optimization algorithm, big data visualization technology, and metadata sharing technology for the four parts of risk assessment of financial information, optimization of financial database, digital processing of financial information, and financial data sharing, respectively, which reacted within 2s, and the data packet loss probability is less than 20%. The difference is that literature [32] utilizes financial risk probability and related damage matrix, neural network model to assess and classify part of the risk, overall risk assessment, respectively, and then combines RFID technology and big data analysis platform to design financial risk control management information system to realize real-time monitoring, assessment and classification, and automatic control of financial risk. And the literature [33] starts from the principle of enterprise financial risk and realizes the digital platform of enterprise financial management through visualization processing technology, which not only improves the risk management environment and objectives, but also gives the strategy of efficient information transfer and financial supervision. The financial management system not only has risk management, but also includes budget, capital flow, capital structure, capital planning and collection, investment decision-making and so on. However, at present, there is a lack of optimization research in decision-making.

3. Realization of Intelligent Decision Support System

3.1. Data Collection

The automated data interface design aims to develop and integrate interfaces with various financial software and databases using API technology to realize real-time data acquisition of data sources such as ERP (Enterprise Resource Planning) systems, financial software and databases, as shown in Figure 1. This paper provides an in-depth understanding of the data structure and interaction of different data sources, designs a standard-compliant API interface, and utilizes API technology to connect with ERP systems, financial software and databases to achieve real-time data extraction and transmission. In order to match the overall information technology structure and business processes of the enterprise, we work closely with the internal IT (Information Technology) team and business departments to ensure the seamless connection between data interfaces and business processes, so as to realize the automated acquisition and integration of financial data, and to provide reliable data support for the enterprise's decision-making.

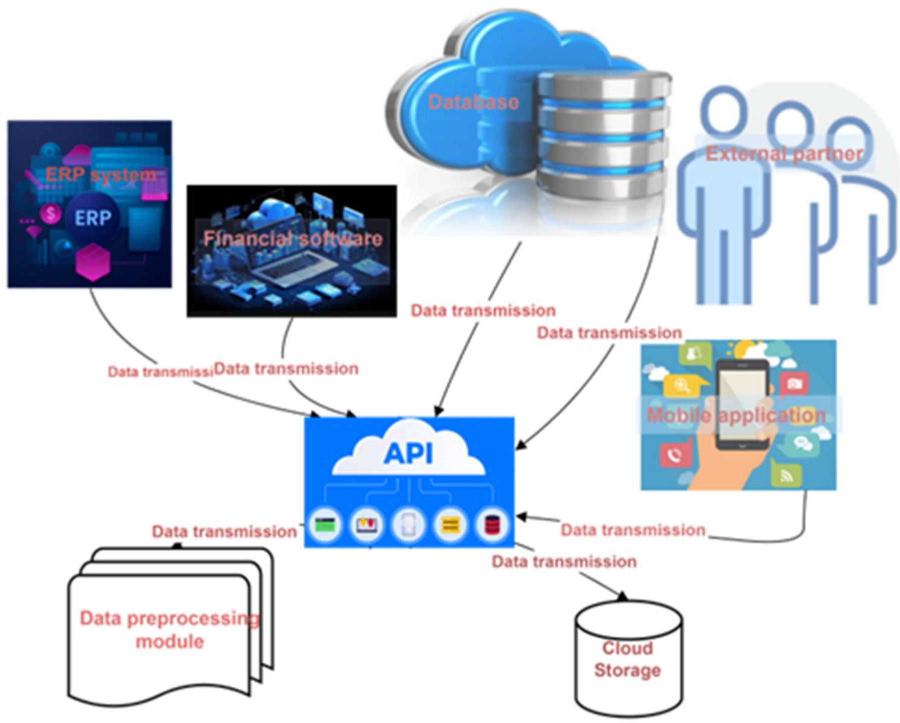

Fig. 1. Data interface diagram

In the process of data format conversion, the ETL tool Talend is utilized to achieve the following steps: in-depth understanding of the characteristics and structure of different data sources, and the design of the conversion logic, including date formatting, text cleaning, and numerical conversion. This paper uses Talend's graphical interface to build a data conversion process that includes format conversion and computation components, emphasizing performance and efficiency by optimizing speed, and ensuring accuracy and stability by testing and tuning.

3.2. *Data Preprocessing*

Data preprocessing aims to improve the quality and consistency of financial data and enhance the accuracy and reliability of subsequent analysis and decision making. Data cleaning focuses on handling outliers, missing values, and duplicates to ensure complete and accurate data. In this study, IQR (Interquartile Range) method was used to set threshold to identify and filter outliers. K-nearest neighbors are used to fill the missing values. Duplicate records are deleted using a deduplication algorithm. Data standardization aims to unify the scale and scope of data. A Z-score standardization method was used to transform the data into a standard normal distribution with a mean of 0 and a standard deviation of 1 by calculating the mean and standard deviation of each feature, allowing for comparable scales and ranges of variation between different features. After the exhaustive data preprocessing process described above, the financial data was successfully cleaned and standardized, laying a solid data foundation for subsequent in-depth data analysis and decision modeling.

