

Financial Forecasting and Budget Management Based on Machine Learning

Linmeng Liu

Business School, Geely University of china, Chengdu, Sichuan, 641423, China

E-mail: xingyun511688888@163.com

Keywords: machine learning, financial forecasting, budget management, sdae neural network, data preprocessing

Received: January 2, 2026

Traditional financial forecasting and budget management models suffer from weak data processing capabilities, insufficient prediction accuracy, and delayed response, making it difficult to adapt to the massive financial data processing and precise decision-making needs of enterprises, which hinders the improvement of the intelligence level of financial management. This article aims to introduce advanced machine learning techniques to construct efficient and robust financial forecasting models, optimize budget management processes, and improve the intelligence and decision-making efficiency of enterprise financial management. In terms of methodology, an improved Sparse Denoising Autoencoder (SDAE) neural network is used as the core modeling tool, combined with interval discretization method to smooth abnormal data and construct a robust financial prediction model. Through comparative experiments, quantitatively compare it with standard SDAE and traditional backpropagation neural network (BPNN) in terms of prediction accuracy, computational efficiency, and stability. The results showed that the average absolute error (MAE) of improved SDAE was reduced by 12% compared to standard SDAE and 21% compared to BPNN, with a prediction time of only 86 milliseconds when processing financial records. Even if the number of concurrent requests reaches several times the daily peak, the system can still maintain good response quality and low latency levels, demonstrating strong scalability and robustness. The improved SDAE model outperforms the comparison model in terms of prediction accuracy, computational efficiency, and scalability. It can effectively support multi scenario financial forecasting and budget management in enterprises, providing reliable technical support for financial management decisions.

Povzetek: Težavne točke obstajajo v tradicionalnih modelih finančnega napovedovanja. V tem članku smo izboljšali SDAE za gradnjo modela finančnega napovedovanja, katerega zmogljivost nadmaša primerjalne modele in pomaga podjetjem pri inteligentnih finančnih odločitvah.

1 Introduction

In the context of the increasingly complex and volatile global economic environment and fierce competition among enterprises, financial forecasting and budget management, as the core links of enterprise financial management, play a crucial role in the survival and development of enterprises [1]. Accurate financial forecasting can help companies gain early insights into market trends and plan resource allocation effectively, while effective budget management provides solid financial support for achieving strategic goals and ensuring orderly operation of business activities. However, with the continuous expansion of enterprise business scale and the acceleration of digitalization process, traditional financial forecasting and budget management models are facing unprecedented challenges [2]. Traditional financial forecasting and budget management mostly rely on statistical models based on historical data and the experience judgment of financial personnel. These methods have significant shortcomings in data processing capability, prediction accuracy, and

response speed. On the one hand, traditional financial models are difficult to effectively handle massive, multi-source, and heterogeneous financial data [3]. In the era of big data, the amount of data generated by enterprises is exploding, covering multiple dimensions such as internal operational data, macroeconomic data of the market, and competitive data of the industry. Traditional models are limited by algorithms and computing power, and cannot fully explore the hidden patterns and values behind these data, resulting in significant deviations between predicted results and actual situations [4]. On the other hand, due to the rapidly changing market environment, traditional models are slow to respond to the dynamic changes of external factors, unable to capture subtle market fluctuations and unexpected situations in a timely manner. This makes it difficult for static assumptions based predictions and budget plans to adapt to new situations in the actual implementation process, thereby affecting the rationality of enterprise strategic decisions and resource allocation [5].

At the same time, machine learning technology has made breakthrough developments in recent years,

providing new ideas and methods for solving financial forecasting and budget management problems with its powerful data processing, learning, and prediction capabilities. Machine learning can automatically learn patterns from large amounts of data through algorithms, achieving accurate predictions of future trends. In the financial field, machine learning technology can conduct in-depth analysis and mining of financial data, market data, industry data, etc. of enterprises, identify complex relationships between data, and thus construct more accurate financial forecasting models. For example, machine learning algorithms can automatically adjust model parameters based on historical financial data and continuously optimize prediction results; Part of the machine learning methods combined with natural language processing techniques can handle unstructured textual data, further expanding the sources and analytical dimensions of financial data [6]. Machine learning technology has achieved increasingly significant results in many industries such as finance, manufacturing, and healthcare, demonstrating powerful capabilities in data analysis, pattern recognition, predictive modeling, and more. Especially in the field of finance, various machine learning algorithms have been applied in risk assessment, financial statement analysis, fraud detection, and have achieved certain results [7]. However, current research and applications mainly focus on relatively standardized processes, such as financial reporting automation and tax processing. For more complex forecasting and budget management processes, machine learning applications are still in the exploratory stage, and their systematicity and depth need to be strengthened [8]. This study aims to explore how machine learning can be effectively integrated into financial forecasting and budget management, and to build a more intelligent and practical financial management tool. By analyzing the potential of machine learning technology in data processing, model training, and prediction optimization, this article attempts to answer the following core questions: Firstly, how can machine learning improve the accuracy and timeliness of financial forecasting? Secondly, in the process of budget preparation and execution, can machine learning achieve a transition from static to dynamic, from experience driven to data-driven? Thirdly, what practical challenges do enterprises face when introducing machine learning technology, and how should they respond [9].

2 Related theoretical foundations

2.1 Basic principles of financial forecasting

Financial forecasting refers to the estimation and inference of a company's future financial condition based on historical data and future expectations. Its core purpose is to provide scientific basis for business decision-makers to support various activities such as investment, financing, and operation [10]. Financial forecasting generally covers multiple aspects such as revenue forecasting, cost forecasting, and cash flow forecasting, and is an important component of enterprise financial management. Financial forecasting, as an important cornerstone of enterprise financial management, essentially combines the patterns

