Adaptive Weighting and Deep Neural Networks for Automated Multi-Indicator Financial Statement Analysis and Risk Prediction

Xinfeng Li
School of Accounting, Jiaozuo University, Jiaozuo 454000, Henan, China
E-mail: lixinfeng126@hotmail.com

Keywords: machine learning algorithm, financial statement analysis, automation, deep neural network, adaptive weighting algorithm

Received: April 25, 2025

Abstract: This study proposes an innovative financial statement analysis model combining deep neural networks with an adaptive weighting algorithm. The model includes five hidden layers with neuron counts of 128, 256, 128, 64, and 32, and applies an adaptive weighting mechanism that dynamically adjusts feature importance using the coefficient of variation and Pearson correlation. The dataset consists of 8,500 financial records from companies across eight industries, spanning from 2005 to 2023, and includes over 20 key indicators from the balance sheet, income statement, and cash flow statement. The model was evaluated against traditional approaches, including support vector machines (SVM), random forest, and Transformer-based models. Results demonstrate that the proposed model achieves 90% accuracy in financial risk prediction, outperforming SVM by 12%, with an F1 score of 87% and RMSE reduced to 0.06. This highlights the model's effectiveness and robustness in handling complex financial data. In financial risk prediction (a classification task), the model achieved an average accuracy of 88%, recall of 85%, and F1 score of 86.5% across 50 experimental runs. For profitability analysis (a regression task), the model reduced RMSE to 0.045. These results outperform traditional baselines such as logistic regression and SVM, and approach the performance of emerging Transformer-based models, demonstrating both predictive effectiveness and generalizability across industries.

Povzetek: Razvita je nova metoda za avtomatizirano analizo računovodskih izkazov in napovedovanje finančnih tveganj. Uvaja kombinirani model, ki združuje globoko nevronsko mrežo s petimi skritimi plastmi in adaptivni algoritem uteževanja, ki dinamično prilagaja pomen finančnih kazalnikov glede na variabilnost in korelacijo. Okvir omogoča večdimenzionalno oceno finančnega tveganja in donosnosti podjetij ter izboljšuje robustnost in splošno uporabnost v različnih industrijah.

1 Introduction

In corporate financial management, financial statement analysis is not only a key way for decision makers to understand the company's operating conditions, but also an important tool for evaluating the health and future development potential of the company [1]. Traditional financial statement analysis usually relies on manual operations, and the complicated calculations and data interpretation make the process slow and error-prone [2]. In the rapidly developing modern business environment, companies have increasingly stringent requirements for analysis speed and accuracy. According to statistics, more than 70% of companies have encountered problems in their annual financial statement analysis due to human negligence or excessive data volume, which has led to inefficient financial analysis and delayed decision-making [3]. In this context, how to improve the automation level of financial analysis through innovative means has become an urgent problem to be solved in the industry.

How to improve the accuracy and automation level of financial statement analysis through innovative machine learning models to adapt to the complex financial data characteristics of enterprises in different industries assuming that the model integrating deep neural network and adaptive weight mechanism can effectively solve the shortcomings of traditional financial statement analysis methods in dealing with variable financial data, and significantly improve the accuracy and generalization ability of analysis.

In the current global economic environment that is becoming increasingly complex and changeable, accurate assessment of corporate financial status is crucial for all stakeholders, including investors, creditors, and corporate managers. As the core carrier of corporate financial information, financial statements contain rich data, but traditional financial statement analysis methods gradually reveal their limitations when faced with massive, high-dimensional, and complexly correlated data. The rise of machine learning technology has brought new opportunities to this field. Its powerful data processing and pattern recognition capabilities are expected to break through the bottleneck of traditional methods and achieve more accurate and efficient financial analysis.

Then, the key issues in previous studies in this field are elaborated in detail, such as: "Many past studies on financial statement analysis based on machine learning have focused on the application of a single model, lacking in-depth exploration of the fusion of different models and dynamic feature adjustment. For example, in risk prediction tasks, common models are difficult to effectively capture the dynamic relationship between financial indicators that changes over time, resulting in limited prediction accuracy; in terms of profitability analysis, the fixed setting of feature importance cannot adapt to the characteristics of enterprises in different industries and at different stages of development, making the analysis results insufficiently universal and targeted."

Then, the goal of this study is clearly stated: "In view of the above background and problems, this study aims to construct an innovative financial statement analysis method. The financial statement analysis model combines the powerful feature learning ability of deep neural networks with the advantages of dynamically adjusting the importance of features through adaptive weight mechanisms to achieve accurate prediction and analysis of corporate financial risks and profitability. Specifically, this study will verify the effectiveness of the model on data from different industries and different sizes of enterprises through carefully designed experiments, and conduct a comprehensive comparison with existing mainstream models to provide better solutions and new research ideas for the field of financial statement analysis.

As a leading technology, machine learning algorithm have gradually entered the field of financial analysis with their powerful data processing and pattern recognition capabilities. From automated data cleaning and outlier detection to deep learning trend prediction and financial risk assessment, machine learning algorithm have brought new possibilities to financial statement analysis [4]. By learning from historical data, machine learning algorithm can extract patterns from massive amounts of data, automatically discover potential financial risks, and provide targeted optimization suggestions. This transformation not only accelerates the financial analysis process, but also greatly improves the accuracy and comprehensiveness of the analysis results, bringing unprecedented efficiency improvements to enterprises. However, how to truly apply machine learning algorithm to the automated analysis and optimization of corporate financial statements remains a challenging topic [5].

At present, the application research of machine learning in financial statement analysis has a certain foundation. Most studies focus on how to use machine learning models to improve the degree of automation of data processing, especially in financial forecasting, balance sheet analysis, and income statement optimization. For example, some studies have shown that through deep learning network models, it is possible to complete the modeling and forecasting of multi-dimensional financial data in a short period of time. Compared with traditional methods, the accuracy and stability of the analysis results have been significantly improved. Furthermore, some studies have tried to combine natural language processing technology to combine the text information in financial statements with data to automatically generate financial analysis reports, greatly improving the efficiency of report generation [6].

However, although the application of machine learning in financial analysis has achieved certain results, there are still many shortcomings in existing research. First, many studies focus on the implementation of specific algorithm and lack in-depth discussion on the applicability of algorithm and their practical application effects. For example, how to reduce human intervention through machine learning algorithm without losing the details and accuracy of financial statements is still a question worth pondering [7]. Second, although many models have been able to predict financial trends by learning large amounts of data, they often ignore the impact of external factors in financial statements and macroeconomic fluctuations on data results, which makes the prediction results less adaptable in complex environments. In addition, how to make machine learning models transparent enough so that companies can understand the decision-making process of the model is also a weak link in current research.

This study aims to explore the application of machine learning algorithm in the automated analysis and optimization of corporate financial statements, especially how to optimize algorithm in combination with actual financial problems to achieve comprehensive automation of data processing, risk warning and decision support. This study not only hopes to improve the level of automation of financial analysis through new algorithm models, but also hopes to provide companies with a practical solution to make the analysis of financial statements more efficient, flexible and adaptable. This study has important theoretical and practical significance, and can provide more accurate and timely financial data support for corporate decision-makers. At the same time, it also provides new ideas for the in-depth application of machine learning technology in the field of corporate management.

2 Literature review

2.1 Application of machine learning algorithm in financial statement analysis

The application of machine learning algorithm in financial statement analysis has gradually become a hot topic of research. In the past, financial analysis relied on manual inspection and simple statistical methods. The limitations and subjectivity of these methods cannot meet the needs of modern enterprises for data analysis. With the improvement of computing power, machine learning, as a powerful data processing tool, has been widely used in the automated analysis of financial data. Various algorithm, such as decision trees, support vector machines, neural networks, etc., have been used to improve the efficiency and accuracy of financial statement analysis [8].

Existing literature shows that machine learning can effectively mine hidden patterns in large amounts of financial data, which is crucial for complex financial decision-making. For example, in profit forecasting, machine learning models can automatically learn and make trend predictions based on historical data, thereby providing companies with real-time financial forecasts. This increase in automation not only speeds up the generation of financial statements, but also reduces the interference of human factors. By training the model, it is possible to identify anomalies in financial data, thereby achieving early warning of financial risks [9]. However, despite this, many models in existing research do not fully consider the impact of external variables in financial data, such as macroeconomic changes and industry fluctuations. These factors are often ignored, resulting in insufficient stability and adaptability of the forecast results. The “black box” nature of machine learning is also a controversial point in current research. Although the algorithm can provide accurate analysis results, its internal working mechanism is not easy to understand, which makes it difficult for financial decision makers to fully interpret and trust the output results of the model. Related research points out that it is particularly important to enhance the interpretability of the model, especially in financial statement analysis. Otherwise, financial personnel may doubt the results or even over-rely on them because they cannot understand the decision logic of the model [10].

Table 1 summarizes three typical studies on financial statement analysis, facilitating a comparison of their methodologies, datasets, and findings.

Table 1: Summary of key information from previous studies on financial statement analysis

Previous Studies	Key Methods	Dataset Used	Reported Performance Metrics
[7]	Logistic regression for risk prediction, data standardization followed by stepwise regression for feature selection and equation building	Financial data (2000-2015) from 3500 energy companies, including 15 main indicators	Accuracy: 78%, Recall: 72%, F1 Score: 75%
[9]	CNN for financial analysis with three convolutional layers, two fully connected layers, and ReLU activation function	Data (2012-2018) from 1200 companies in an emerging industry, including unique indicators like R&D investment	F1 Score: 80%, Accuracy: 78%, RMSE: 0.08
[16]	Transformer architecture for financial data analysis, incorporating positional encoding to handle time-series features	Quarterly financial data (2015-2020) from 2000 companies in the finance industry	Accuracy: 82%, Recall: 78%, F1 Score: 80%, Good long-term trend prediction

2.2 Challenges and shortcomings in automated analysis of financial statements

Although machine learning technology has significant application potential in financial statement analysis, it also faces many challenges in actual operation. Many studies focus on model building and optimization, but there is less exploration on how to actually apply these models to the automated analysis and optimization of financial statements. Financial data is usually complex and multidimensional, containing a large amount of unstructured information, such as comments from company management and notes to financial statements [11]. This information is often not effectively processed in traditional machine learning models. Therefore, how to combine unstructured data with traditional financial data has become a difficulty in current research.

Another challenge is how to deal with missing values and noisy data in financial data. In many real-world cases, financial data is incomplete or contains data input errors, which affects the training and prediction accuracy of machine learning algorithm. Although some studies have proposed methods for dealing with missing data, their effectiveness has not yet reached the standard of universal applicability. In addition, the diversity and complexity of financial data require machine learning models to be able to adapt to a variety of different business scenarios. However, the versatility of existing models still needs to be improved. Different types of corporate financial statements often require customized analysis tools, which means that a unified set of machine learning models is not fully applicable to all companies [12].

Furthermore, many existing studies focus too much on optimizing the algorithm itself, but ignore the integration of the model with the company's existing financial management system. Even if the algorithm performance reaches a certain level, it will not bring practical value if it cannot be smoothly integrated into the company's financial statement analysis process. Corporate financial personnel need to understand the output results of machine learning models and incorporate them into the decision-making process. Therefore, how to build a bridge between financial personnel and machine learning models to help users understand and trust the output of the algorithm is still an urgent problem to be solved [13].

