Optimization of Automated Financial Statement Information Disclosure System Based on AI Models

Yonghui Xiao[1], Haikuan Zhang[2]*
School of Accounting, Guangdong University of Finance and Economics, Guangzhou 510320, China[1]
Guangdong Industry Polytechnic University, Guangzhou 510300, China[2]

***Abstract*—In the context of the digital transformation of the global economy and the rapid advancement of enterprise informatization, ensuring accurate and timely financial statement disclosure has become a critical priority for businesses and regulatory bodies. This study aims to address the inefficiencies, high error rates, and slow response times inherent in traditional financial information disclosure processes, which fail to meet the real-time data accuracy demands of modern enterprises. The study introduces an AI-driven optimization scheme for an automated processing network system for financial statement information disclosure. By leveraging advanced machine learning techniques and large language models, the proposed system enhances the accuracy, speed, and cost-effectiveness of disclosure processes. The system was tested and compared against traditional manual methods, focusing on processing time, accuracy rates, and operational cost savings. The optimized system significantly reduces the average processing time from three hours to 20 minutes, achieving a 90% efficiency improvement. Accuracy is enhanced from 92% to over 97%, while the response speed increases by 40%. Additionally, the system reduces operational costs by 15%, resulting in annual labor cost savings of approximately 12 million yuan. These findings demonstrate the transformative potential of AI technologies in addressing the limitations of traditional financial disclosure processes. This study highlights an innovative application of AI in the realm of intelligent finance, offering a scalable solution that aligns with the evolving demands for real-time, accurate financial information. The research contributes to the growing field of AI-driven automation by showcasing its practical implications and substantial benefits in financial statement disclosure.**

Keywords*—*Information disclosure of financial statements; artificial intelligence; automated processing; system optimization

I. INTRODUCTION

In the dynamic landscape of capital market development, the significance of certified public accountants (CPAs) in China's auditing industry has been steadily escalating [1, 2]. The reliance of government supervision, enterprise risk identification, and investor decision-making on the financial reports published by listed companies underscores the pivotal role of CPAs' audit opinions. However, recent audit failures and associated lawsuits, including the Enron scandal in the United States and the Yinguangxia incident in China, have eroded public trust in CPAs and tarnished their professional image [3, 4]. These failures often stem from CPAs' inadequate understanding of the audited entity and its environment, leading to failures in accurately identifying the risk of material mis-statement. Notably, over 40 CPAs have faced penalties since 2007 for failing to identify such risks.

The core of modern risk-oriented audits lies in identifying and assessing the risk of material misstatement. China's adoption of the modern risk-oriented audit model emphasizes initiating audit work through the identification and evaluation of this risk, guiding the design of substantive test procedures and the allocation of audit resources. However, Zhang Qingqiong's empirical analysis reveals a significant decline in audit quality among domestic local firms after implementing modern risk-oriented audits, whereas the audit quality of "Big Four" firms remained relatively stable [5, 6]. This suggests that local firms struggle with applying the modern risk-oriented audit model, often leading to superficial risk assessments.

This paper focuses on how to use artificial intelligence technology to improve the automation, accuracy and processing efficiency of financial statement information disclosure. The traditional financial statement disclosure process often relies on manual review and rule driven system, which are inefficient and prone to error in the face of a large number of complex financial data. With the increase of the amount of information and data complexity, the existing system is facing many challenges in processing financial data, such as insufficient data cleaning, inconsistent information, frequent omissions and other issues. The main goal of the research is to develop and optimize an automatic processing system based on artificial intelligence technology to improve the efficiency, accuracy and reliability of financial statement information disclosure. Specifically, the research aims to reduce manual intervention and error rate by introducing AI model to automate data cleaning, formatting, anomaly detection and information verification in financial statements.