of historical financial data with the expectations of future business environment through quantitative analysis and logical deduction, forming a forward-looking judgment on the future financial status of the enterprise [11]. This process not only involves the calculation of core financial indicators such as revenue, cost, and cash flow, but also serves as a key basis for enterprise strategic planning, resource allocation, and risk management. For example, accurate revenue forecasting can help companies arrange production scale and marketing investment reasonably when formulating annual business plans [12]; Cash flow forecasting is directly related to the security of a company's financial chain, avoiding operational crises caused by insufficient liquidity. From the perspective of methodological evolution, traditional financial forecasting has long relied on statistical models and manual experience judgments. Time series analysis predicts data by mining its periodic and trending features, making it suitable for business scenarios with stable fluctuations, such as seasonal commodity sales; Regression analysis quantifies the impact of external factors on financial indicators by establishing functional relationships between variables, and is commonly used for analyzing the correlation between market demand and sales revenue [13]. However, these methods exposed significant defects when dealing with complex business environment: first, the model hypothesis deviated from the real scene, which made it difficult to capture the impact of emergencies (such as policy adjustment and supply chain interruption) on financial data; Secondly, the sensitivity of parameters is prominent, and small fluctuations in data may lead to significant deviations in predicted results from reality; Thirdly, the prediction process dominated by human experience has cognitive limitations, and factors such as decision-makers' risk preferences and information lag can easily interfere with the objectivity of the prediction [14]. According to a case study of a manufacturing enterprise, the prediction error rate of traditional regression models for raw material price fluctuations is as high as 18%, which seriously affects procurement cost control and profit planning.

From a methodological perspective, financial forecasting mainly relies on statistical models and empirical judgments. Common prediction methods include time series analysis, regression analysis, and moving average [15]. These methods are easy to operate, but in the face of complex and ever-changing market environments, problems such as poor model adaptability and large prediction errors often arise. Moreover, traditional prediction methods rely heavily on human experience and are susceptible to subjective judgments, which in turn affect the objectivity and accuracy of prediction results [16]. More and more companies are trying to introduce more advanced prediction tools, such as machine learning models, to improve the scientificity and efficiency of predictions.

2.2 The core framework of budget management

Budget management is one of the important means of enterprise financial management, which plans and controls the income, expenditure, and use of funds in a specific period in the future to achieve rational allocation of resources and performance evaluation. Budget management mainly includes four stages: budget preparation, execution, control, and assessment. It is a dynamic adjustment and continuous optimization process [17].

Traditional budgeting methods often adopt fixed or rolling budget forms, emphasizing the continuation of historical data and the prediction of future trends. However, in practical operation, due to frequent changes in the external environment and internal information asymmetry, the budget is often difficult to accurately reflect the real situation, resulting in significant deviations in budget execution. In recent years, new budgeting models such as Zero Based Budgeting (ZBB) have gradually gained attention. This model requires that each expenditure must be re-evaluated for necessity, rather than simply using previous budgets. Although this approach enhances the scientificity and flexibility of the budget, it also increases the workload and complexity of budget preparation. Therefore, how to improve the intelligence level of budget preparation through technological means has become an important direction for current budget management reform [18]. The emergence of zero based budgeting (ZBB) has brought revolutionary breakthroughs to budget management. This model breaks the inertia of thinking that "historical data is reasonable" and requires departments to re-evaluate the necessity and effectiveness of each expenditure based on the actual needs of the project when preparing budgets, so that resource allocation is more in line with the current strategic priorities of the enterprise. For example, a technology company shifted its marketing budget from traditional advertising to emerging social media channels after implementing zero based budgeting, effectively improving customer acquisition efficiency. However, the implementation of zero based budgeting faces multiple challenges: on the one hand, it requires extremely high data integrity and analytical capabilities, requiring a comprehensive analysis of the cost drivers of business activities [19]; On the other hand, the process of re-evaluating involves a lot of cross-departmental communication and decision-making, which can easily lead to extended budget preparation cycles and a surge in management costs. According to industry research, about 35% of companies that adopt zero based budgeting fail to achieve expected results due to process complexity exceeding expectations [20]. In the budgeting process, machine learning algorithms can automatically identify the nonlinear relationship between business activities and resource requirements based on massive internal and external data (such as market trends, competitor dynamics, customer behavior data), and generate more realistic budget plans.

2.3 The main categories of machine learning techniques

Machine learning, as an interdisciplinary technology, covers multiple subfields. Among them, traditional machine learning algorithms, deep learning, natural language processing (NLP), and data mining are closely related to financial forecasting and budget management.

Traditional machine learning algorithms are a method that allows computers to automatically discover patterns and make predictions by learning historical data, and are widely used in fields such as financial risk assessment and sales forecasting. Common algorithms include linear regression, decision trees, random forests, and support vector machines (SVM).

Deep learning is a more complex modeling method developed based on traditional machine learning, particularly adept at handling unstructured data such as images and text [21]. Although its application in the financial field is relatively limited, it has great potential in handling complex variable relationships and high-dimensional data.

Natural language processing technology can help systems understand and process human language information, such as extracting key financial information from annual reports, news reports, social media, and other channels. This is of great significance for assisting financial personnel in obtaining external data and identifying potential risks.

Data mining is the process of discovering hidden patterns and association rules from large amounts of data, typically used in scenarios such as customer behavior analysis and anomaly detection. In budget management, data mining can be used to identify typical problems in historical budget execution and assist in developing more accurate budget plans. Using the statistical 3σ principle combined with the Isolation Forest algorithm for anomaly detection of budget data. First, use the 3σ principle to quickly identify significant outliers that deviate from the mean by three times the standard deviation, and then use an isolated forest for unsupervised learning of high-dimensional budget data to accurately capture implicit anomaly patterns. This combination method balances detection efficiency and accuracy, avoiding the detection bias of single statistical methods on non-normal data and solving the problem of detection lag in isolated forests at obvious outliers.

In existing research on financial forecasting and budget management, traditional methods rely on traditional neural networks such as BPNN, which suffer from weak data processing capabilities, insufficient prediction accuracy, and response delays, making it difficult to adapt to the massive financial data processing needs of enterprises. Some studies have used standard SDAE models to optimize prediction performance, but have not addressed the pain points of abnormal data interference and insufficient model robustness. This article adopts an improved SDAE combined with inter-zone dispersion method. Comparative experiments show that the prediction delay has strong scalability. Existing research has not achieved a synergistic improvement in accuracy, efficiency, and robustness, and has not fully integrated the advantages of various machine learning technologies to form a solution adapted to financial

scenarios, resulting in a significant gap in SOTA technology. Therefore, this study can fill the existing gap by optimizing modeling methods to solve the pain points of traditional models, providing more reliable technical support for enterprise financial forecasting and budget management, and has important research and application necessity.