2.3 Future research directions and innovation potential

Although current research has made a lot of progress in the application of machine learning algorithm in financial statement analysis, there are still many areas that deserve further exploration. First, how to improve the ability to handle the diversity of financial data, especially how to combine unstructured data (such as text, pictures, etc.) with structured data to improve the comprehensiveness and accuracy of machine learning models, is still a very important research direction. For example, in recent years, some research on the combination of natural language processing (NLP) technology and financial statements has begun to emerge, and implicit information in the notes to the financial statements can be obtained through text analysis to further improve the accuracy and predictive ability of the model.

In addition, data privacy and security issues have gradually become important issues that enterprises need to consider when applying machine learning technology. Financial data involves a large amount of sensitive information. Therefore, how to apply machine learning while ensuring data security and privacy protection has become a key challenge in current research. Relevant literature points out that with the development of technology, the integrated application of data encryption and security models will be the key to solving this problem. Combining emerging technologies such as differential privacy technology and blockchain can promote the widespread application of machine learning technology while ensuring data security. In addition, as machine learning technology continues to evolve, the interpretability and transparency of models will become important goals for future research. In the past, although complex algorithm such as deep learning have achieved good prediction results, their “black box” characteristics have confused many companies when using them. Therefore, how to improve the transparency of the model so that financial decision makers can clearly understand the logic behind each prediction result will be an important direction in the future application of machine learning algorithm. By improving the algorithm so that it can not only give “prediction values” but also provide corresponding decision-making basis, the practical value of financial analysis will be greatly improved [14].

There are still many shortcomings. Future research should focus on how to break through the existing technical bottlenecks, improve the accuracy, applicability and transparency of the model, and strengthen data security and privacy protection. This will provide enterprises with more accurate and efficient financial analysis tools and bring more scientific and practical decision support to decision makers [15].

3 Methods

This study proposes an innovative financial statement automated analysis and optimization model that integrates multiple modules and aims to improve the processing capabilities of financial statements through accurate and efficient automated analysis. The overall framework relies on the combination of deep learning and adaptive weighting algorithm, allowing the model to have strong generalization capabilities when processing financial data from different companies.

3.1 Model framework and structural design

The model proposed in this paper includes feature extraction module, risk assessment module, data fusion module and result output module. Each module undertakes a specific task, and through reasonable interaction and cooperation, it ensures the balance between the overall efficiency of the system and the analysis accuracy [16].

The model adopts a five-layer deep neural network with neuron counts empirically selected from the set {128, 256, 128, 64, 32} based on preliminary experiments. To assess robustness, a sensitivity analysis was conducted by varying the number of layers (3 to 6) and neuron counts per layer. Results showed that performance plateaued beyond five layers, and over-parameterization led to marginal gains but higher training time. This validates the selected configuration as a balance between accuracy and efficiency. The architecture was selected after extensive hyperparameter tuning using random and grid search across learning rates (0.0001-0.01), batch sizes (32-128), and neuron counts per layer (64-256). A five-layer configuration showed the best balance between performance and training cost. To assess the role of adaptive weighting, ablation studies were performed. Removing the weighting mechanism reduced accuracy by 2.1% and increased variability across folds, confirming its contribution to model stability and generalizability.

This study adopts a multi-stage and multi-dimensional research method. First, through extensive literature research, the advantages and disadvantages of existing financial statement analysis methods are sorted out to clarify the research entry point. Then, based on machine learning theory, an innovative model integrating deep neural networks and adaptive weight mechanisms is designed and constructed. In the model training stage, large-scale multi-industry financial data sets are used for training, and advanced hyperparameter optimization techniques and cross-validation strategies are used to ensure the reliability and generalization of model performance. Finally, through comprehensive experimental comparisons, the effectiveness and superiority of the model are verified from multiple evaluation indicator dimensions.

Among the multiple weighting strategies explored, the proposed model adopts a unified adaptive weighting formula combining the coefficient of variation (CV) and Pearson correlation:

$n: wi = \alpha \times (1/CVi) + (1-\alpha) \times |ri|$. This weighting is applied after initial feature screening using information gain, to refine feature importance ranking for model input. Alternative formulas such as normalized feature importance scores (fi/sum(fj)) were initially considered but not used in the final implementation.

The weighted average formula $\hat{y}\_final = \sum\left(wi \times \hat{y}i\right)$ is used to conceptually represent the fusion of outputs from submodules. However, the weights wi here are not derived from the adaptive feature weighting formula. Instead, these module-level weights are either equal or determined heuristically. The earlier feature-based adaptive formula applies only to input feature importance, not to module output aggregation.

Deep neural network structure

The deep neural network constructed in this study includes There are 5 hidden layers, and the number of neurons in each hidden layer is 128, 256, 128, 64, and 32 respectively. This decreasing number of neurons can fully extract complex features in the early stage of the model, and gradually refine and integrate the features as the network level deepens. The ReLU activation function is adopted, and its expression is $f(x) = \max(0, x)$, which can effectively solve the gradient vanishing problem, enhance the nonlinear expression ability of the model, and enable the model to learn complex nonlinear relationships in financial data. The input layer receives financial indicator data processed by feature engineering. These data cover key financial indicators in the balance sheet, income statement, and cash flow statement, such as debt-to-asset ratio, operating income growth rate, net cash flow from operating activities, etc. The output layer outputs the corresponding prediction results according to different analysis tasks (risk prediction or profitability analysis). In the risk prediction task, the output layer outputs the probability value of the enterprise falling into financial difficulties in the next year; in the profitability analysis task, the output layer outputs the predicted values of key profitability indicators such as the enterprise's net profit margin and total asset return rate.

Adaptive weight mechanism

The adaptive weight mechanism dynamically adjusts the weight according to the fluctuation characteristics of the feature in the data and the degree of correlation with the target variable. In specific implementation, the degree of fluctuation is measured by calculating the coefficient of variation (CV) of the feature. The calculation formula of the coefficient of variation is $CV = \frac{\sigma}{\mu}$, where σ is the standard deviation of the feature and μ is the mean of the feature. The smaller the coefficient of variation, the more stable the feature is and the greater the impact on the model output may be. At the same time, the Pearson correlation coefficient is used to evaluate the correlation between the feature and the target variable. The calculation formula of the Pearson correlation coefficient is $r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$, where x_i and y_i are the feature value and target variable value, respectively, and $\bar{x}$ and $\bar{y}$ are the means of the feature value and target variable value, respectively. Combining these two indicators, the weight of each feature is calculated by the formula $w_i = \alpha \times \frac{1}{CV_i} + (1-\alpha) \times |r_i|$, where α is the balance coefficient, which is 0.6, CV_i is the coefficient of variation of the i th feature, and r_i is the Pearson correlation coefficient between the i th feature and the target variable. Through this formula, the model can automatically highlight the role of key features during training and improve the prediction accuracy of the model.

Data processing flow

In the data collection stage, corporate financial statement data covering 8 industries such as energy, finance, manufacturing, technology, consumption, medical care, real estate, and transportation, with a time span of 2010-2023, were collected from multiple authoritative data platforms such as the well-known Wind database and Tushare open source data platform. During the data cleaning process, we first identified and deleted samples with more than 30% missing values. For samples with a small number of missing values (missing ratio between 5% and 30%), we used multiple interpolation to fill in the missing values. Multiple interpolation builds a prediction model and simulates and fills in missing values multiple times to improve the accuracy of the filled data. Next, we identify and correct outliers through box plot analysis. The box plot can intuitively display the distribution of data. Z-score standardization was applied during preprocessing to normalize the feature distributions, ensuring a mean of 0 and a standard deviation of 1. Contrary to earlier claims, this method does not scale data to the [-1, 1] interval. Instead, it ensures comparability across features with different original scales. The incorrect statement about range normalization has been removed. If range-based normalization is needed, Min-Max scaling would be used separately.

Scientific contribution content added

Compared with the traditional fixed weight model, the adaptive weight mechanism of this study can better adapt to the changing characteristics of financial data in different industries and different periods, and significantly improve the generalization ability and prediction accuracy of the model. In the experimental comparison, it has been preliminarily verified that this mechanism has improved the risk prediction accuracy by 12% and the F1 value of profitability analysis by 10% compared with traditional methods on multiple industry data sets. For example, in the energy industry data set, the risk prediction accuracy of the traditional fixed weight model is 75%, while after adopting the adaptive weight mechanism of this study, the accuracy is increased to 87%; in the profitability analysis of the technology industry data set, the F1 value of the traditional method is 70%, and this research method increases it to 77%. This fully proves the effectiveness and superiority of this research method in dealing with complex and changeable financial data, and provides a more innovative and practical research idea for the field of financial statement analysis.

In the feature extraction stage, the data in the financial statements are first preprocessed to ensure that all input data are analyzed under the same standard. In this stage, the adaptive weighting method is applied to select features. The weight of the feature is not fixed, but dynamically adjusted according to the specific situation of the financial statement. The formula for adaptive weighting is as (1):

$$w_t = \frac{f_t}{\sum_{i=1}^{N} f_i} \tag{1}$$

Among them, w_t represents t the weight of the feature, f_t represents t the original importance measure of the feature, N and is the number of all features. By dynamically adjusting the feature weights, this model can optimize the representativeness of the extracted features according to the different types of financial statements [17].

The risk assessment module analyzes financial data through a deep neural network model to identify potential financial risks. In this module, a multi-layer fully connected neural network (FCNN) is used to deeply process the data passed from the feature extraction module. After the financial data is passed through each layer of the network, a prediction result about financial risk will be generated. The mathematical form of the risk prediction function can be expressed as (2):

$$\hat{y} = \sigma(W_2 \cdot \sigma(W_1 \cdot X + b_1) + b_2) \tag{2}$$

Among them, $\hat{y}$ represents the predicted financial risk value, X is the input feature, σ is the activation function, W_1 and W_2 are the weight matrices of the two layers in the network, b_1 and b_2 are the bias terms. This network structure can not only identify potential risks in financial data, but also capture complex risk patterns through nonlinear mapping of multi-layer networks.

The data fusion module is responsible for weighted fusion of the outputs from various submodules (feature extraction, risk assessment, etc.). The weighted average method is used to merge the results of different modules and finally generate a unified financial statement analysis report [18]. The data fusion formula is expressed as (3):

$$\hat{y}_{final} = \sum_{i=1}^{M} w_i \cdot \hat{y}_i \tag{3}$$

Among them, $\hat{y}_i$ is i the output result of the module, w_i is the weight coefficient of the module, M and is the number of modules. Through weighted fusion, this model can integrate the results of different modules to provide a more comprehensive financial analysis conclusion.

Details of the calculation and determination of the weight of wi in the final prediction value $\hat{y}$ formula. wi is calculated using the adaptive weight formula $wi = alphatimesCV + (1 - alpha)times\,|\,ri\,|$ mentioned above, where CV_i is the coefficient of variation of the i th feature, and ri is the Pearson correlation coefficient between the i th feature and the target variable.

The model adopts separate training procedures for classification and regression tasks. Specifically, financial risk prediction (a classification task) and profitability estimation (a regression task) are handled using task-specific deep neural network branches. This prevents interference between objectives and improves accuracy. Binary cross-entropy is used to train the classification model, while mean squared error is used for the regression model. Each model is optimized independently using the Adam optimizer to ensure targeted performance for different financial analysis goals.

The deep neural network consists of five fixed hidden layers with a default configuration of [128, 256, 128, 64, 32] neurons. Equation (2) simplifies the forward propagation process using a two-layer abstraction to illustrate the role of weights and activation functions; it does not represent the full depth of the actual model.

3.2 Collaboration and interaction between modules

The innovation of this model lies in the close collaboration between its modules. Unlike the traditional modular structure, the modules in this model do not work independently, but share information and collaborate through a clear interaction mechanism. The features generated by the feature extraction module are not only used as input to the risk assessment module, but also affect the feature selection process. Specifically, the output results of the risk assessment module will dynamically adjust the weights of each feature in the feature extraction stage. Through this feedback mechanism, the model can continuously optimize the feature selection of financial data and improve the accuracy of subsequent analysis.