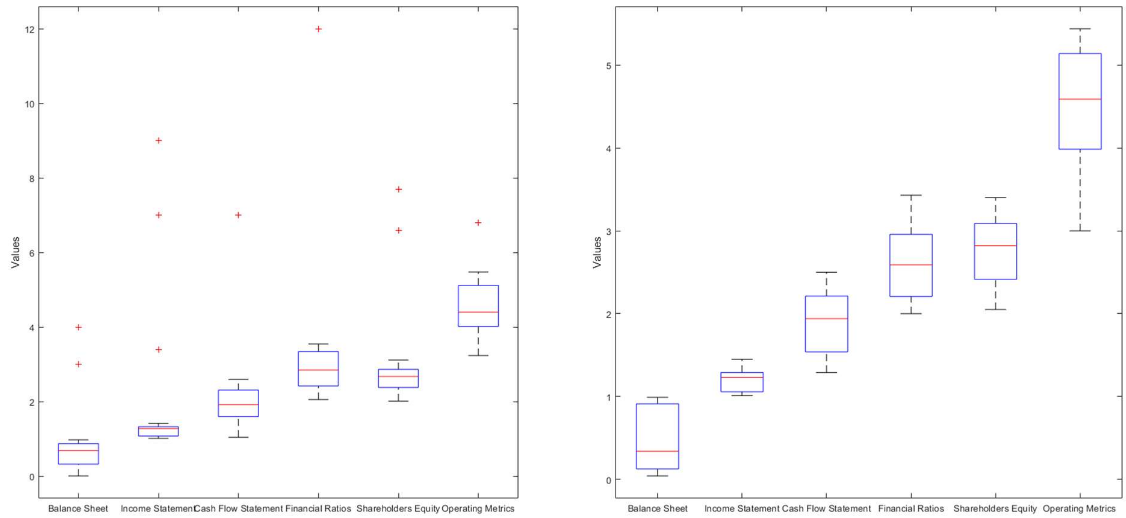

Fig. 2. Outlier handling diagram

As shown in Figure 2, data cleaning is performed on six types of financial data, and the range of outliers on the distribution of financial data before data cleaning is large, and there is a significant deviation compared with other data. After processing by IQR method, the number of outliers is significantly reduced, the data distribution is more compact, and the outliers have been removed. The range and distribution of the data are closer to the normal financial data characteristics, which helps in the subsequent data analysis and modeling work.

3.3. Data Analysis

Association rule analysis is used in financial data mining to mine the relationships between different financial variables through rigorous steps to improve the performance of subsequent machine learning models. As shown in Figure 3, Apriori algorithm is used to generate frequent itemsets, which are filtered by generating candidate itemsets step by step and calculating the support degree, and verified by scanning the data several times. After generating frequent item sets, confidence thresholds are set to generate and filter out high-confidence association rules. Transforming these high-quality association rules into feature variables can effectively enhance the input of machine learning models. Association rule analysis not only provides rich features for financial data mining, but also helps to understand the underlying patterns and relationships in the data, thus enhancing the informatization level of financial management and the quality of decision-making.