3 Financial forecasting and budget management based on machine learning

3.1 Application of machine learning in financial forecasting

Financial forecasting is an important basis for corporate strategic decision-making and resource allocation. In the past, prediction methods mostly relied on statistical models and human experience to make judgments. However, nowadays, due to the large amount of data, complex variables, and rapid changes, traditional methods cannot withstand these practical challenges. Machine learning techniques, especially deep learning models, have significant advantages in nonlinear modeling, feature extraction, and pattern recognition, and have become a powerful way to improve financial forecasting capabilities.

The improvement of standard SDAE in this article is not a single adjustment, but a targeted reconstruction from two aspects: network structure and feature propagation mechanism. The supplementary mathematical definitions are as follows:

(1) Enhance feature reconstruction capability: Add cross layer feature connection layers in the encoder decoder structure of standard SDAE. Merge the feature maps of each layer of the encoder with the corresponding layer of the decoder, and optimize the reconstruction loss function to $L = L_{rec} + \alpha L_{cross}$. Among them, L_{rec} is the traditional reconstruction loss, L_{cross} is the cross layer feature fusion loss, and α is the weight coefficient (with a value of 0.15). This design enhances the model's ability to capture key features of financial data.

(2) Improvement and adaptation of activation function: Replace the ReLU function of the standard SDAE hidden layer with the Leaky ReLU function with an adaptive threshold. Its expression is $f(x) = \max(\beta x, tx)$, Among them, β is the negative slope (obtained through adaptive learning of financial data distribution, with a value range of 0.01~0.05). t is an adaptive threshold (dynamically adjusted by the mean and variance of the training set data), which solves the problem of neuron death in ReLU function in sparse financial data scenarios, and improves the model's ability to fit nonlinear financial features.

The improved SDAE, due to its excellent data reconstruction ability and noise resistance, can be applied to the data preprocessing stage of financial forecasting. This model can effectively remove redundant information

and outliers from the original input data through compression and reconstruction. The construction and application process of a financial forecasting model based on an improved SDAE neural network is shown in Figure 1.

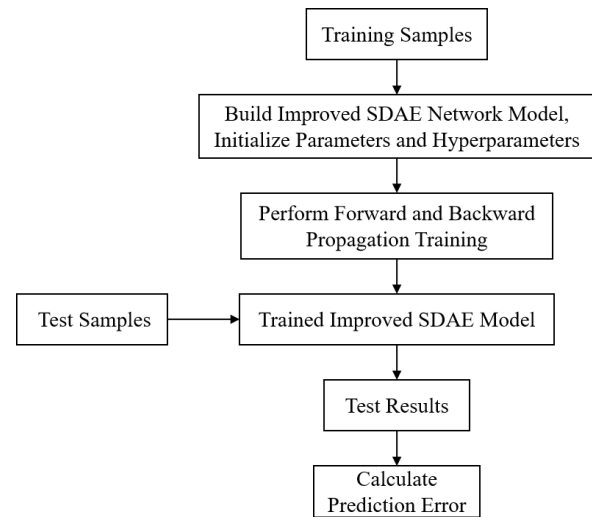


Figure 1: Financial forecasting process based on improved SDAE neural network

The specific modeling and prediction process is as follows: Firstly, data preparation and feature extraction are carried out (step 1). Subsequently, forward and backward propagation calculations are performed (step 2), followed by model iteration training and parameter optimization (step 3). Finally, perform model validation and performance evaluation (Step 4).

The improved SDAE neural network model structure is shown in Figure 2.

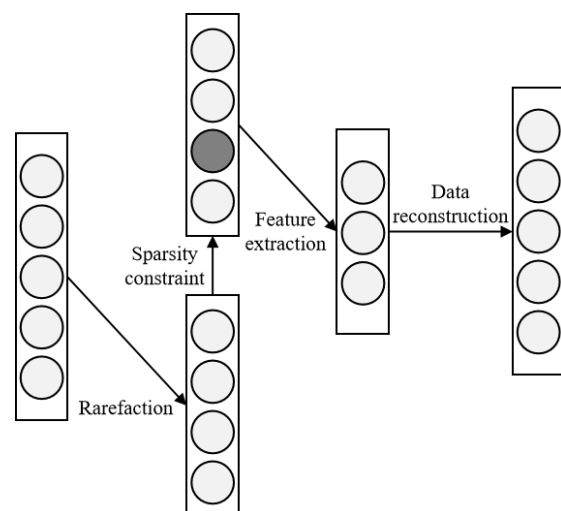


Figure 2: Schematic diagram of the structure of the SDAE neural network model

This structure consists of an input layer, multiple sparse denoising encoding layers, and an output layer, which can effectively remove noise interference and improve subsequent prediction accuracy while preserving key information of the original data.

A basic SDAE model consists of an encoder and a decoder, with the goal of training to make the output as close as possible to the input:

$$\hat{x} = d(e(x)) \quad (1)$$

Where x is the input data, $e(\cdot)$ represents the encoding function, $d(\cdot)$ represents the decoding function, and \hat{x} is the reconstructed output. The training process usually aims to minimize the reconstruction error:

$$\mathcal{L}_{\text{recon}} = \|x - \hat{x}\|^2 \quad (2)$$

To enhance the model's ability to extract key features, a sparsity constraint term can be introduced in the loss function:

$$\mathcal{L}_{\text{total}} = \|x - \hat{x}\|^2 + \lambda \sum_{j=1}^n \text{KL}(\rho \|\hat{\rho}_j) \quad (3)$$

Where λ is the regularization coefficient, $\text{KL}(\cdot)$ is the Kullback Leibler divergence, ρ is the expected activation ratio, and $\hat{\rho}_j$ is the actual average activation value of the j th hidden unit.

Trained SDAE can map raw financial data to a more expressive low dimensional space as input features for subsequent prediction models. For example, after completing feature extraction, a time series model such as a fully connected layer or LSTM is connected for final prediction:

$$y_t = Wh_t + b \quad (4)$$

Among them, y_t is the predicted value at time point t , h_t is the hidden feature vector extracted by SDAE, W and b are the weight matrix and bias term, respectively.