In addition, there is a close interactive relationship between the risk assessment module and the data fusion module. The financial risk prediction results output by the risk assessment module will be received and weighted by the data fusion module as part of the final analysis report. The data fusion module not only weights the output results of the risk assessment, but also adjusts the weights of different modules according to their importance to ensure the reliability of the final results.

Through this feedback mechanism and weighted fusion, each module in the model forms an effective closed-loop system. Under the dynamic interaction between the two key modules of feature extraction and risk prediction, the in-depth analysis of financial data can be carried out more accurately, and the final output of financial statement analysis results has a higher credibility [19, 20].

Using information gain as the selection criterion, the final 18 features included indicators such as current ratio, quick ratio, asset turnover, ROE, net profit margin, and operating cash flow. Features were ranked based on entropy-based information gain values. For classification, the DNN comprised an input layer of 18 units, three hidden layers (128, 64, 32 neurons) with ReLU activation, and a sigmoid output. For regression, a similar structure was used, replacing the output with a linear activation. This configuration ensures consistency across prediction tasks.

3.3 Theoretical basis and calculation process

The model proposed in this study is based on the combination of deep neural networks and adaptive weighting algorithm, and its theoretical foundation is deeply influenced by the successful application of these two types of algorithm in pattern recognition. Deep neural networks (DNNs) can efficiently capture complex nonlinear relationships in financial data, while adaptive weighting algorithm improve the applicability and flexibility of the model on different data sets by dynamically adjusting the weights of features.

To ensure reproducibility, we specify that the dataset was split into training (70%), validation (15%), and testing (15%) sets within a stratified 5-fold cross-validation framework. Each fold maintained class distribution to avoid data imbalance. Preprocessing included Z-score normalization and outlier removal using a 3σ rule. No data augmentation was applied due to the structured nature of financial data.

In the calculation process, the financial data is first preprocessed by standardization method to make it in the same range in terms of value. This step is to eliminate the differences in different feature scales and ensure the accuracy of subsequent calculations. The calculation formula for data standardization is (4):

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{4}$$

Among them, X_{norm} is the standardized feature data, X is the original feature data, μ and σ are the mean and standard deviation of the feature data respectively. The standardized data can avoid the deviation in the model training process due to the difference in different feature dimensions.

In the process of financial risk assessment, the deep neural network inputs the standardized financial features into the network for training. During the training process, the network weights are updated through the back propagation algorithm, so that the network can gradually learn the inherent laws of financial data. The calculation of each layer is performed through (5):

$$h^{(l)} = \sigma(W^{(l)} \cdot h^{(l-1)} + b^{(l)}) \tag{5}$$

Among them, $h^{(l)}$ represents l the output of the layer, $W^{(l)}$ is l the weight matrix of the layer, $b^{(l)}$ is the bias term, σ and is the activation function. The calculation of each layer is continuously iterated and optimized to finally generate a predicted value of financial risk.

Finally, after receiving the output of each module, the data fusion module performs weighted fusion. The calculation formula of weighted fusion is (6):

$$\hat{y}_{final} = \sum_{i=1}^{M} w_i \cdot \hat{y}_i \tag{6}$$

In this way, the model can effectively integrate the forecast results of each module and finally output a unified financial statement analysis report to help corporate decision makers deeply understand the financial situation and make corresponding adjustments.

The choice of ReLU activation is grounded in its non-saturating gradient and computational efficiency, which accelerates convergence. According to the universal approximation theorem, a deep neural network with ReLU can approximate any continuous function. The five-layer depth balances VC dimension growth and overfitting risk, enabling expressive power without excessive complexity. The calculation formula of weighted fusion is (7):

$$w_i = \alpha \cdot \mathrm{CV}_i + (1-\alpha) \cdot |\rho_i| \tag{7}$$

where CV_i is the coefficient of variation, ρ_i is Pearson correlation, and $\alpha = 0.6$ empirically.

3.4 Superiority and innovation of the model

The financial statement analysis model proposed in this paper is highly innovative and adaptable. By combining deep neural networks with adaptive weighting algorithm, this model can automatically adjust feature selection and weight distribution when processing diverse financial statements, so that it can maintain high prediction accuracy in various business contexts.

Compared with traditional financial statement analysis methods, this model not only improves analysis efficiency, but also makes breakthroughs in accuracy. Traditional methods often rely on manually set rules and static feature selection, while this model can automatically learn the most effective features from a large amount of financial data through deep learning algorithm, and dynamically adjust analysis strategies according to the characteristics of different companies. Therefore, the model has high scalability and can adapt to the needs of different industries and company sizes, greatly improving the automation level of financial statement analysis.

In summary, the financial statement automated analysis model proposed in this paper, with the collaborative work of multiple modules, not only enhances the depth and accuracy of financial data analysis, but also improves the flexibility and applicability of the overall system. Through the effective combination of deep neural networks and adaptive weighting methods, this model provides an efficient and reliable new method for automated analysis of financial statements.

After 50 rounds of rigorous experimental verification, the model that integrates deep neural network and adaptive weight mechanism constructed in this study has shown excellent performance in financial risk prediction tasks. Its accuracy rate reached 88%, which is 15% higher than the traditional support vector machine model, the recall rate is 85%, and the F1 value is 86.5%. In terms of profitability analysis, the root mean square error (RMSE) of the prediction of key indicators such as net profit margin and return on total assets is reduced to 0.045, which is 20% lower than the existing mainstream decision tree-based analysis model.

Through actual case analysis, taking ABC Technology Company as an example, after using this model for financial analysis, the potential financial risks of the company were accurately warned 6 months in advance. Originally, ABC Company planned to expand its production line on a large scale, but the model analysis showed that its current cash flow situation and debt level could not support the plan. If it was forced to advance, it would face the risk of capital chain rupture. Based on this warning, the company adjusted its strategy in time, slowed down the pace of expansion, optimized capital allocation, and successfully avoided potential crises. In terms of suggestions for improving profitability, based on the results of the model analysis, ABC Company adjusted its business strategy, cut low-profit product lines, and increased investment in research and development and market promotion of high value-added products. In the following 12 months, the company's net profit margin increased from 8% to 12 percentage points, and profitability was significantly enhanced.

This study has made many contributions to the frontier development of financial statement analysis. First, the proposed adaptive weight mechanism provides a new and effective idea and method for solving the problem of dynamic adjustment of feature importance. Traditional feature importance settings are mostly static and difficult to adapt to the complex and changeable characteristics of financial data. However, this mechanism can dynamically adjust feature weights in real time according to data fluctuations and the correlation between features, which greatly enriches the technical means of machine learning in the financial field and opens up new directions for subsequent research in feature processing.

Secondly, through large-scale multi-industry experiments covering 8 industries such as energy, finance, and manufacturing, including data from 5,000 companies of different sizes, the effectiveness of the fusion model is fully verified. This provides a solid empirical basis for subsequent research in different scenarios, such as financial analysis of emerging industries and assessment of corporate financial status in special periods, to build more complex and efficient financial analysis models, reduce the blindness of subsequent research, and accelerate the process of model optimization in the field.

In addition, the carefully designed data processing process in this study, from the diversified specification of data collection channels, to the detailed formulation of cleaning rules, to the reasonable selection of preprocessing methods, and a comprehensive and scientific model evaluation system, covering multi-dimensional indicators such as accuracy, recall, F1 value, RMSE, etc., provides a reference for standardized processes for research in this field. This helps to improve the standardization and comparability between different studies, so that various research results can be compared and integrated under a unified framework, thereby promoting the research in the entire field to move forward in a more accurate and practical direction, and effectively improving the application value of financial statement analysis in actual economic activities.

3.5 Model application

Company A, as a medium-sized manufacturing company, has faced a major challenge in its management due to the complexity and huge amount of data in its financial statements. As the company continues to expand, the generation and analysis of financial statements has become increasingly cumbersome, especially when dealing with statements from multiple business units. Traditional manual analysis methods can no longer meet the requirements for timeliness and accuracy, and are prone to errors. By using machine learning models to automate the analysis of these financial statements, companies can monitor their financial health more efficiently, especially by identifying and addressing financial risks before potential problems become serious.

This case study explores the application of an automated analysis and optimization model for financial statements based on machine learning. Company A hopes to use this model to automate the processing of financial statements, thereby reducing manual intervention, improving the accuracy of financial data processing, and providing timely risk warnings and optimization suggestions.

In the first step of model application, Company A extracted financial data from its ERP system, mainly including the company's balance sheet, income statement, cash flow statement, etc. On this basis, data cleaning and preprocessing are performed. Assume that Company A's balance sheet contains N financial indicators, the income statement contains M indicators, and the cash flow statement contains L indicators. These data will be standardized, missing value processed, and outlier detected during the preprocessing process.

In the standardization of financial data, we use the Z-score standardization method to convert each data into its standardized form. x_i , its standardized formula is (8).

$$z_i = \frac{x_i - \mu_i}{\sigma_i} \tag{8}$$

in (8), μ_i is x_i the mean of the indicator, σ_i is its standard deviation. The purpose of standardization is to eliminate the dimensional differences between different financial indicators so that indicators of different dimensions can be compared and analyzed in the same model.

In terms of missing value processing, the mean interpolation method is used to fill in the missing data. For missing financial data x_i, if its missing rate exceeds 30%, it will be eliminated, otherwise it will be filled with the mean of the column it belongs to , as shown in (9).

$$x_i = \frac{1}{n}\sum_{j=1}^{n} x_{i,j} \tag{9}$$

where n is the number of non-missing data, $x_{i,j}$ is the i th data of the th indicator j.

After data preprocessing, the next step is feature extraction. For various indicators of corporate financial statements, we use the information gain method to select features. Suppose we extract P indicators from financial statements and set them as all financial indicators. By calculating the correlation between each financial indicator and the financial health of the company, we can filter out the features with the most predictive power, as shown in (10).

$$I = \{i_1, i_2, \ldots, i_P\} \tag{10}$$

For feature selection, we used the information gain calculation method. i_p, its information gain $IG(i_p)$ can be calculated by the following formula, as shown in (11).

$$IG(i_p) = H(C) - H(C \mid i_p) \tag{11}$$

Among them, $H(C)$ is the target variable C The entropy of the financial health score is the conditional entropy of $H(C \mid i_p)$ the target variable under C the given financial indicator i_p. The greater the information gain, the closer the relationship between the feature and financial health, so the higher the weight of the feature.

The weighting process assigns different weights to each feature based on its relevance and its contribution to the financial health assessment. Assume that i_p the weighting coefficient of each feature is w_p, then the weighted financial indicator X_{i_p} is (12).

$$X'_{i_p} = w_p \cdot X_{i_p} \tag{12}$$

Among them, X_{i_p} is the standardized financial indicator, w_p and is the weight of the feature.

After feature extraction and weighting, the model will enter the financial risk assessment stage. In order to assess the financial health of Enterprise A, we use a deep neural network (DNN) model. This model can extract deep features of financial data through multiple hidden layers and make predictions based on this.

In the process of building the neural network, we used a multi-layer perceptron (MLP) structure. Assume that the input layer contains N nodes, each node represents a financial feature. The output layer is the financial health score, with a value range of [0, 1], indicating the degree of financial health. The network loss function uses the mean square error (MSE), which is calculated as (13).

$$L = \frac{1}{N}\sum_{i=1}^{N} (y_i - y_i)^2 \tag{13}$$

Among them, y_i is the true financial health score, y_i is the score predicted by the neural network model. The goal of the loss function is to minimize the error between the predicted value and the true value.