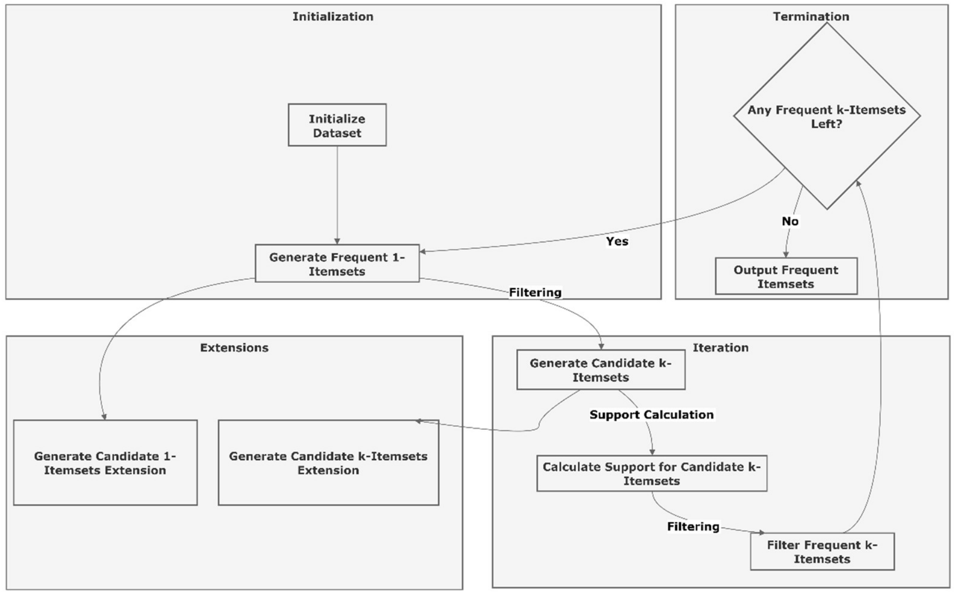

Fig. 3. The flowchart of Apriori algorithm

Feature selection is one of the key aspects in the realization of intelligent decision support system, aiming to screen out the most predictive features from financial data to provide a reliable basis for subsequent model training and predictive analysis. Comprehensively using data mining techniques and domain knowledge, high-quality features are obtained through association rule analysis, and then evaluated and screened using information gain methods to ensure that the selected feature set has the best predictive performance and generalization ability. The information gain method quantifies the contribution of each feature to the target variable, identifies the key features, and improves the prediction accuracy and stability of the model. Combined with data mining technology and domain knowledge, the features with representative and high predictive performance are selected through rigorous evaluation and screening, which provides reliable data basis for intelligent decision support system.

3.4. Model Training

Model training is a key part of intelligent decision support system, which aims at using financial data to build a prediction model by support vector machine (SVM) to achieve accurate prediction of future financial data. The kernel function of Gaussian radial basis function (RBF) is chosen in this study, because it has strong adaptability and flexibility in processing nonlinear data, and can map the data to high-dimensional feature space, so as to better adapt to the complex features of financial data.

The Gaussian radial basis function kernel function is as follows:

$$K(x,x') = \exp\left(-\gamma \|x - x'\|^2\right) \tag{1}$$

Among them, x and x' are the eigenvectors of the two samples in the original feature space, and γ is a parameter of the RBF kernel function that controls the distribution of the samples mapped to the higher-dimensional feature space.

When using the RBF kernel function, two important parameters need to be adjusted: C and γ. The regularization parameter C controls how much the model punishes misclassified samples. Cross-validation and grid search are two methods to determine the best combination of parameters. Ten-fold cross-validation divides the training set into ten subsets, each receiving nine training sets and one verification set, for a total of ten training and verification sessions. By evaluating the average of the ten validation results, the best parameter combination is selected. In order to determine the best combination of parameters, grid search performs an exhaustive search on a defined parameter grid. We define a set of candidate values for parameters C and γ, perform exhaustive search on the parameter grid, and use the cross-validation results to evaluate the performance of each set of parameter combinations. Comprehensively evaluating the performance of the model by using both methods and determine the best combination of parameters to ensure that the model has higher predictive accuracy and broadness to support financial data forecasting.

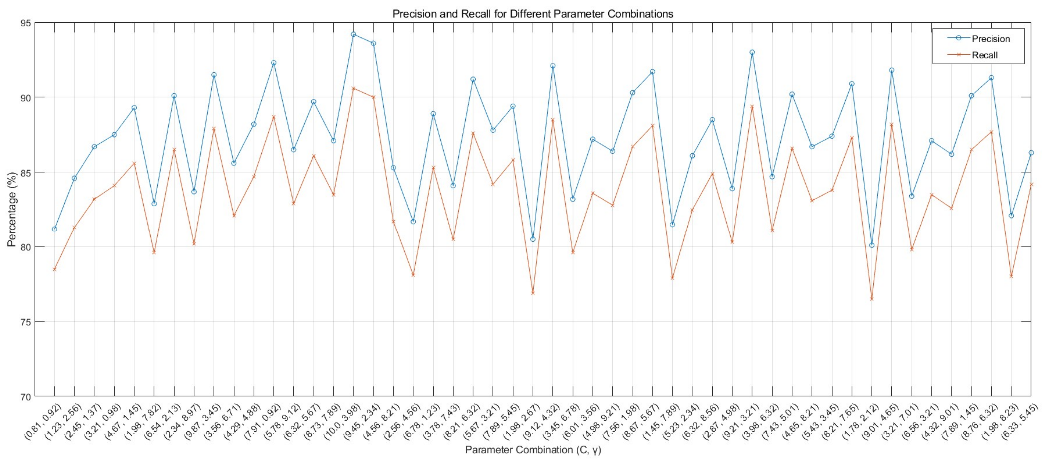

Fig. 4. Evaluation of parameter combinations

According to the data in Figure 4, the optimal parameter combination is (10.0, 3.98), with an accuracy of 94.2% and a recall rate of 90.6%.