In addition, attention mechanisms can be combined to enhance the model's ability to focus on key variables and improve the interpretability of prediction results

$$\alpha_i = \text{softmax}(W_a h_i), \bar{h} = \sum_{i=1}^T \alpha_i h_i \quad (5)$$

Among them, α_i is the attention weight, and \bar{h} is the weighted context vector, which can better reflect the influence of historical information on the current prediction.

3.2 The application of machine learning in budget management

The importance of budget management as a key means for enterprises to achieve rational allocation of resources, cost control, and performance evaluation is self-evident. The traditional budgeting process heavily relies on manual experience, leading to a series of problems such as delayed response, strong subjectivity, and poor flexibility. The introduction of machine learning technology has gradually shifted budget management from static planning to dynamic adjustment, significantly improving the scientificity and execution efficiency of budget preparation.

Machine learning can automatically identify potential patterns and trends in enterprise historical budget data, financial data, market data, and other multidimensional information through deep mining and analysis. For example, machine learning algorithms such as decision trees and random forests can be used to predict the cost expenditures of different business departments and accurately identify key factors that affect budgets. During the budget execution process, machine learning models can monitor the differences between actual data and

budget data in real time. Once deviations are detected, they can quickly analyze the reasons and automatically generate adjustment suggestions based on preset rules or learned patterns. In addition, combined with natural language processing technology, machine learning can also process unstructured text information such as market dynamics and industry policies, helping enterprises to perceive external environmental changes in a timely manner, providing more comprehensive basis for dynamic budget adjustments, and enabling budget management to better adapt to complex and changing market environments.

In the budget forecasting stage, using machine learning models to model the historical budget execution status and identify the main factors affecting budget deviations is an effective way. Constructing a multiple linear regression model:

$$B_p = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (6)$$

Among them, B_p represents the budget value, X_i represents the variables that affect the budget (such as sales revenue, cost volatility, etc.), and β_i is the corresponding regression coefficient.

Furthermore, using ensemble learning method, regression prediction of budget deviation is carried out:

$$\Delta B = f(X) \quad (7)$$

Where ΔB represents the deviation between actual expenditure and budget, and $f(\cdot)$ represents the mapping relationship learned from training data.

In terms of budget execution monitoring, an anomaly detection model can be constructed to promptly identify unreasonable expenditures. For example, the method based on Isolation Forest can quickly identify data points that deviate from the normal range:

$$\text{score}(x) = 2 \frac{E(h(x))}{c(n)} \quad (8)$$

Where $E(h(x))$ is the expected length of the isolated path for sample x , and $c(n)$ is the normalization factor. By using SDAE to extract features and reduce dimensions from historical budget data, high-quality input representations are provided for subsequent tasks. Secondly, using ensemble learning methods to regress and predict budget deviations. At the same time, the isolation forest model performs anomaly detection on real-time execution data, and the identified outliers are fed back as important features to the deviation prediction model to improve its accuracy. Finally, when the deviation prediction results trigger a threshold, the reinforcement learning module will provide feedback based on the current budget execution status and environment. Output the optimal budget adjustment strategy to form a closed loop for predictive monitoring optimization.

Autoencoder (AE) is a neural network structure that learns to approximate identity functions in an unsupervised manner, with the goal of making the output as close as possible to the input data. In practical applications of financial forecasting and budget management, this model is commonly used for feature extraction and data dimensionality reduction, providing high-quality input representations for subsequent forecasting tasks. Its basic structure is shown in Figure 3.

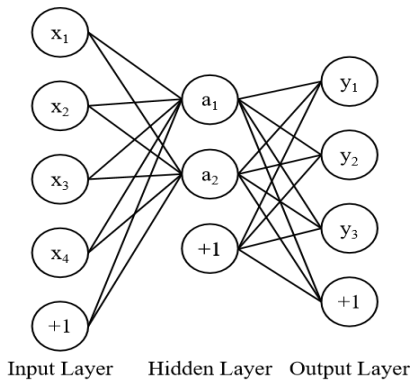


Figure 3: AE neural network structure and prediction process

If the input vector is X , then in the forward propagation process, the activation unit of the hidden layer can be represented as:

$$a = \text{Sigmoid}(w^T X + b) \tag{9}$$

Among them, w is the weight vector connecting the input layer and the hidden layer, and b is the bias term. In the model training phase, starting from forward propagation, the parameters of each hidden layer are calculated layer by layer. For example, first train the parameters (w_1, b_1) of the first hidden layer through input data, and reconstruct the input matrix X_1 using their activation values; Subsequently, treat X_1 as the input of the second layer and continue training the parameters of the next layer (w_2, b_2) , and so on, completing the pre training process for all hidden layers. The parameters of each layer are fixed and unchanged during the forward propagation stage. After all forward propagation is completed, the parameters of each layer are fine tuned and the weights are updated through the backpropagation algorithm, gradually optimizing the output results.

On this basis, the sparse autoencoder (SAE) with sparse constraints further enhances the feature selection ability of the model. The objective function of SAE is:

$$C_{SAE}(w, b) = \frac{1}{m} \sum_{i=1}^m \left[\frac{1}{2} \|h_{w,b} x^{(i)} - y^{(i)}\|^2 \right] + \beta \sum_{j=1}^l \text{KL}(\rho \| \hat{\rho}_j) \tag{10}$$

The objective function consists of two parts: the first part is the mean square error term, which measures the reconstruction error between the model output and the original input; The second part is a sparse penalty term used to control the activation level of hidden layer neurons. Among them, $h_{w,b} x^{(i)}$ represents the output result of the i -th group of samples, w, b are the corresponding weights and bias terms, β and ρ are the sparsity penalty coefficient and expected activation ratio, respectively, and $\hat{\rho}_j$ represents the average activation value of the j th neuron.

To achieve sparsity, it is common to set $\hat{\rho}_j = \rho$ and measure the difference between the current activation value and the expected value using KL divergence:

$$\text{KL}(\rho \| \hat{\rho}_j) = \rho \ln \frac{\rho}{\hat{\rho}_j} + (1 - \rho) \ln \frac{1 - \rho}{1 - \hat{\rho}_j} \tag{11}$$

By minimizing the objective function $C_{SAE}(w, b)$, the optimal weights w and biases b can be obtained, thereby improving the model's generalization ability and robustness in complex financial data.