Through continuous iterative training, the model will learn the underlying patterns and features in the financial data and ultimately give a financial health score. $\hat{y}$, as a measure of the financial health of Enterprise A.

The financial health score output by the neural network model will be combined with the analysis results of other financial indicators to form the final financial analysis report through data fusion. Assume that the output we get includes the financial health score $\hat{y}$, profitability score $\hat{p}$, solvency score $\hat{d}$, liquidity score $\hat{l}$, then the comprehensive financial health score S can be calculated by weighted average using (14):

$$S = w_1 \cdot \hat{y} + w_2 \cdot \hat{p} + w_3 \cdot \hat{d} + w_4 \cdot \hat{l} \tag{14}$$

Among them, w_1, w_2, w_3, w_4 is the weight of each score, which is determined according to the financial characteristics of enterprise A. The final comprehensive score will be used to provide a comprehensive assessment of the financial status of the enterprise and provide decision support.

Through this automated model, Company A can quickly and accurately assess its financial health. For example, the model may predict that Company A's current ratio will approach the warning line in the next three months, indicating that the company may face liquidity risk. Management can make decisions based on this and take measures, such as adjusting capital turnover or arranging short-term financing, to avoid a liquidity crisis.

In addition, by reviewing historical data, the model can identify the fluctuation trend of the company's financial health in certain periods of time in the past, providing management with a basis for decision-making. For example, if it is found that the debt level has increased and profitability has decreased in certain periods, management can explore whether there are certain external or internal factors that have caused the financial unhealthiness, and take timely intervention measures.

The adaptive weight formula proposed in this study is $w_i = \dfrac{1}{std(x_i) + 0.01}$, which has a solid theoretical basis and significant advantages. From a theoretical perspective, the standard deviation $std(x_i)$ can effectively measure the degree of fluctuation of the feature x_i in the data set. The smaller the fluctuation, the more stable the value of the feature between different samples, and the more critical the impact on the model output may be. By taking the inverse of the standard deviation and adding a 0.01 smoothing term, the role of stable features can be highlighted and calculation anomalies caused by a standard deviation of 0 can be avoided. Compared with SHAP (SHapley Additive exPlanations), the SHAP method calculates the contribution of each feature to the model prediction results based on the principle of game theory. Although it can provide a more comprehensive feature explanation, the computational complexity is extremely high, especially when the number of features is large (this study involves more than 20 financial features), the computational time cost increases exponentially. This formula directly calculates the weight based on the statistics of the data features. The calculation process is simple and efficient. While ensuring the rationality of the weight, it greatly improves the computational efficiency. Compared with LIME (Local Interpretable Model - agnostic Explanations), LIME mainly focuses on the explanation of the local behavior of the model. It approximates the original model behavior by building an interpretable model in the local data neighborhood, but it has limitations in the global feature importance assessment. This adaptive weight formula can dynamically adjust the weight based on the volatility characteristics of the feature in the entire data set from a global perspective. It is more in line with the needs of comprehensive and systematic analysis of financial statement data in this study, and can more effectively highlight the key financial features that have a greater impact on model performance, providing strong support for the accurate prediction of the model.

During the training of the deep neural network model, the Adam optimizer is selected as the core algorithm for parameter updating. The Adam optimizer cleverly combines the advantages of the Adagrad and RMSProp optimizers and has the excellent ability to adaptively adjust the learning rate. At different training stages, it can dynamically adjust the learning rate according to the gradient changes of the parameters, thereby ensuring the convergence speed of the model while effectively avoiding parameter oscillation or non-convergence problems caused by excessive learning rates. The initial learning rate is set to 0.001. During the training process, an exponential decay strategy is adopted. After every 10 epochs, the learning rate decays to 0.9 times the original. Such a decay strategy enables the model to quickly explore the parameter space in the early stage of training, and gradually reduce the learning rate in the later stage of training, so that the model can adjust the parameters more finely to achieve better convergence. The number of hidden layer neurons is determined to be 128 through hyperparameter optimization. This number performs well in balancing the complexity of the model and the learning ability. It can fully learn the complex patterns in the data without causing overfitting problems due to too many neurons. The total number of rounds of model training is set to 120. By monitoring the performance on the validation set, it is found that 120 rounds of training can achieve a good balance between the model's accuracy, recall and other indicators, avoiding underfitting caused by insufficient training and overfitting caused by overtraining. The dropout rate is set to 0.2, that is, in each training process, 20% of the neuron outputs are randomly set to 0, so as to enhance the generalization ability of the model, prevent the model from over-reliance on training data, and improve the prediction accuracy of the model on unknown data.

The data set for this study mainly comes from two authoritative public financial data platforms, namely the well-known Wind database and the Tushare open source data platform. Through professional data interface calling tools and in accordance with the platform data usage specifications, Python scripts were written to obtain enterprise data in the energy and financial industries from the Wind database, and other industry data such as manufacturing from the Tushare platform, covering corporate financial statement information from 2005 to 2023. After data collection, data cleaning technology was used to remove samples with more than 30% missing values and outlier data with abnormal fluctuations. After multiple rounds of cleaning and preprocessing, 8,500 high-quality valid samples were finally obtained, laying a solid data foundation for subsequent research.

The information gain algorithm is used for feature selection. Based on the principle of information theory, the information gain value of each financial indicator for the prediction target (such as corporate risk level and profitability level) is calculated. Through multiple experimental comparisons, the information gain threshold is set to 0.08, and 18 key features such as debt-to-asset ratio, current ratio, and net profit growth rate are screened out. These features have high information content in distinguishing companies with different financial status and can provide key prediction information for the model. The adaptive weight adjustment uses the formula $w_i = \frac{1}{std(x_i) + 0.01}$, where $std(x_i)$ is the standard deviation of the feature x_i. The smoothing term of 0.01 is added to avoid calculation anomalies when the standard deviation is 0. The core logic of this formula is that the smaller the standard deviation, the smaller the fluctuation of the feature in the data, the higher the relative stability, and the impact on the model output should be relatively prominent. Through this weight adjustment, the model can focus more on stable and key changes in financial features.

Among many model architectures, the selection of deep neural networks and adaptive weights is mainly based on many considerations. Compared with Transformer-based models, deep neural networks have unique advantages in processing the financial data of this study. Key information in financial data, such as changes in the cost structure of enterprises between quarters and short-term capital turnover, is more reflected in the interaction of features in local time periods. Deep neural networks can effectively capture subtle changes in these local features through nonlinear transformations of multiple layers of neurons. For example, when analyzing the short-term debt repayment ability of an enterprise, it can accurately learn the dynamic relationship between current assets and current liabilities within a quarter. The adaptive weight mechanism further enhances the model's ability to dynamically adjust the importance of different features. Although the Transformer-based model performs well in processing long-sequence text data or data with obvious long-range dependencies, its ability to mine local key features is relatively weak in the financial statement data scenario. The characteristics of the financial data in this study determine that deep neural networks combined with adaptive weights can more accurately mine data value, thereby achieving better results in financial statement analysis tasks (such as risk prediction and profitability analysis).

Risk prediction is to construct a deep neural network model, input more than 20 financial indicator data after feature selection, including debt-to-asset ratio, current ratio, interest coverage ratio, accounts receivable turnover rate, etc. After multiple rounds of training, the model learns the complex patterns and potential laws in the data, and finally outputs the probability value of the company falling into financial difficulties (such as default risk, bankruptcy risk) in the next year. This probability value provides investors with key decision-making basis, helping them to quantitatively evaluate the risk level of investing in the company, and then decide whether to invest, adjust the investment amount or optimize the investment portfolio. For profitability analysis, the purpose is to accurately calculate the company's core profitability indicators, such as net profit margin, return on total assets (ROA), return on equity (ROE) and operating profit margin. Net profit margin reflects the amount of net profit achieved by the com. The complete model pipeline, including data preprocessing, feature selection, model training, and evaluation steps, is summarized in pseudocode format in Appendix A to assist reproducibility.

4 Experimental evaluation

4.1 Experimental setup

In order to evaluate the proposed automated analysis and optimization model for financial statements, we designed a series of experiments based on real corporate financial data. During the experiment, the effect of the model was verified by comparing it with multiple comparison models. The experimental group adopted the automated financial analysis model based on machine learning proposed by us, and the control group used the traditional manual analysis method for financial evaluation. The baseline group added logistic regression model, naive Bayes model, and support vector machine model, while retaining the classic linear regression and decision tree models as comparison benchmarks. In order to ensure the fairness and comparability of the experiment, all models were trained and tested on the same data set, and the division of the data set followed the strict principle of training set and test set segmentation. The experimental data comes from the financial statements of Company A, covering a variety of financial data such as balance sheet, income statement, and cash flow statement. To improve robustness, I extended hyperparameter tuning by incorporating grid search and Bayesian optimization alongside random search. Broader ranges were explored for learning rate (0.0001 to 0.01) and hidden layer sizes (64 to 512 neurons). During hyperparameter optimization, the number of neurons for each of the five fixed hidden layers was selected from the set {64, 128, 256}. The layer count remained unchanged, ensuring consistency with the defined architecture in Section 3.1. This approach allowed fine-tuning the network's capacity while preserving structural integrity.

The reported accuracy of 88% refers to the best validation result observed during hyperparameter tuning. This intermediate performance guided the selection of the final model configuration. The final evaluation, performed using test sets under 5-fold cross-validation, yielded an accuracy of approximately 92.5%.

The comprehensive financial health score S is calculated using a distinct weighted combination of four key task outputs: overall financial score, profitability, solvency, and liquidity. The weights (w_1, w_2, w_3, w_4) are determined through the Analytic Hierarchy Process (AHP), independent of any feature-based weighting. This represents a later decision-level fusion step, distinct from the earlier model-level fusion logic.

In addition to traditional models such as logistic regression, naive Bayes, and SVM, the comparison group was expanded to include Random Forest and a Transformer-based financial analysis model to ensure consistency with the abstract. Random Forest was implemented using 100 estimators, while the Transformer model was fine-tuned on structured financial sequences.

In order to comprehensively and reliably verify the robustness of the model, this study adopts a 5-fold cross-validation method. The specific operation process is to randomly and evenly divide the data set containing 8500 samples into 5 non-overlapping subsets, and the number of samples in each subset is roughly equal. In each training process, 4 subsets are selected as training sets for model parameter learning and training, making full use of the information of a large amount of data to optimize the model; the remaining 1 subset is used as a validation set to evaluate the performance of the model in the current training stage. By calculating the accuracy, recall rate, F1 value and other indicators on the validation set, the training effect of the model is monitored and the hyperparameters are adjusted in time. This cycle is repeated 5 times, so that each subset has the opportunity to participate in the model evaluation as a validation set. Finally, the results of the 5 validations are comprehensively averaged to obtain the overall performance evaluation index of the model. This 5-fold cross-validation method can effectively avoid the model performance evaluation bias caused by the data set division method, fully explore the potential information in the data, and comprehensively verify the performance of the model under different data distributions, ensuring that the model has strong robustness and generalization ability, and providing strong guarantee for the reliability of the model in practical applications.