Defining the objective function is a crucial step in training an SVM model, which includes a loss function and regularization term. In this paper, a combination of the Hinge loss function and L2 regularization is used to enable the model to select simpler decision boundaries and improve generalization ability.

The Hinge loss function is:

$$L\left(y, f(x)\right) = \max(0, 1 - y \cdot f(x)) \tag{2}$$

y is the actual label, and $f(x)$ is the predicted value of the model. The Hinge loss function indicates that when the difference between the predicted result and the actual label exceeds a certain threshold (1), the loss is 0, otherwise the loss increases with the increase of the difference.

L2 regularization is:

$$R(w) = \frac{1}{2}\|w\|^2 \tag{3}$$

w is the weight vector of the model. L2 regularization uses the size of penalty weights to encourage the model to choose simpler decision boundaries, thereby improving the model's generalization ability.

The combination of objective functions is as follows:

$$J(w) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \max(0, 1 - y_i \cdot f(x_i)) \tag{4}$$

Among them, C is a regularization parameter used to balance the importance of the loss function and regularization term. By adjusting the value of C, the complexity and fitting degree of the model can be controlled.

The column minimum optimization (SMO) used in the study is an efficient support vector machine training algorithm for solving optimization problems on small to medium-sized datasets. This algorithm decomposes a large SVM optimization problem into multiple small problems, selects two variables for each iteration, and solves them through analytical methods to accelerate the training process.

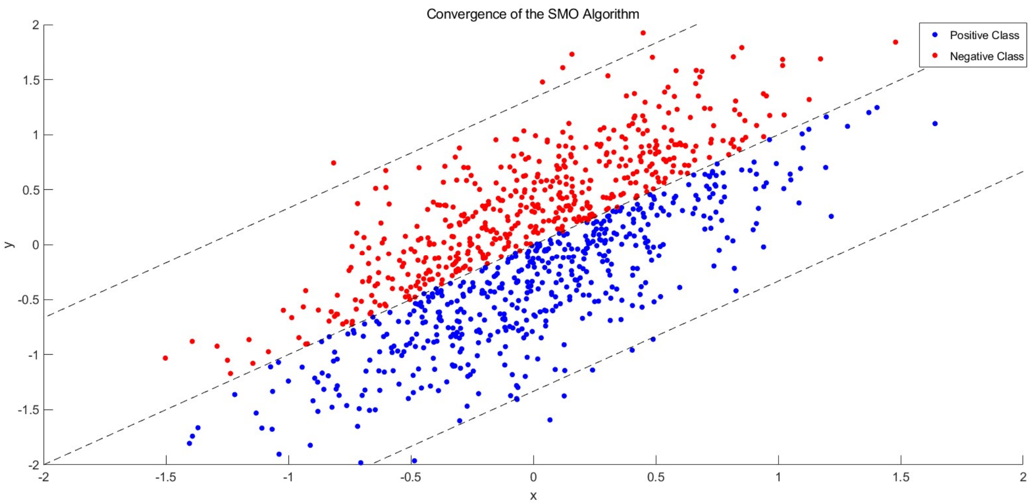

Fig. 5. The convergence of SMO algorithm

Figure 5 shows the convergence of the SMO algorithm. From the scatter plot, it can be seen that there is a clear separation between the blue and red dots, indicating that the SMO algorithm has successfully learned to classify data points based on diagonal decision boundaries.

3.5. Model Evaluation

After the model training is completed, its performance is evaluated. Through confusion matrix analysis, calculation of accuracy, recall, precision, F1-score and other indicators, as well as drawing ROC curves (Receiver Operating Characteristic), the performance of the system was comprehensively evaluated, and then verified its effect in improving the speed and accuracy of data processing and enhancing the support of financial decision-making.

Confusion matrix analysis is performed on the classification results of the system to assess the predictive accuracy and misclassification of the model on different categories. The confusion matrix is constructed to clearly understand the categorization performance of the model.