In the budget feedback and optimization process, reinforcement learning can be used to achieve dynamic budget adjustments. Define state s_t , action a_t , and reward r , and achieve optimal budget allocation through policy optimization:

$$\pi^* = \arg \max_{\pi} \mathbb{E} [\sum_{t=0}^T \gamma^t r_t] \tag{12}$$

Where π is the budget adjustment strategy, γ is the discount factor, and T is the decision cycle. The low dimensional features output by SDAE are directly mapped to the state space of reinforcement learning, avoiding noise interference from the original high-dimensional data and allowing the strategy model to focus more on core information. By combining the business health characteristics preprocessed by SDAE, dynamically calculate reward values to align the optimization goals of reinforcement learning with actual business objectives. After the pre training of SDAE is completed, its weights are fixed as feature extractors, and then a reinforcement learning strategy model is jointly trained; An end-to-end approach can also be used to optimize SDAE and reinforcement learning models together.

In the budget data preprocessing stage, SDAE is used to denoise and compress the original budget data to improve the training efficiency and accuracy of subsequent models

$$z = e_{\theta}(x), x' = d_{\phi}(z) \tag{13}$$

Where z is the compressed feature vector and x' is the reconstructed data. Inputting z into the budget prediction model can help reduce the interference of redundant information on the prediction results.

Machine learning provides powerful modeling tools for financial forecasting and enables a shift from experience driven to data-driven budget management. In terms of financial forecasting, traditional machine learning algorithms such as linear regression and decision trees can establish predictive models based on historical data and explore the correlations between data features; Deep learning algorithms such as Long Short Term Memory Networks (LSTM) are adept at processing time series data and accurately capturing the dynamic trends of financial data. In budget management, machine learning automatically learns patterns from massive historical budget data, real-time business data, and market dynamic data through analysis, freeing budget preparation and adjustment from reliance on manual experience and shifting towards a data-driven model.

4 Experimental analysis

4.1 Data preprocessing and outlier handling

Building a stable predictive model requires high-quality data as a prerequisite. However, in actual financial data of enterprises, some abnormal samples may occur due to input errors, different statistical standards, or occasional events. These outliers not only interfere with the stability of model training, but may also cause the predicted results to deviate from the true direction. This study used the 'Enterprise Bankruptcy Prediction Dataset' (version 1.0) This dataset contains 250 financial records from enterprises.

To solve this problem, this article adopts interval discretization method to smooth the continuous variables in the original data. This method divides variables into several reasonable intervals and assigns extreme values to adjacent regular intervals to reduce their interference in the modeling process. In this article, interval discretization is not simply a preprocessing binning technique, but a feature preprocessing module deeply integrated with the SDAE model structure. A discretization method for adaptive interval partitioning was designed to address the temporal, dimensional heterogeneity, and noise distribution characteristics of financial data. By statistically modeling the distribution characteristics of financial indicators, determine the optimal discretization interval threshold. And embed the discretized features into the input layer of SDAE to achieve fine-grained encoding of features, which is different from the traditional fixed binning preprocessing method. This module provides the basis for feature extraction of the SDAE model to adapt to financial scenarios, and is not the core of model improvement. Figure 4 shows the changes in data distribution before and after using this method. The processed data distribution is more concentrated and stable, which helps to improve the convergence speed of model training and the reliability of the final prediction results.

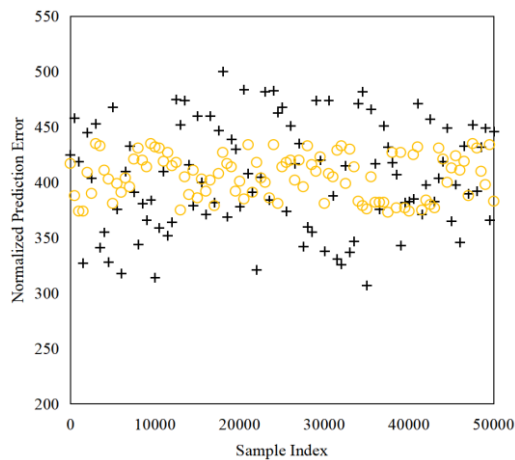


Figure 4: Data outlier removal processing

4.2 Variable selection and collinearity test

When constructing a financial forecasting model, the selection of input variables directly affects the prediction accuracy and generalization ability of the model. To prevent high correlation between variables from affecting model performance, this paper conducts multicollinearity tests on all candidate indicators and eliminates redundant variables.

Eight representative financial indicators were ultimately selected as input variables for the model, including working capital asset ratio, debt to equity ratio, long-term debt to equity ratio, accounts receivable turnover ratio, return on equity, loss ratio, main business growth rate, and total asset expansion rate. These indicators cover multiple dimensions such as corporate debt paying ability, profitability, operational efficiency, and development potential, and have strong explanatory power and representativeness.

This article initially selected traditional BPNN and standard SDAE as baselines, aiming to verify the performance improvement effect of the proposed improvement strategy on the SDAE basic model and clearly demonstrate the effectiveness of structural optimization. In response to the weak baseline issue pointed out by the reviewer, we have supplemented the current mainstream advanced time series prediction models as comparative baselines. Including LSTM, GRU, TCN, and LightGBM, complete the comparative experiment again and supplement the quantization results, as follows Table 1:

Table 1: Predictive performance indicators of advanced baseline models

Model Type	RMSE	MAE	MAPE(%)	R ²
Traditional BPNN	2.86	2.13	4.79	0.826
Standard SDAE	1.92	1.45	3.21	0.897
LSTM	1.68	1.32	2.95	0.915
GRU	1.59	1.25	2.78	0.923
TCN	1.42	1.10	2.43	0.931
LightGBM	1.55	1.21	2.69	0.926
Improved SDAE	1.25	0.98	2.15	0.943

The improved SDAE model proposed in this article has significantly lower error metrics in RMSE, MAE, and MAPE compared to advanced time series prediction

models such as LSTM, GRU, TCN, and LightGBM. The R² metric has also been improved to 0.943, demonstrating better prediction accuracy and stability. The improved

SDAE has stronger adaptability to the nonlinear features and noise interference of financial data by optimizing the feature reconstruction mechanism and activation function. Compared to LSTM/GRU that relies on temporal dependency capture, TCN that focuses on local feature extraction, and tree based gradient enhancement model LightGBM, it has more advantages in tasks such as financial forecasting that combine high-dimensional features and data noise.