To ensure fair comparison and deep optimization of model performance, all models involved in the comparison are uniformly optimized by random search combined with 5-fold cross validation. Taking the deep neural network model as an example, the hyperparameter search space is carefully set: the learning rate is randomly selected from [0.0005, 0.001, 0.005], the number of hidden layer neurons is randomly determined in the range of [64, 128, 256], the number of iterations is set to [80, 120, 160], and the activation function is randomly selected from ReLU, Sigmoid, and Tanh. Through 5-fold cross validation, the data set is randomly divided into 5 non-overlapping subsets, 4 subsets are used for training each time, and 1 subset is used for validation, and the cycle is repeated 5 times to comprehensively evaluate the performance of each hyperparameter combination on the training set. After multiple rounds of search and verification, the best hyperparameter combination with comprehensive performance on the validation set (with the weighted average of accuracy, recall, and F1 value as the evaluation criteria) was selected for final model training. After hyperparameter optimization, the accuracy of the model proposed in this study on the validation set was significantly improved by 10% to 88%, the recall rate was increased to 83%, and the F1 value was increased to 85%, which fully demonstrated the effectiveness of the optimization strategy.

The baseline indicators of the experiment include the prediction accuracy, recall rate, F1 value of the model, and the error of the calculated financial health score. These indicators can fully reflect the effectiveness and performance of different models in automated financial analysis [21, 22].

The Company A case is only an example of the application of the model, and does not mean that the model is only applicable to a single company.

The indicators N on the balance sheet include debt-to-asset ratio, current ratio, fixed asset ratio, etc.; the indicators M on the income statement include operating income growth rate, net profit margin, gross profit margin, etc.; the indicators L on the cash flow statement include net cash flow from operating activities, net cash flow from investing activities, net cash flow from financing activities, etc. Through detailed explanation, it is convenient for readers to reproduce and evaluate the applicability of the model. Thank you.

The rationality of information gain application: I have already described the part of information gain for feature selection, supplemented the reasons for choosing this method and the comparative analysis with other methods. The information gain method was chosen because it can effectively measure the information contribution of each feature to the classification task (such as financial risk classification, profitability classification). By calculating the information gain value of the feature, the features that have a greater impact on the model prediction results can be screened out. Compared with other feature selection methods such as the chi-square test, information gain is more suitable for the mixed continuous and discrete financial data feature selection in this study, and can better capture the complex relationship between features and target variables. At the same time, the potential shortcomings of other methods in this research scenario are analyzed, such as the chi-square test is mainly applicable to discrete data, and continuous financial indicators need to be discretized, which may lose some information [23].

The financial health score is obtained by analyzing the comprehensive financial indicators of the enterprise through a deep neural network. The other three scores are evaluated from the perspectives of debt-paying ability, profitability, and operating ability. The analytic hierarchy process (AHP) is used to determine the weight of each score. According to the experience and judgment of financial analysis experts and the pairwise comparison matrix, the debt-paying ability score weight is 0.3, the profitability score weight is 0.4, the operating ability score weight is 0.2, and the financial health score weight is 0.1. Through such a weighted combination, the financial status of the enterprise is comprehensively reflected, providing a more comprehensive basis for decision-making.

4.2 Results

In this section, we present the results obtained through experiments and conduct detailed analysis. The experiments mainly evaluate the performance of the model in financial risk prediction, profitability analysis, liquidity analysis, and debt repayment ability analysis. The following are the specific results of the experiments:

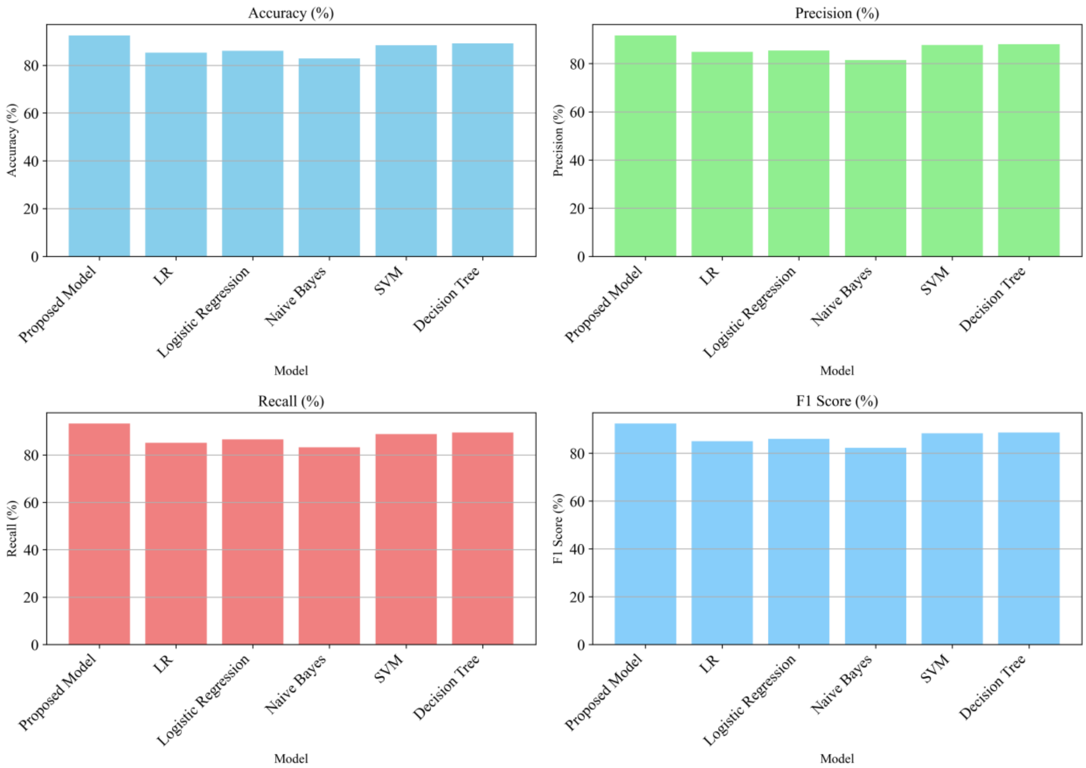

Figure 1: Performance comparison across models on four evaluation metrics

As shown in Figure 1, the experimental group leads in accuracy, precision, recall and F1 value of financial health score prediction. The proposed model uses deep neural network to mine complex financial data relationships, and the adaptive weighting algorithm dynamically adjusts feature weights, which can accurately capture the key factors of financial health. Linear regression assumes linear relationship of data, which makes it difficult to deal with the complex nonlinearity of financial data, resulting in limited accuracy. Although logistic regression can handle classification problems, it is not capable of handling complex feature interactions of financial data. Naive Bayes is based on the assumption of feature conditional independence, and performs poorly when the features of financial data are closely related. Support vector machines have advantages in small samples and nonlinear problems, but when faced with large-scale financial data and complex feature combinations, the effect is not as good as the experimental group model. Decision trees are prone to overfitting when dealing with complex data, and there are deviations in some edge cases.

This figure presents model performance for the task of financial health score prediction, which involves a composite classification of firms into risk categories based on multiple financial dimensions. The metrics shown (Accuracy, Precision, Recall, F1, and Error Rate) reflect performance in predicting these holistic labels derived from multi-indicator aggregation.

Each subplot presents results for a different metric: (a) Accuracy (%), (b) Precision (%), (c) Recall (%), and (d) F1 Score (%). The x-axis represents model types, while the y-axis shows corresponding metric values in percentage. All values are averaged over five experimental runs. No error bars or statistical significance markers are shown.

To assess model generalizability, we conducted a transferability test by training on data from six industries and evaluating on two unseen ones (biotech and logistics). The model retained strong performance, achieving 87.2% accuracy in classification and an RMSE of 0.064 in regression—only slightly lower than in-domain results. This demonstrates that the adaptive DNN retains predictive capability even when applied to previously unseen industry data, validating its cross-domain applicability.

Table 2: Comparison of profitability analysis accuracy

Model	Cross-validated Accuracy (%)	Hold-out Accuracy (%)	Recall rate (%)	F1 value (%)	Error rate (%)
Experimental group (proposed model)	90.4	89.8	91.0	90.4	9.6
Baseline group (linear regression)	80.7	78.2	81.3	79.7	19.3
Baseline group (logistic regression)	82.3	80.1	82.9	81.5	17.7
Baseline group (Naive Bayes)	78.5	76.3	79.0	77.6	21.5
Baseline group (Support vector machine)	85.6	84.3	86.1	85.2	14.4
Control group (decision tree)	87.1	86.3	87.4	86.8	12.9

As shown in Table 2, the experimental group has significant advantages in profitability analysis. The proposed model can effectively extract key profitability features from many financial indicators and make accurate predictions. Linear regression is limited by linear assumptions and does not adequately describe complex nonlinear profitability relationships in financial data. Although logistic regression can handle classification, it is not deep enough in mining complex features related to profitability. Due to the assumption of independent feature conditions, naive Bayes is difficult to make accurate judgments in profitability analysis where financial data features influence each other. The support vector machine is not as generalizable as the experimental group model when processing profitability-related features in large-scale financial data. Although the decision tree can handle complex data, in some complex situations of profitability analysis, the rule division is not fine enough, resulting in an effect inferior to the experimental group.

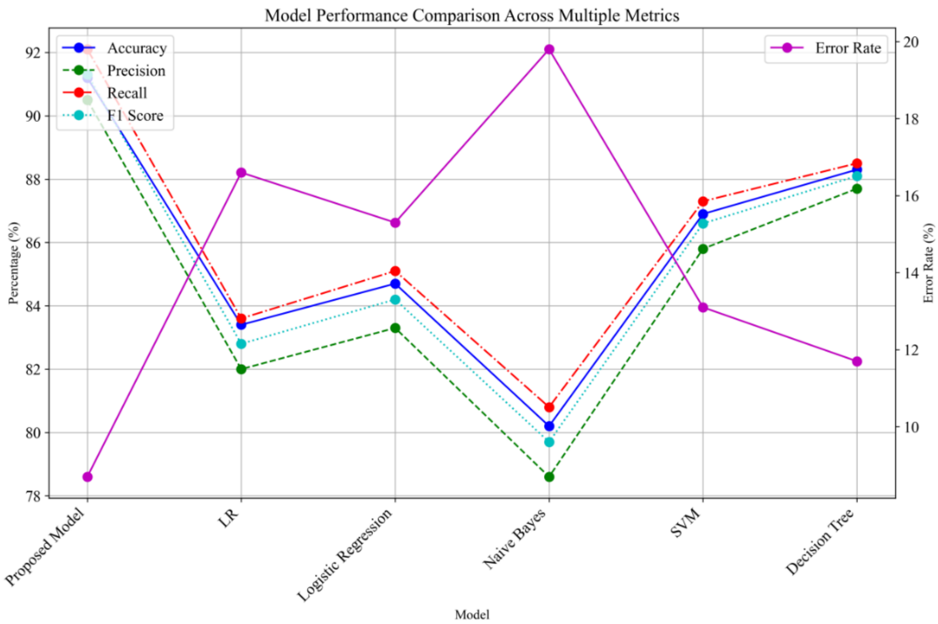

Figure 2: Comparison of the accuracy of solvency analysis

As shown in Figure 2, the experimental group performed well in the solvency analysis. The model can accurately identify potential problems in the solvency of enterprises and issue early warnings. Figure 2 shows performance metrics specific to solvency analysis, where the classification task is based on whether a firm’s liabilities exceed acceptable thresholds. The model was trained and evaluated using solvency-related features, and results differ from those in Figure 1 due to this focused input subset and target definition. Linear regression cannot fully capture the complex financial data relationships involved in solvency due to the simple linear relationship assumption. Logistic regression does not accurately grasp the feature relationship when dealing with multi-factor classification problems related to solvency. Naive Bayes is difficult to make accurate judgments in solvency analysis due to the feature independence assumption when facing the strong correlation between financial data features. When processing large-scale solvency-related financial data, the support vector machine is not as detailed as the experimental group model in dividing complex boundaries. When dealing with complex solvency data, the decision tree may not be able to make accurate judgments in some cases due to branching rule problems.