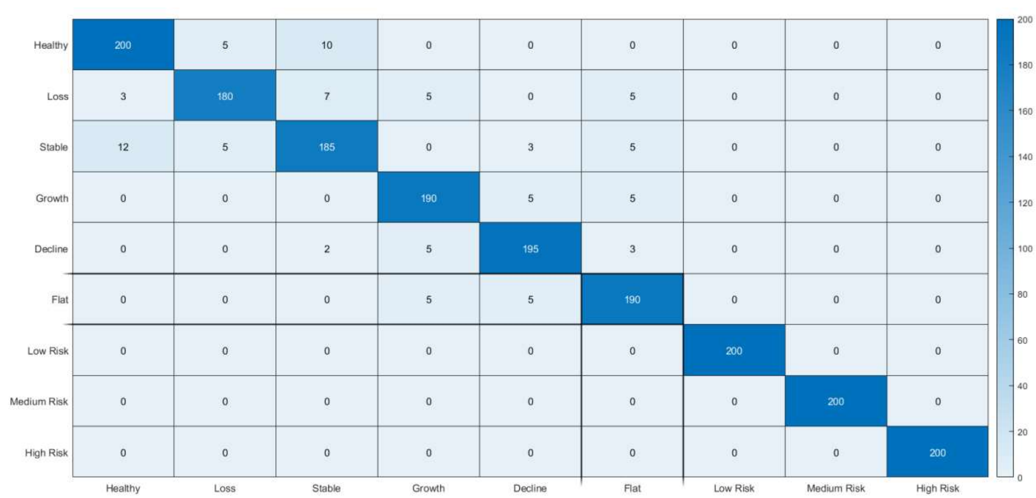

Fig. 6. Confusion matrix

As shown in Figure 6, the assessment involves several financial data categorization categories, including financial health status, market outlook forecast, and investment risk level. Based on the confusion matrix analysis, the model performs well on most of the categories, with high accuracy especially in the financial health status.

Based on the confusion matrix, the system's metrics such as accuracy, recall, precision and F1-score are calculated. These metrics enable a comprehensive assessment of the model's classification performance, leading to a better understanding of the model's strengths and weaknesses.

The Accuracy is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

The Recall is as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

The Precision is as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

The $F1$-score is as follows:

$$F1 = 2 \times \frac{\Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{8}$$

Among them, TP denotes True Positive, TN denotes True Negative, FP denotes False Positive and FN denotes False Negative.

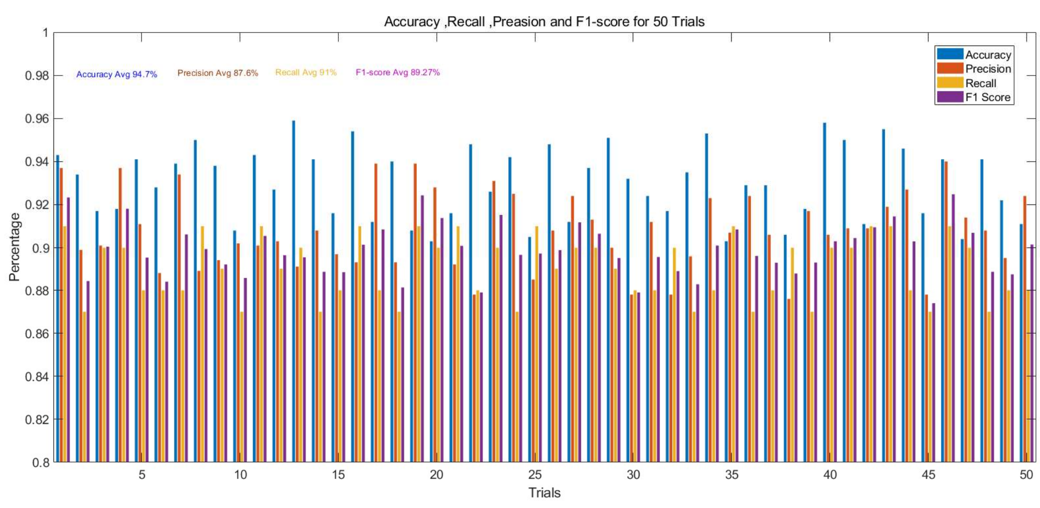

Fig. 7. Graph of accuracy, precision, recall, and F1 value

As shown in Figure 7, the average value of the accuracy rate is about 94.7%, the lowest accuracy rate is 90.20%, and the highest accuracy rate is 95.90%; the average value of the precision rate is about 87.60%; the average value of the recall rate is about 91.00%; and the average value of the F1 value is about 89.27%. The comprehensive analysis shows that the system exhibits good performance in these metrics.

In addition to the computation of single metrics, ROC (Receiver Operating Characteristic) curves are plotted to further evaluate the system performance. The ROC curves show the classifier properties at different thresholds with the false positive rate on the horizontal axis and the true positive rate on the vertical axis. In this paper, two sets of experiments were conducted to visualize the classification ability and stability of the system by evaluating the SVM curve against the ROC curve of the other three mainstream models, versus the AUC (Area Under Curve) value, as shown in Figure 8.