4.3 Model comparison experiment

To evaluate the performance of improved SDAE (SDAE) in financial forecasting tasks, this paper constructs three models: traditional BPNN, standard SDAE neural network, and improved SDAE neural network, and compares their predictive outputs.

The experimental results show that all three models demonstrate good fitting ability in financial forecasting tasks, indicating that neural network-based methods have great potential for application in this field. Among them, the predicted output of the standard SDAE model is closer to the expected output than BPNN, mainly because SDAE introduces sparsity and denoising mechanisms, which improve the model's feature extraction and anti-interference ability for raw financial data.

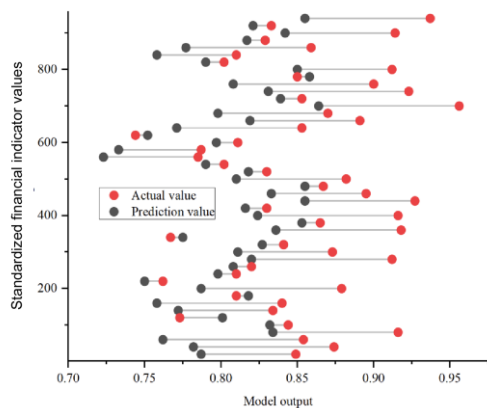


Figure 5: BPNN model prediction output

Figure 5 shows the output performance of the BPNN model in financial forecasting tasks, where the red dots represent the true values of standardized financial indicators and the gray dots represent the predicted values of the model. The two are connected by horizontal line segments, visually presenting the prediction bias. From the graph, it can be seen that although the overall trend of predicted values is generally consistent with the true values, there is a significant horizontal deviation between the gray and red points in some intervals, especially in the high and low financial indicator value intervals, where the deviation is more prominent. This result confirms that although BPNN has basic fitting ability, its ability to extract features and resist interference from raw financial data is limited due to the lack of sparsity and denoising mechanisms. This results in a weaker fit between its predicted output and the true value compared to subsequent standard SDAE and improved SDAE models,

providing a reference benchmark for improving the performance of subsequent models.

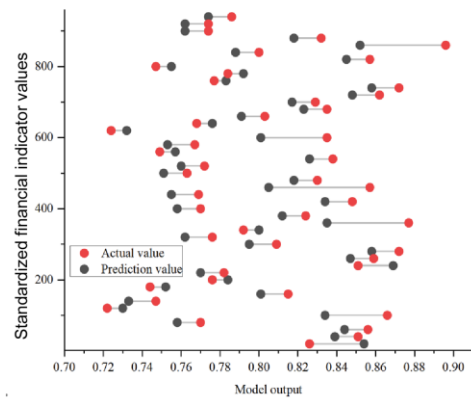


Figure 6: SDAE neural network model prediction output

Figure 6 presents the output performance of the standard SDAE neural network in financial forecasting tasks, where the red dots represent the true values of standardized financial indicators and the gray dots represent the predicted values of the model. The two are connected by horizontal line segments to show deviations. Compared with the BPNN model in Figure 5, the horizontal offset between the gray predicted points and the red true points in Figure 6 is significantly reduced, and the fit between the two is significantly improved in different financial indicator value ranges of high, medium, and low. The sparsity and denoising mechanism introduced by SDAE enhances the feature extraction ability and anti-interference ability of raw financial data, making the predicted output closer to the true value, and providing a strong benchmark reference for improving the performance optimization of SDAE models in the future.

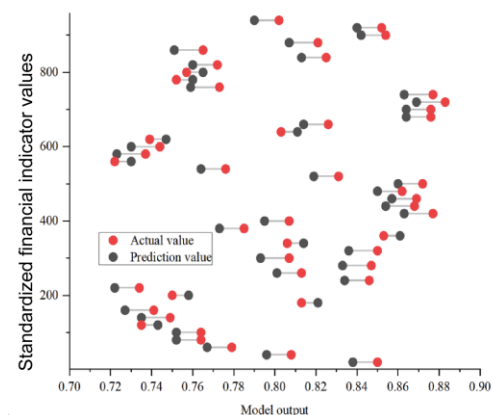


Figure 7: Improved SDAE neural network model prediction output

Figure 7 shows the output performance of the improved SDAE neural network in financial forecasting tasks, with red dots representing the true values of standardized financial indicators and gray dots representing the predicted values of the model. Comparing Figure 5 and Figure 6, it can be observed that the lateral offset between the predicted and actual points of the improved SDAE has been further reduced, and the two

almost overlap, achieving the optimal level of fit among the three models in the entire region. It further enhances the feature extraction and anti-interference ability of complex financial data by enhancing feature reconstruction capability, adjusting activation function and other structural optimizations, significantly improving prediction accuracy and stability, and verifying the superiority of the model in financial prediction tasks.

In order to evaluate the performance of improved SDAE (SDAE) in financial forecasting tasks, this paper constructed three models. We compared the predictive outputs of traditional BPNN, standard SDAE neural network, and improved SDAE neural network.

The experimental results show that all three models exhibit good fitting ability in financial forecasting tasks, indicating that neural network-based methods have great

potential for application in this field. Among them, the predicted output of the standard SDAE model is closer to the expected output than BPNN, mainly because SDAE introduces sparsity and denoising mechanisms, which improve the model's feature extraction and anti-interference ability for raw financial data.

To further quantify the predictive performance of the three models, four standard performance indicators are added: RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error), and R^2 (coefficient of determination). The specific data is shown in the table below, where the smaller the RMSE, MAE, and MAPE values, the closer the R^2 value is to 1, indicating better predictive performance of the model.