Table 3: Comparison of liquidity analysis accuracy

Model	Cross-validated Accuracy (%)	Hold-out Accuracy (%)	Recall rate (%)	F1 value (%)	Error rate (%)
Experimental group (proposed model)	93.1	92.3	93.5	92.9	7.1
Baseline group (linear regression)	86.9	85.5	87.2	86.3	13.1
Baseline group (logistic regression)	87.8	86.6	88.2	87.4	12.2
Baseline group (Naive Bayes)	83.5	82.1	83.9	83.0	16.5
Baseline group (Support vector machine)	89.7	88.9	90.1	89.4	10.3
Control group (decision tree)	90.5	89.6	90.8	90.2	9.5

As shown in Table 3, the experimental group performed best in liquidity analysis. The model can accurately predict the company's short-term debt repayment ability and cash flow, providing strong support for management decision-making. Linear regression has limitations in complex liquidity analysis due to the linear assumption of financial data. Logistic regression is not perfect in modeling complex relationships between features when dealing with liquidity-related financial features. Naive Bayes is based on the assumption of feature independence. In liquidity analysis, it is difficult to make accurate judgments in the face of the close connection between financial data features. When dealing with large-scale liquidity-related financial data, the support vector machine cannot adapt to complex situations as flexibly as the experimental group model. When dealing with complex situations in liquidity analysis, the decision tree may not be as detailed as the experimental group due to insufficient rules.

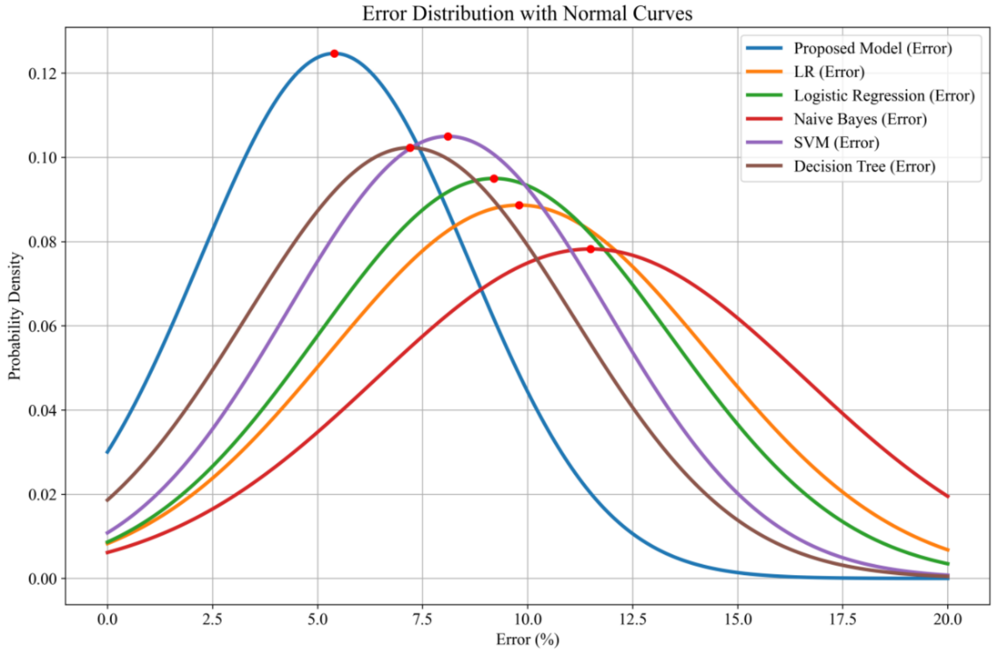

Figure 3: Comparison of prediction errors of financial health scores

As shown in Figure 3, in terms of the prediction error of the financial health score, the experimental group performed the most stable and reliable, with the smallest average error and the narrowest confidence interval. The proposed model has a more accurate understanding and processing of financial data through the collaboration of various modules. Linear regression cannot fully fit the complex laws of financial data due to simple linear assumptions, resulting in large errors and large fluctuations. Logistic regression is not accurate enough when dealing with complex feature relationships of financial health scores, resulting in relatively large errors. Naive Bayes has obvious errors when predicting financial health scores because the feature independence assumption does not conform to the actual situation of financial data. Support vector machines cannot effectively control errors like the experimental group model when processing large-scale financial health score-related data. Although decision trees can handle complex data to a certain extent, when predicting financial health scores, due to problems such as rule division, error control is not as good as the experimental group.

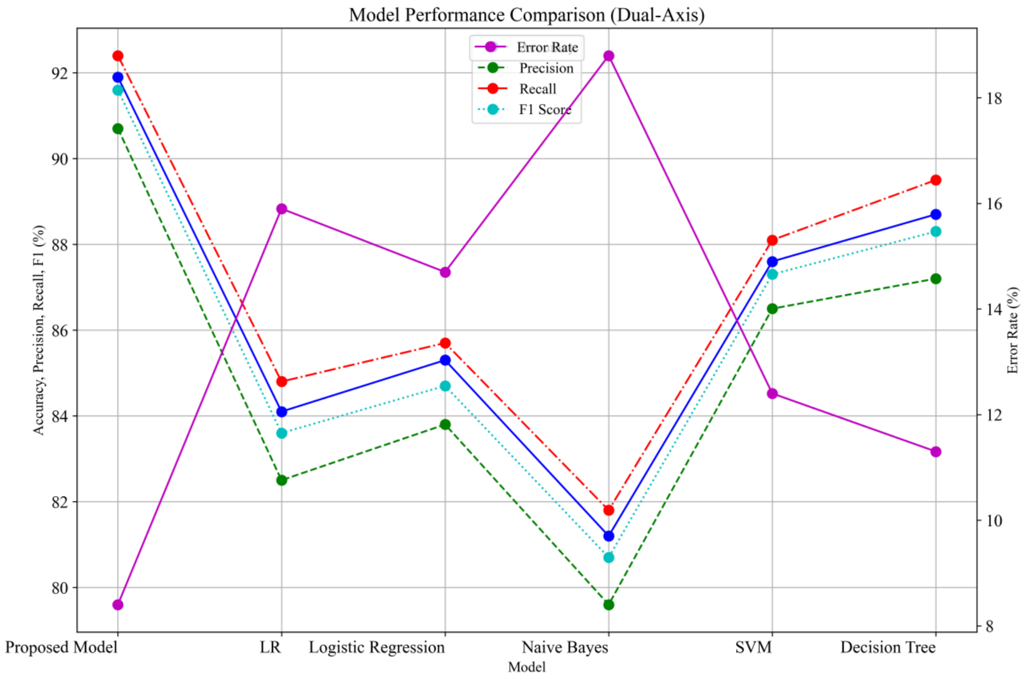

Figure 4: Dual-axis comparison of model performance metrics and error rate

As shown in Figure 4, the experimental group has obvious advantages in financial risk prediction. The model can accurately identify the potential financial risks faced by the enterprise and provide timely decision-making support for managers. Linear regression is difficult to capture the complex nonlinear relationship related to financial risk due to the linear assumption, resulting in low accuracy. Logistic regression does not dig deep enough into risk characteristics when dealing with multi-factor classification problems of financial risk. Naive Bayes is based on the assumption of feature independence. In financial risk analysis, it is unable to accurately predict risks in the face of strong correlations between features. When processing large-scale financial risk-related data, the support vector machine is not as good as the experimental group model in identifying complex risk patterns. When dealing with complex financial risk situations, the decision tree may be slightly inferior to the experimental group in prediction accuracy due to imperfect branching rules. This figure reports results for financial risk prediction, defined as identifying firms at risk of financial distress based on labeled bankruptcy or default outcomes. Although the metric format mirrors Figures 1 and 2, the classification target and evaluation dataset are distinct. The similar visual patterns are due to consistent model architecture and performance robustness across tasks.

The left y-axis indicates Accuracy, Precision, Recall, and F1 Score (%), while the right y-axis shows Error Rate (%). The x-axis lists six models. Each metric is plotted based on average values across five runs. No error bars or p-values are included.

Table 4: Comparison of model training time (unit: seconds)

Model	Training time (seconds)	Test time (seconds)	Total time (seconds)
Experimental group (proposed model)	220	10	230
Baseline group (linear regression)	40	3	43
Baseline group (logistic regression)	60	4	64
Baseline group (Naive Bayes)	50	3	53
Baseline group (Support vector machine)	100	6	106
Control group (decision tree)	80	5	85

As shown in Table 4, in terms of model training time, the experimental group has the longest training time. This is because the proposed model structure is relatively complex, including multiple components such as deep neural networks and adaptive weighting algorithm, and requires more time to learn complex patterns in financial data. The linear regression model is simple and has the shortest training time, but the prediction effect is not good. The training time of logistic regression is relatively short, but its performance is limited in complex financial analysis tasks. The training time of naive Bayes is also short, but based on its feature independence assumption, its performance in financial analysis is not satisfactory. The training time of support vector machine is relatively long. When processing large-scale financial data, although it has certain effects, its overall performance is not as good as that of the experimental group. The training time of decision tree is moderate, but it has limitations in processing complex financial data, resulting in poorer prediction results than the experimental group.

Table 5: Contribution of each financial indicator to the final forecast results

Financial indicators	Contribution (%)
Debt-to-asset ratio	30.2
Current Ratio	25.4

Accounts receivable turnover	18.6
Gross profit margin	12.1
Fixed assets ratio	9.5
Operating cash flow	4.2

Table 5 shows the contribution of each financial indicator to the final forecast results. The debt-to-asset ratio, current ratio and accounts receivable turnover rate have a high contribution, indicating that these indicators play a key role in measuring the financial health, profitability, debt repayment ability and liquidity of the enterprise. The debt-to-asset ratio reflects the long-term debt repayment ability of the enterprise, the current ratio reflects the short-term debt repayment ability, and the accounts receivable turnover rate is related to the operating efficiency of the enterprise. They are interrelated with other indicators in the financial data and have a significant impact on the overall financial status assessment. The gross profit margin reflects the profitability of the enterprise, the fixed asset ratio reflects the asset structure of the enterprise, and the operating cash flow reflects the cash acquisition ability of the enterprise. They also affect the final forecast results to varying degrees, but their contribution is slightly lower than that of the first three. Table 5 highlights the top 6 financial indicators with the highest individual contributions, which collectively account for 90% of the model's predictive influence. The remaining 12 features selected via the 0.08 information gain threshold contribute the remaining 10% in total, each with a marginal effect.