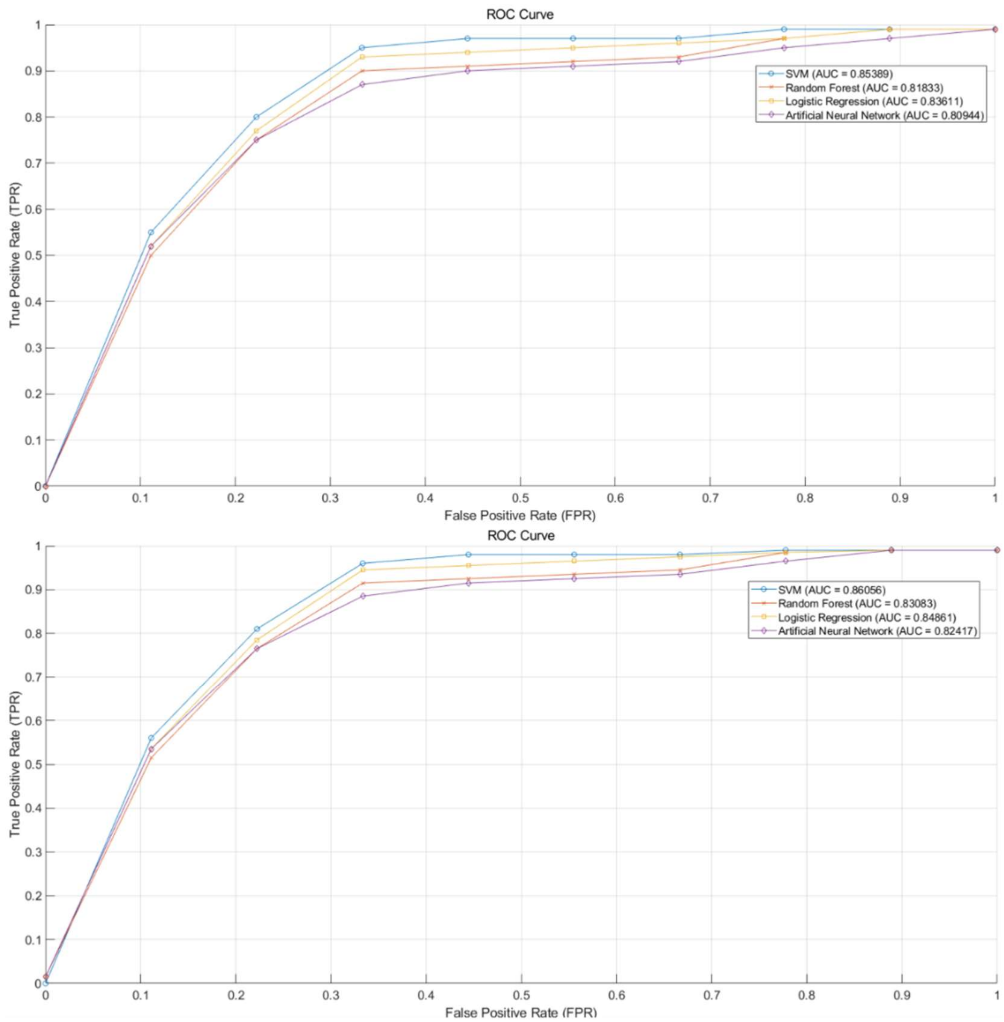

Fig. 8. ROC curve

Overall analysis shows that the SVM model is the best choice in financial data processing tasks, as it outperforms other models in terms of overall ROC curve performance and AUC value. Random forest and logistic regression also perform well in performance, but slightly inferior to SVM, while artificial neural networks perform relatively poorly in this task.

4. Decision Support Module

4.1. Decision Model Construction

When constructing the decision support module of the enterprise financial management information platform, it is first necessary to clearly define the decision problem, including investment project selection, fund allocation, cost control, etc., and describe the relevant background, objectives, and constraints. Obtaining the needs of decision-makers and stakeholders through interviews and questionnaire surveys to determine system functionality and performance requirements. Identifying factors that influence decision-making, including financial conditions, resource allocation, macroeconomic environment, industry policies, market demand, and competitive conditions. Determining the time range and frequency of decision-making to support long-term, medium-term, and short-term decisions. These help to comprehensively understand decision-making needs and lays the foundation for building effective decision support models.

Establishing a hierarchical structure is one of the key steps in constructing a decision support model, aiming to decompose the decision problem into factors at different levels in order to understand the structure of the problem more clearly, to clarify the relationship between factors, and to provide a framework for the determination of weights, as shown in Figure 9. First, the objective layer is identified, which defines the overall goal of the decision. Then the criterion layer is identified, which includes the various criteria or factors used to evaluate and compare different options, such as return on investment, market demand, technical feasibility, etc. Finally, the program layer is identified, which is the specific decision options or solutions. Hierarchy diagrams are created to clearly show the relationships between the layers, and consistency tests are performed to ensure that the structure is sound.