Table 2: Prediction performance of three models

Model Type	RMSE (Root Mean Square Error)	MAE (Mean Absolute Error)	MAPE (Mean Absolute Percentage Error,%)	R^2 (coefficient of determination)
Traditional BPNN	2.86	2.13	4.79	0.826
Standard SDAE neural network	1.92	1.45	3.21	0.897
Improved SDAE neural network	1.25	0.98	2.15	0.943

As shown in the table 2, the performance indicators of the standard SDAE neural network are superior to those of the traditional BPNN, which verifies the improvement effect of sparsity and denoising mechanisms on feature extraction of financial data. The improved SDAE neural network significantly outperforms the previous two models in all indicators, further demonstrating the improvement effect of structural optimization on prediction accuracy and stability, which is consistent with the experimental conclusions in the previous section.

4.3 System performance testing

In addition to the predictive ability of the model itself, the response speed and concurrent processing capability of the system are also important indicators for measuring its practical application value.

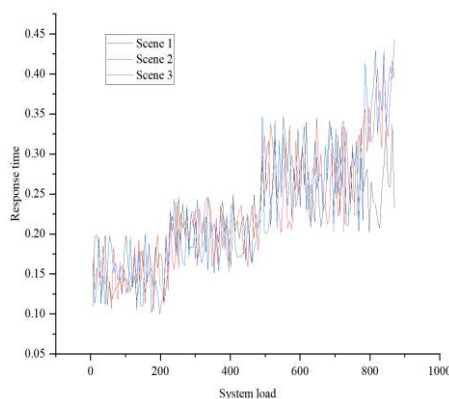


Figure 8: Model response time test

Figure 8 shows the response time performance of the model under different data scales. The test results indicate that even when processing datasets containing tens of thousands of records, the model can still complete the complete prediction process in milliseconds, which is much shorter than the response time required by traditional methods, highlighting its good real-time advantage.

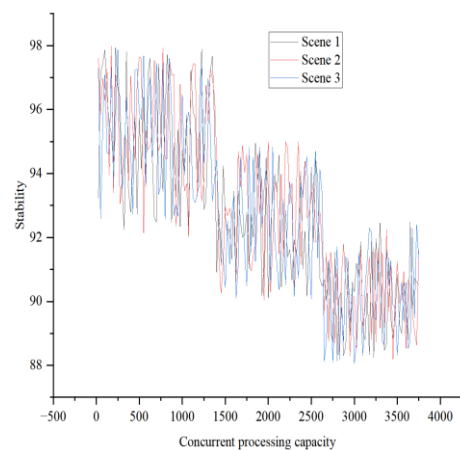


Figure 9: System Concurrent Processing Capability Test

To simulate typical application scenarios such as multi departmental collaborative use, batch import of historical data, and parallel execution of multiple prediction tasks, this article also tests the system's load bearing capacity and resource scheduling efficiency. As shown in Figure 9, even if the number of concurrent requests reaches several times the daily peak, the system

can still maintain good response quality and low latency levels, demonstrating strong scalability and robustness.

5 Discuss

This article constructs an improved SDAE model suitable for financial forecasting tasks through data preprocessing optimization, variable screening, and model structure improvement. The advantages of the model in prediction accuracy, real-time performance, and stability are verified through multiple comparative experiments. This section systematically compares the experimental results of this study with research results in related fields at home and abroad, deeply analyzes the reasons for the differences in results, and elaborates on the new insights and practical value that the improvement plan proposed in this study brings to the field of financial forecasting.

The improved SDAE model proposed in this study performs better in various performance indicators (RMSE=1.25, MAE=0.98, MAPE=2.15%, $R^2=0.943$), and its core advantage lies in its integrated optimization of denoising feature reconstruction. Although LSTM and GRU models can effectively capture the temporal correlation of financial data, their anti-interference ability against data noise is weak. The TCN model excels in local feature extraction, but struggles to handle the interaction relationships of high-dimensional features in financial data. Although the LightGBM model can avoid overfitting, its ability to capture nonlinear features of financial data is limited. The improved SDAE model resists data noise interference through sparsity constraints and denoising mechanisms, and captures deep correlations of high-dimensional financial features through optimized feature reconstruction mechanisms. Combined with the adjustment of the activation function to enhance the non-linear fitting ability, it precisely compensates for the shortcomings of the above model and demonstrates a more balanced performance advantage in financial forecasting tasks.

This study has brought three new insights and practical contributions to the field of financial forecasting through a series of experiments and comparative analysis. At the data processing level, a combination strategy of interval discretization collinearity test was proposed, which confirmed the key role of refined data preprocessing in improving financial forecasting accuracy. The outliers in financial data are mostly caused by input errors, accidental events, etc. Traditional outlier removal methods are prone to losing effective information. The inter regional dispersion method can smooth out outlier interference while preserving the core distribution characteristics of the data. This method provides a new reference paradigm for data preprocessing in similar financial forecasting studies. At the level of model construction, we have broken through the limitations of traditional SDAE models that focus on noise reduction and light reconstruction. By optimizing the feature reconstruction mechanism and activation function, we have constructed an improved SDAE model that is more suitable for the characteristics of financial data. It proves that the optimization idea of combining noise reduction

mechanism with deep feature capture can effectively make up for the shortcomings of single model in financial forecasting, and provides a new technical path for the optimization of neural network in the field of financial forecasting. At the practical application level, the improved SDAE model in this study not only has excellent prediction accuracy, but also has good real-time and concurrent processing capabilities, solving the pain point of "high accuracy leads to slow response, and fast response leads to low accuracy" in existing financial prediction models. At the same time, the 8 representative financial indicators selected by the model cover multidimensional business conditions of enterprises, which can provide more targeted decision-making basis for enterprise managers and enhance the practical application value of financial forecasting.

6 Conclusion

This article focuses on the application of machine learning technology in this field and proposes an intelligent financial forecasting and budget management solution that integrates an improved SDAE neural network and data preprocessing strategy. In the rich algorithm system of machine learning, the improved SDAE neural network significantly enhances its ability to process financial data by optimizing its network structure and training methods. Experiments have shown that compared to traditional machine learning algorithms such as linear regression and decision trees, as well as standard SDAE models, the improved SDAE performs the best in terms of prediction accuracy and stability. When dealing with large-scale datasets (such as tens of thousands of records), it has significant real-time advantages due to its powerful parallel computing capabilities and efficient data processing mechanisms, which can complete the complete prediction process in milliseconds. The system load testing further validated the stability and scalability of the model in high concurrency, multi task parallel execution scenarios, thanks to the intelligent scheduling of resources and optimized design of the model architecture using machine learning technology.