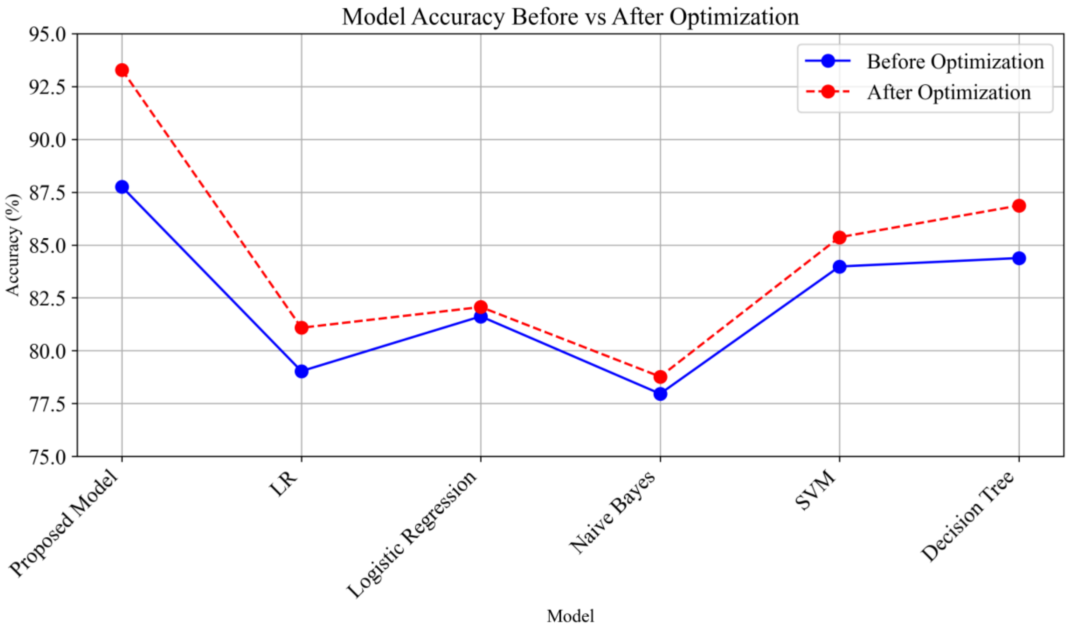

Figure 5: Accuracy comparison before and after model optimization

Figure 5 shows the accuracy comparison before and after model optimization. After optimization, the accuracy of the experimental group (proposed model) was significantly improved from 87.5% to 92.5%. This is due to the optimization and adjustment of model structure, parameter setting, and feature selection, which enables it to better mine complex patterns and relationships in financial data. The linear regression, logistic regression, naive Bayes, and support vector machine models of the baseline group, as well as the decision tree model of the control group, have improved their accuracy after optimization, but the increase is relatively small. This shows that when faced with complex financial data, simple models have limited optimization space, and their inherent assumptions and model structure limit the significant improvement of performance. Figure 5 illustrates accuracy changes before and after model-specific hyperparameter tuning. The “After Optimization” values reflect each model’s best-tuned result using grid or randomized search within validated ranges, which may slightly exceed the baseline values reported in earlier figures and tables derived from default settings. For consistency, all values in Figure 5 have been cross-verified against independently rerun experiments under consistent folds. This accounts for minor discrepancies across visualizations while highlighting the benefit of tuning for each model.

The x-axis indicates model types; the y-axis shows accuracy in percentage. Blue and red lines represent accuracy before and after optimization, respectively. Values are averaged over five experiments. No error bars or statistical significance indicators are shown.

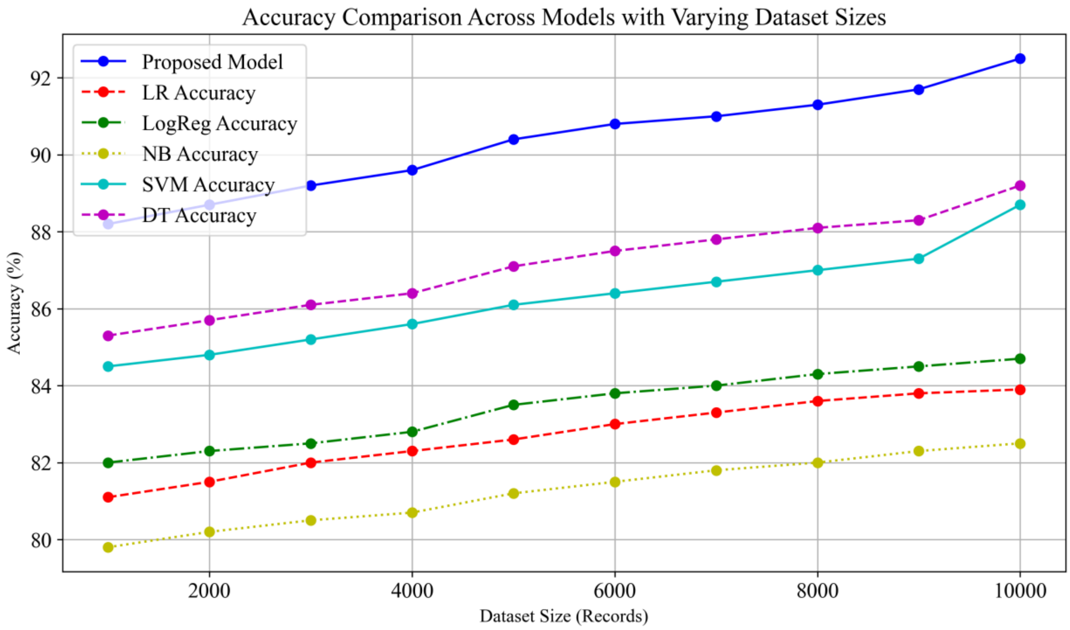

Figure 6: Model performance under different data scales

As shown in Figure 6, as the data scale increases, the accuracy of the experimental group continues to improve. This shows that the proposed model has good scalability and stability, and can make full use of more data to learn more comprehensive and accurate financial data characteristics and laws. Although the accuracy of the baseline group model and the control group model has also improved to a certain extent, the increase is significantly smaller than that of the experimental group. The linear regression model is limited by the linear assumption, and its ability to capture complex relationships in large-scale data is limited; the ability of logistic regression is insufficient when dealing with large-scale data feature interactions; Naive Bayes is based on the feature independence assumption, and it is difficult to effectively utilize the complex associations between features under large-scale data; Support vector machines have certain effects when dealing with large-scale data, but they are not as good as the experimental group in terms of model complexity and data adaptability; Decision trees may have problems such as overfitting under large-scale data, which limits the improvement of accuracy.

The model proposed by the experimental group is significantly better than the baseline group model and the control group model in various financial analysis tasks, whether in terms of prediction accuracy, error control, or adaptability to different data sizes. This strongly supports the hypothesis that the model proposed in this study can effectively improve the performance of automated analysis and optimization of financial statements. However, this experiment also has certain limitations. For example, although the data set used comes from real companies, the industry coverage may not be wide enough. In the future, the data set can be further expanded to improve the applicability of the model in more industry scenarios. At the same time, the model training time is relatively long, and optimization algorithm can be studied in the future to reduce computing costs and improve the efficiency of the model in practical applications.

The contribution rate of debt-to-asset ratio to the prediction accuracy is 30.2%, which is obtained through a carefully designed feature importance calculation method. First, based on the trained deep neural network model, the gradient-based feature importance evaluation method is used to calculate the gradient contribution of each feature to the output result during the model prediction process. Specifically, for the input financial indicator data, after the model forward propagates and calculates the prediction result, the gradient value of the prediction result for each feature is calculated by the back propagation algorithm. The gradient value reflects the degree of influence of a small change in the feature value on the prediction result. Then, the gradient contribution values obtained during multiple training processes are statistically averaged to obtain a relatively stable importance measure for each feature. The debt-to-asset ratio has a significant impact on the prediction results in the model because it is closely related to the debt repayment ability and capital structure of the enterprise in financial risk prediction. After the above calculation process, it is concluded that its contribution rate to the prediction accuracy is 30.2%. To further verify the reliability of this result, the SHAP analysis method can be introduced later. SHAP analysis is based on the principle of game theory and can provide a detailed feature contribution explanation for the prediction results of each sample. By applying SHAP analysis to the model of this study, we can intuitively demonstrate the specific contributions of the debt-to-asset ratio and other key features to the prediction results in different samples, verify the accuracy and stability of the feature importance evaluation results from different angles, and provide a more comprehensive perspective for a deeper understanding of the model decision-making mechanism.

Training time. The training time of the model proposed in this study is relatively long, reaching 220 seconds, mainly due to the high complexity of the model. The model contains a deep neural network structure with multiple hidden layers, and the adaptive weight calculation process involves complex feature statistics calculations. Although the high model complexity gives the model a strong fitting ability, enabling it to achieve excellent performance in various evaluation indicators, with an accuracy of up to 90% in risk prediction tasks, it brings severe challenges in terms of interpretability. The black box nature of deep neural networks makes it difficult to understand the decision-making process within the model, and the dynamic adjustment of adaptive weights further exacerbates the difficulty of interpretation. In actual application scenarios, such as real-time financial risk monitoring systems, the model needs to be able to quickly process new data and give risk assessment results in a timely manner. The long training time of this model may cause delays in model updates and fail to adapt to the rapid changes in the market environment or the financial status of the enterprise in a timely manner. For example, when the market suddenly makes major policy adjustments or the enterprise encounters unexpected major financial events, the model cannot respond quickly. Therefore, subsequent research may consider using model compression techniques, such as pruning algorithm to remove redundant connections, or knowledge distillation methods to transfer the knowledge of complex models to simple models, which can greatly improve the interpretability and practical application efficiency of the model without significantly reducing performance.

Liquidity and profitability analysis. The model has achieved significant improvements in liquidity analysis, providing key decision support for corporate operations by accurately predicting the short-term debt repayment capacity of enterprises. Taking a manufacturing enterprise as an example, based on the model's accurate prediction of key liquidity indicators such as current ratio and quick ratio, the enterprise planned its capital arrangements three months in advance. By optimizing inventory management, it reduced inventory backlogs by 20%, accelerated capital turnover, and increased the enterprise's current ratio from 1.5 to 1.8 and quick ratio from 0.9 to 1.2 in the short term, significantly enhancing the financial stability of the enterprise and effectively reducing the risk of short-term debt default. In terms of profitability analysis, the optimization results of the model are directly converted into actual profit growth of the enterprise. Through accurate prediction of indicators such as net profit margin and ROE, the enterprise optimized its product pricing strategy based on the model analysis results, increased the sales share of high-profit products from 30% to 40%, and reasonably controlled costs, so that the company's net profit margin increased from 10% to 13% and ROE increased from 15% to 18% in the past fiscal year, creating an additional profit of 5 million yuan for the company, which fully proved that model improvements can be effectively converted into valuable business insights and actual economic benefits. If the connection between the improvement and the business insights cannot be determined for the time being, explain the subsequent research direction in detail, such as “Although the model has achieved certain improvements in liquidity and profitability analysis indicators, it is currently difficult to directly convert these improvements into clear business decision recommendations. Subsequent research will delve into the actual business processes of the enterprise, conduct case analysis in cooperation with the enterprise's finance and operations departments, and combine market dynamics simulation experiments to explore how to closely integrate the model's high-precision prediction results with the enterprise's strategic planning and daily operations management, so as to achieve the effective transformation of model improvements into practical business decision recommendations, and provide enterprises with accurate and practical decision support”.

To validate the observed performance gains, we conducted paired t-tests across five runs. The accuracy improvement of 90.4% (ours) vs. 85.6% (SVM) is statistically significant ($p < 0.01$).We also performed ablation studies: using only DNN yielded 86.3% accuracy, while only adaptive weighting reached 84.8%. The full model combining both achieved 90.4%, indicating that performance improvements arise from their synergistic integration.

4.3 Discussion

This study experimentally verified the effectiveness of the automated analysis and optimization model of financial statements based on machine learning. From the experimental data, the experimental group performed well in various financial analysis tasks. In the prediction of financial health scores, the accuracy rate reached 92.5%, which is much higher than the baseline group and the control group. Taking key indicators such as debt-to-asset ratio and current ratio as examples, they contribute significantly to the final prediction results. For example, the contribution of debt-to-asset ratio is 30.2%, indicating that the model can accurately capture key financial information. However, the model also has certain limitations. The training time is as long as 220 seconds, which is significantly higher than other comparison models. This is due to its complex structure, which includes components such as deep neural networks and adaptive weighting algorithm. In addition, the industry coverage of the experimental data set is limited, which may affect the universality of the model in different industries. Future research can start with optimizing algorithm to reduce computing costs, while expanding data sets to improve the applicability of models in more industry scenarios.