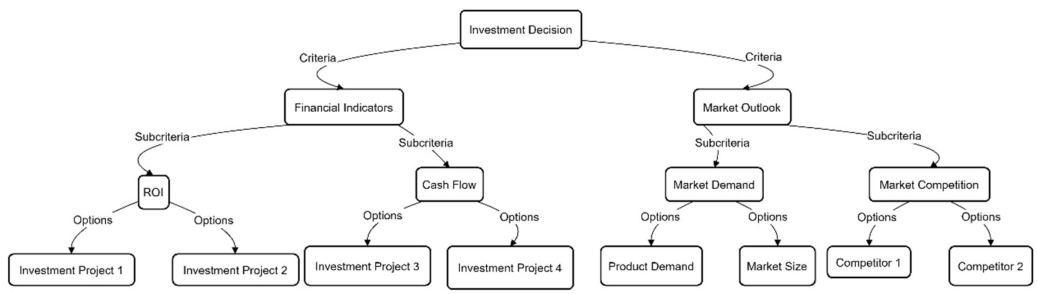

Fig. 9. Hierarchy chart

4.2. Simulation and Optimization

The aim of this study is to optimize the decision-making scenarios through Monte Carlo simulation and linear programming in order to select the optimal scenario, generate a large number of scenarios using Monte Carlo simulation techniques, and evaluate each scenario to calculate its performance metrics. In this study, the decision-making problem is modeled as a linear programming model and a linear programming solver is used to find the optimal solution, the results of simulation and optimization are considered together, the final decision-making plan is formulated, and tracking and evaluation are conducted to ensure effective implementation and continuous improvement.

5. Evaluation of the Intelligent Decision Support System

In order to assess the improvement of data processing efficiency by the intelligent decision support system, the time consumption of data processing before and after the introduction of the system was recorded. Prior to the introduction of the intelligent system, data processing was usually time and human resource intensive, whereas the introduction of the intelligent system was expected to significantly reduce the data processing time. By comparing the data processing time in the two cases, the improvement effect of the intelligent system in data processing speed can be visually observed. After recording the data processing time, the time comparison method is used to calculate the percentage improvement of the data processing efficiency. As shown in Figure 10, the efficiency improvement ratio of all data categories is more than 70%, and the processing time is greatly reduced after the introduction of intelligent decision support system.

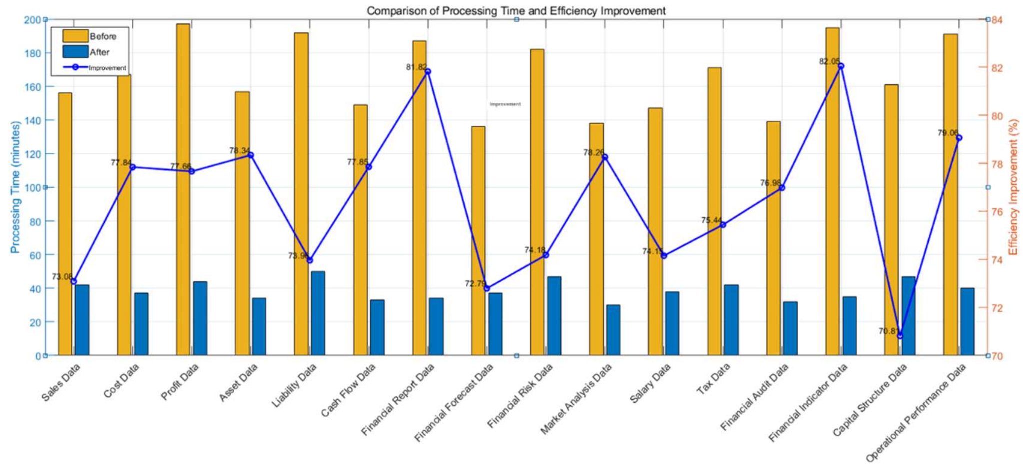

Fig. 10. Comparison of data processing time

In order to verify the accuracy of the intelligent decision support system in the process of data processing, the Mean Square Error (MSE) index is used for evaluation. Mean square error is a common method to measure the difference between two sets of data. It quantifies the accuracy of data processing by calculating the average of the square of the difference between the data processed by the system and the actual financial data.