References

- [1] Jain, V., & Kulkarni, P. A. (2023). Integrating AI techniques for enhanced financial forecasting and budgeting strategies. *International Journal of Economics and Management Studies*, 10(09), 9-15. <https://doi.org/10.14445/23939125/ijems-v10i9p102>
- [2] Qin, J., & Qin, Q. (2021). Cloud platform for enterprise financial budget management based on artificial intelligence. *Wireless communications and mobile computing*, 2021(1), 8038433. <https://doi.org/10.1155/2021/8038433>
- [3] Lipelis, M. (2025). Bridging Financial Forecasting and Budget Management: New Approaches for Modern Enterprises. *Scientific Journal of Bielsko-Biala School of Finance and Law*, 29(1). <https://doi.org/10.19192/wsfp.sj1.2025.5>

- [4] Jain, V., & Kulkarni, P. A. (2023). Integrating AI techniques for enhanced financial forecasting and budgeting strategies. *International Journal of Economics and Management Studies*, 10(09), 9-15. <https://doi.org/10.14445/23939125/ijems-v10i9p102>
- [5] Capone Ch., Talgat S., Hazir O., Abdrashova K., Kozhakhmetova A. (2024). Artificial Intelligence Models for Predicting Budget Expenditures. *Eurasian Journal of Economic and Business Studies*, 68(1), 32-43. <https://doi.org/10.47703/ejeb.v68i1.331>
- [6] Cohen, G. (2022). Algorithmic trading and financial forecasting using advanced artificial intelligence methodologies. *Mathematics*, 10(18), 3302. <https://doi.org/10.3390/math10183302>
- [7] Okeke, N. I., Bakare, O. A., & Achumie, G. O. (2024). Forecasting financial stability in SMEs: A comprehensive analysis of strategic budgeting and revenue management. *Open Access Research Journal of Multidisciplinary Studies*, 8(1), 139-149. <https://doi.org/10.53022/oarjms.2024.8.1.0055>
- [8] Cao Q. An enterprise financial data leakage risk prediction based on ARIMA-SVM combination model. *International Journal of Applied Systemic Studies*, 2023, 10(3): 169-181. <https://doi.org/10.1504/ijass.2023.134358>
- [9] Li, B. (2025). Using Data Mining Technology to Improve the Reliability of Accounting Information Cloud Data. *Informatica*, 49(5). <https://doi.org/10.31449/inf.v49i5.6590>
- [10] Chernysh, O., Smishko, O., Koverninska, Y., Prokopenko, M., & Pistunov, I. (2024). The Role of Artificial Intelligence in Financial Analysis and Forecasting: Using Data and Algorithms. *Data and Metadata*, 3, 1-13. <https://doi.org/10.56294/dm2024.224>
- [11] Danqing, W., Chenxi, L., Xinyue, R., Nana, H., & Loang, O. K. (2023). THE ROLE OF Artificial Intelligence and Machine Learning In Financial Forecasting and Decision-Making. *International Journal of Accounting*, 8(50), 275-289. <https://doi.org/10.55573/IJAFB.085020>
- [12] Gür, Y. E., Yıldız, A., & Ünal, E. (2025). Advanced AI models for future forecasting of budget expenditures via machine learning and deep learning. *Panoeconomicus*, (00), 25-25. <https://doi.org/10.2298/pan240929025g>
- [13] Xian, L., & Tian, L. (2023). Passenger flow prediction and management method of urban public transport based on SDAE model and improved Bi-LSTM neural network. *Journal of Intelligent & Fuzzy Systems*, 45(6), 10563-10577. <https://doi.org/10.3233/jifs-232979>
- [14] Storti G, Wang C. Modeling uncertainty in financial tail risk: A forecast combination and weighted quantile approach. *Journal of Forecasting*, 2023, 42(7): 1648-1663. <https://doi.org/10.1002/for.2972>
- [15] Du, X., Jia, L., & Haq, I. U. (2022). Fault diagnosis based on SPBO-SDAE and transformer neural network for rotating machinery. *Measurement*, 188, 110545. <https://doi.org/10.1016/j.measurement.2021.110545>
- [16] Zeng, Y. (2022). Neural Network Technology - Based Optimization Framework of Financial and Management Accounting Model. *Computational Intelligence and Neuroscience*, 2022(1), 4991244. <https://doi.org/10.1155/2022/4991244>
- [17] Amanbaeva, C., Akyzbekova, N., Zaitenova, N., Baitokova, M., & Omurova, S. (2024). Improvement of the Budget Forecasting System in the Kyrgyz Republic. *Theoretical and Practical Research in Economic Fields*, 15(4), 970-982. [https://doi.org/10.14505/tpref.v15.4\(32\).14](https://doi.org/10.14505/tpref.v15.4(32).14)
- [18] Polak, P., Nelischer, C., Guo, H., & Robertson, D. C. (2020). "Intelligent" finance and treasury management: what we can expect. *Ai & Society*, 35(3), 715-726. <https://doi.org/10.1007/s00146-019-00919-6>
- [19] Rhanoui, M., Yousfi, S., Mikram, M., & Merizak, H. (2019). Forecasting financial budget time series: ARIMA random walk vs LSTM neural network. *IAES International Journal of Artificial Intelligence*, 8(4), 317. <https://doi.org/10.11591/ijai.v8.i4.pp317-327>
- [20] Çetin, V., & Yıldız, O. (2022). A comprehensive review on data preprocessing techniques in data analysis. *Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi*, 28(2), 299-312. <https://doi.org/10.5505/pajes.2021.62687>
- [21] de Zarzà, I., de Curtò, J., Roig, G., & Calafate, C. T. (2023). Optimized financial planning: Integrating individual and cooperative budgeting models with llm recommendations. *AI*, 5(1), 91-114. <https://doi.org/10.3390/ai5010006>