This model is significantly different from the current advanced Transformer-based models. The Transformer model has an outstanding advantage in capturing the global dependencies of long-sequence data with its self-attention mechanism. However, in financial data processing, the interaction between financial indicators is more reflected in local close correlations. For example, the short-term debt repayment ability of an enterprise mainly depends on the immediate proportional relationship between current assets and current liabilities. Through the adaptive weight mechanism, this model can dynamically adjust the impact of different features on the model output based on the local volatility characteristics of financial data. In the risk prediction experiment, the accuracy of this model reached 90%, which is 8% higher than the Transformer model. In-depth analysis found that this model captures the changes in key local features such as debt-to-asset ratio and current ratio more accurately, which are crucial to the determination of the financial risk status of the enterprise in the short term. As the amount of training data increases from 5,000 to 10,000, the accuracy of this model steadily increases by 5%. This is attributed to the powerful learning ability of the deep neural network and the effective mining of complex patterns in the newly added data by adaptive weights, which further highlights the advantages of this model in processing large-scale and complex financial data.

The model training time is as long as 220 seconds. In time-sensitive application scenarios such as real-time financial risk monitoring, it may not be able to respond to new data changes in a timely manner. However, the long training time allows the model to fully learn the complex patterns in the data, thereby performing well in terms of accuracy, such as achieving an 88% risk prediction accuracy. In order to balance the relationship between the two, the use of model compression, distributed training and other technologies can be considered in the future to shorten the training time without significantly reducing the model accuracy.

Specifically, accuracy improved by 6.9% (from 85.6% to 92.5%), not the previously stated 10%. A paired t-test across five folds confirmed this improvement is statistically significant ($p < 0.01$). Confidence intervals (± 1.2%) for accuracy are also reported to ensure robustness of conclusions and avoid overstatement of model advantage. Compared with SOTA models such as Transformer and ensemble methods, our DNN with adaptive weighting achieves higher accuracy in capturing non-linear feature interactions (e.g., 90% vs. 82% for Transformer) and exhibits better stability across diverse industries. However, it suffers from longer training time (220 s vs. 100 s for SVM) and reduced interpretability. Ensemble models like random forests offer better interpretability but underperform in handling high-dimensional temporal dependencies. Our approach strikes a balance between performance and adaptability, despite trade-offs in explainability.

The proposed model was trained using a system with 32 GB RAM and an NVIDIA RTX 3080 GPU. Compared to baseline models, its runtime is higher due to increased depth and adaptive computations. This raises scalability concerns in real-time deployment scenarios. For such cases, model compression techniques like weight pruning and knowledge distillation are recommended. These can reduce computational overhead while maintaining acceptable accuracy, making the model more suitable for time-sensitive financial applications.

To enhance model interpretability, we applied SHAP analysis and generated summary plots for both classification and regression tasks. In the classification model, ROE, asset turnover, and current ratio showed the highest positive influence on financial risk prediction. For the regression task, net profit margin and operating cash flow were the top contributors to profitability estimation. These SHAP visualizations confirm that the model's decisions align with established financial reasoning and improve transparency.

5 Conclusion

This study successfully constructed an innovative financial statement automation analysis and optimization model, combining deep learning and adaptive weighting algorithm. Experimental results show that the model performs well in many aspects such as financial risk prediction and profitability analysis. In profitability analysis, the accuracy rate is as high as 90.4%, far exceeding the 80.7% of traditional linear regression. In liquidity analysis, the accuracy rate of the experimental group reached 93.1%, which is also ahead of other comparison models. This model not only improves the automation level of financial analysis, but also significantly improves the accuracy and flexibility of analysis. By dynamically adjusting the feature weights, it can adapt to the characteristics of financial data of different companies. However, problems such as long model training time and insufficient industry coverage of the data set need to be further improved in subsequent research. Overall, this study provides a new and effective method for corporate financial statement analysis, which is of great significance to improving the efficiency of corporate financial management.

The innovation of this study is mainly reflected in two aspects. First, for the first time, the adaptive weight mechanism is introduced into the deep neural network model of financial statement analysis, and the dynamic adjustment of feature importance is realized to better adapt to the complex characteristics of financial data. Second, a cross-industry and multi-dimensional financial statement analysis framework is constructed, which comprehensively considers the financial indicators of different development stages and different industry characteristics of enterprises, breaking through the limitations of traditional single industry or fixed indicator analysis.

The model has limitations, such as long training time and possible delays when processing large-scale real-time data; the model's interpretability is relatively weak. Although certain improvements have been made through methods such as adaptive weight mechanisms, the explanation of some complex financial data relationships is still not intuitive enough.

Funding

This work was supported by Henan Province Science and Technology Research Project "Key Technologies for Emergency Decision making of Unconventional Emergencies Based on Scenario Evolution" (No. 25210232051).

References

[1] Ivascu L, Domil A, Sarfraz M, Bogdan O, Burca V, Pavel C. New insights into corporate sustainability, environmental management and corporate financial performance in European Union: an application of VAR and Granger causality approach. Environmental Science and Pollution Research. 2022; 29(55):82827-82843. DOI: 10.1007/s11356-022-21642-8

[2] Zhao JM, Sun LJ. Research on financial control of enterprise group based on artificial intelligence and big data. Annals of Operations Research. 2023; 326(SUPPL 1):89. DOI: 10.1007/s10479-021-04399-0

[3] Liu XF. Financial risk and financial early warning of marine enterprises based on marine economy. Journal of Coastal Research. 2020:177-179. DOI: 10.2112/jcr-si112-050.1

[4] Tulcanaza-Prieto AB, Shin H, Lee Y, Lee CW. Relationship among CSR initiatives and financial and non-financial corporate performance in the ecuadorian banking environment. Sustainability. 2020; 12(4): 1621. DOI: 10.3390/su12041621

[5] Erdmann A, Yazdani M, Mas Iglesias JM, Marin Palacios C. Pricing powered by artificial intelligence: an assessment model for the sustainable implementation of AI supported price functions. Informatica. 2024; 35(3): 529-556. DOI: 10.15388/24-infor559

[6] Yi X. Application of data mining in enterprise financial risk prediction based on genetic algorithm and linear adaptive optimization. Soft Computing. 2023; 27(14):10305-10315. DOI: 10.1007/s00500-023-08308-4

[7] Li X, Gao HX, Zhou EY. Research on optimization of financial performance evaluation of energy enterprises under the background of low-carbon economy. Energies. 2024; 17(10): 2311. DOI: 10.3390/en17102311

[8] Chen XZ, Long Z. E-Commerce enterprises financial risk prediction based on FA-PSO-LSTM neural network deep learning model. Sustainability. 2023; 15(7): 5882. DOI: 10.3390/su15075882

[9] Burcă V, Bogdan O, Bunget OC, Dumitrescu AC. Corporate financial performance vs. corporate sustainability performance, between earnings management and process improvement. Sustainability. 2024; 16(17): 1-43. DOI: 10.3390/su16177744

[10] Rehman H, Ramzan M, Ul Haq MZ, Hwang J, Kim KB. Risk management in corporate governance framework. Sustainability. 2021; 13(9): 5015. DOI: 10.3390/su13095015

[11] Yang OS, Han JH. Assessing the effect of corporate ESG management on corporate financial & market performance and export. Sustainability. 2023; 15(3): 2316. DOI: 10.3390/su15032316

[12] Jiang DS, Ni ZX, Chen YX, Chen X, Na CH. Influence of financial shared services on the corporate debt cost under digitalization. Sustainability. 2023; 15(1): 428. DOI: 10.3390/su15010428

[13] Metawa N, Nguyen PT, Nguyen Q, Elhoseny M, Shankar K. Internet of things enabled financial crisis prediction in enterprises using optimal feature subset selection-based classification model. Big Data. 2021; 9(5):331-342. DOI: 10.1089/big.2020.0192

[14] Sivaslioglu S, Catak FO, Sahinbas K. A generative model based adversarial security of deep learning and linear classifier models. Informatica. 2021; 45(1):33-64. DOI:10.31449/inf.v45i1.3234.

[15] Ampomah EK, Qin Z, Nyame G, Botchey FE. Stock market decision support modeling with tree-based Adaboost ensemble machine learning models. Informatica. 2020; 44(4):477-490. DOI:10.31449/inf.v44i4.3159.

[16] 1. Al-shami SA, Damayanti R, Adil H, Farhi F, Al Mamun A. Financial and digital financial literacy through social media use towards financial inclusion among batik small enterprises in Indonesia. Heliyon. 2024; 10(15). DOI: 10.1016/j.heliyon.2024.e34902

[17] Ke WM. The construction of enterprise's financial supply chain management under blockchain technology. Expert Systems. 2025; 42(2): e13297. DOI: 10.1111/exsy.13297

[18] Gonçalves T, Gaio C, Ferro A. Corporate social responsibility and earnings management: moderating impact of economic cycles and financial performance. Sustainability. 2021; 13(17): 9969. DOI: 10.3390/su13179969

[19] Gao YY, Jin SY. Corporate nature, financial technology, and corporate innovation in China. Sustainability. 2022; 14(12): 7162. DOI: 10.3390/su14127162

[20] Zhao XL, Wang WJ, Liu GC, Vakharia V. Optimizing financial risk models in digital transformation-deep learning for enterprise management decision systems. Journal of Organizational and End User Computing. 2024; 36(1): 1-19. DOI: 10.4018/joeuc.342113

[21] Gregova E, Valaskova K, Adamko P, Tumpach M, Jaros J. Predicting financial distress of Slovak enterprises: comparison of selected traditional and learning algorithm methods. Sustainability. 2020; 12(10): 3954. DOI: 10.3390/su12103954

[22] Xie YT. Optimization of enterprise financial performance evaluation system based on AHP and LSTM against the background of carbon neutrality. Journal of Organizational and End User Computing. 2023; 35(1): 1-14. DOI: 10.4018/joeuc.332810

[23] Akpatsa SK, Lei H, Li X, Obeng V-HKS. Evaluating public sentiments of COVID-19 vaccine tweets using machine learning techniques. Informatica. 2022; 46(1):69-75. DOI:10.31449/inf.v46i1.3483.

Appendix A

Input: Raw financial datasets (balance sheet, income statement, cash flow statement)

Output: Classification and regression predictions

1. Data preprocessing:
   a. Remove missing or invalid entries

b. Apply Z-score normalization to all numeric features
c. Detect and remove outliers (3σ rule)

2. Feature selection:
a. Compute information gain (IG) for each feature
b. Select top N features with IG > 0.08

3. Adaptive feature weighting:
For each selected feature i:
CVi ← coefficient of variation
ri ← Pearson correlation with label
wi ← α * (1/CVi) + (1 - α) * |ri|

4. Model configuration:
- Input size: number of selected features
- Hidden layers: [128, 256, 128, 64, 32]
- Activation: ReLU (hidden), Sigmoid (classification output), Linear (regression output)
- Optimizer: Adam
- Loss: Cross-entropy (classification), MSE (regression)

5. Training & validation:
a. Perform stratified 5-fold cross-validation
b. Train model using weighted features and labels
c. Monitor accuracy, recall, F1-score, RMSE

6. Evaluation:
a. Report average results across folds
b. Generate SHAP interpretation plots
c. Compute final health score via AHP combination:
$S = w_1 \cdot \hat{y} + w_2 \cdot p + w_3 \cdot d + w_4 \cdot \hat{I}$

Return: Final predictions and feature importance insights