Table 1. Mean squared error table

Data category	Intelligent decision system	Logistic regression model	Decision tree model	Random forest model	Deep neural networks
Sales data	0.31%	0.49%	0.42%	0.58%	0.68%
Cost data	0.21%	0.39%	0.31%	0.49%	0.61%
Profit data	0.49%	0.61%	0.71%	0.88%	0.81%
Asset data	0.41%	0.59%	0.48%	0.69%	0.61%
Liability data	0.32%	0.48%	0.41%	0.59%	0.52%
Cash flow data	0.59%	0.81%	0.72%	0.91%	0.99%
Financial report data	0.39%	0.61%	0.52%	0.72%	0.59%
Financial forecast data	0.71%	0.89%	0.81%	1.01%	0.88%
Financial risk data	0.52%	0.71%	0.59%	0.79%	0.69%
Market analysis data	0.62%	0.79%	0.71%	0.88%	1.02%
Compensation data	0.31%	0.51%	0.39%	0.61%	0.53%

Table 1 shows the mean square error (MSE) evaluation results of intelligent decision systems and logistic regression, decision trees, random forests, and deep neural networks under different types of data. The MSE values of intelligent decision systems in all data categories are lower than those of other models. This shows that intelligent decision systems have higher accuracy and efficiency in data prediction and analysis.

The decision effect evaluation compares the actual effect of the system with the expected goal, and evaluates the role of the system in helping the enterprise to make decisions. In the evaluation of decision-making effect, the evaluation indexes are set: ROI (Return on Investment), cost saving rate, business growth rate, decision-making accuracy, resource utilization rate.

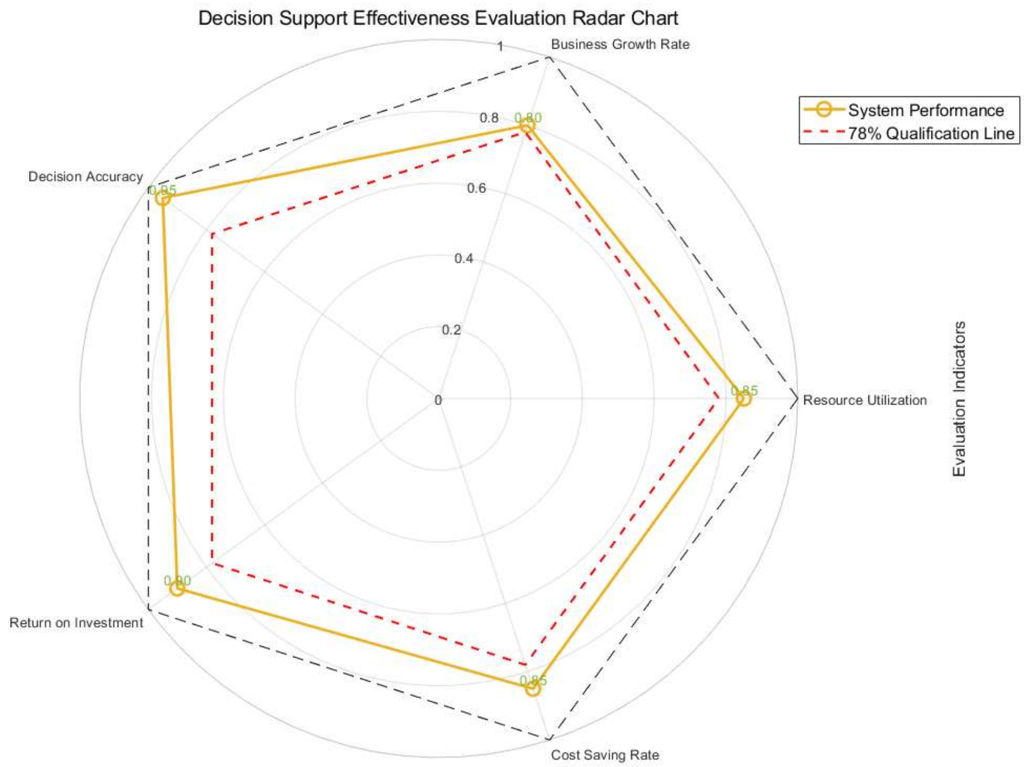

Fig. 11. Decision effect evaluation chart

As can be seen in Figure 11, the system performes well in the areas of resource utilization, business growth rate, decision accuracy and cost savings rate, with scores above the 78% pass line, indicating that the system achieves a high level of performance in these indicators. In particular, the system scores the highest in decision accuracy, at 95%. Intelligent decision-making system in the enterprise financial management informationization platform shows great potential for application, can provide enterprises with more accurate and reliable decision-making support, so as to improve the efficiency of data processing, enhance the scientific and accurate decision-making, and provide strong support for the development of enterprises.

6. Conclusion

The enterprise financial management informatization platform based on intelligent decision support system proposed in this paper significantly improves the data processing efficiency and decision support capability. In-depth analysis and prediction of financial data is achieved through automated data collection, data cleaning and standardization, and the use of support vector machine machine learning algorithms. The decision support model constructed optimizes the decision-making scheme and improves the informatization level of financial management. However, this study still has some limitations, and the optimization of algorithms and the generalization of cross-industry applications are deficient. In the future, more advanced algorithms and techniques can be further explored to enhance the system's generalization capability and user experience, in order to better support corporate financial management decisions.

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