This paper comprehensively discusses how to use AI technology to optimize the automatic processing system of financial statement information disclosure. The research first analyzes the problems of low efficiency and high error existing in the traditional financial disclosure methods, and puts forward the optimization scheme based on AI model. Through the system architecture design and experimental results analysis, the research shows the significant advantages of AI in improving processing efficiency, reducing error rate and optimizing operation cost. The experimental results show that the optimized AI system has outstanding performance in improving the response speed and accuracy of the system, significantly reducing the processing time and improving the success rate of data transmission. Finally, the research emphasizes the application prospect of AI technology in improving the transparency of financial statements and decision-making

efficiency, and provides a valuable reference for future research directions.

A crucial factor contributing to these challenges is the lack of a structured path analysis framework for material misstatement risk formation. Auditors often rely on templates and personal experience to make judgments, which can compromise risk assessment accuracy [7]. Consequently, understanding the influencing factors and path relationships of material misstatement risk is imperative for enhancing CPAs' assessment accuracy.

From a theoretical perspective, exploring the factors influencing the risk of material misstatement in financial statements supports the development of innovative auditing procedures and methods. Despite the recent introduction of the risk-oriented audit model, research on material misstatement risk remains exploratory, lacking mature theoretical frameworks and quantitative operational methods. This study aims to contribute to the advancement of risk-oriented audit theory.

Practically, this research endeavors to improve audit quality and efficiency, aiding CPAs in balancing risk and benefit. By identifying high-risk areas, our findings can help reduce information risk in audits and financial statements, enhancing audit efficiency and optimizing resource allocation. Through scientific application, CPAs can achieve a cost-benefit balance while maintaining rigorous audit risk control.

Given the rapid advancements in artificial intelligence (AI), integrating AI technologies into auditing processes presents a promising avenue for addressing these challenges. Current research lacks a structured review of how AI can enhance risk assessment in auditing, highlighting a research gap that this study aims to address. By bridging this gap, our research aims to contribute to the growing field of AI-driven auditing innovations.

Verification measures and comparison with previous studies are important parts of the study. By setting accurate verification criteria, such as the comparison between the model prediction and the actual financial statements, the paper can evaluate the accuracy and efficiency of AI model in the automatic processing of financial information disclosure. At the same time, the paper will compare with previous studies in related fields to show the advantages of the new method in terms of automation level, processing speed and accuracy, especially on the basis of traditional manual processing and rule driven methods, AI model can better deal with complex and changeable financial data, and improve the transparency and reliability of information disclosure. Through this comparison, this study not only highlights the innovation and practical application value of the new model, but also provides direction for future research.

II. Identification and Analysis of Risk Factors in Financial Statements based on AI Models

This paper suggests a comprehensive analysis of the financial data of enterprises over the years, and predicting the future cash flow by calculating the average of the annual data in the sales percentage method. This method integrates the situation of enterprises in different economic situations, and can more accurately evaluate the value of enterprises and predict the capital needs. The article also presents three suggestions for improvement to optimize the sales percentage method.

A. Financial Statement Risk Formation Mechanism

Related-party transactions refer to the business transactions between interested companies or individuals. Although this kind of transaction can improve the operation level of enterprises, sometimes enterprises may pursue their own interests, violate the principle of market fairness, and damage the interests of shareholders and other stakeholders, thus affecting the normal operation of the capital market [8, 9]. For example, unfair transactions or profit manipulation by related parties may hide the true level of profitability. The net profit margin formula is shown in Eq. (1).

$$N = \frac{N_t}{R_t} \times 100\% \tag{1}$$

Among them, N represents the net interest rate, Nt represents the net profit, and Rt represents the total revenue. The asset-liability ratio formula is shown in Eq. (2).

$$D = \frac{L}{A} \times 100\% \tag{2}$$

Among them, D represents the asset-liability ratio, L represents the total liabilities, and A represents the total assets. Models of Artificial Intelligence assess how likely it is to produce inaccurate financial statements in multiple areas. At outset, the management is identified as potentially intentional inaccuracies, marked by unusual financial signs and signs of profit manipulation. Furthermore, they evaluate internal control deficiencies by linking them with prior misstatements. In essence, AI models closely examine macroeconomic data and sector trends to identify monetary risks stemming from external economic instabilities. The current ratio formula is shown in Eq. (3).

$$CR = \frac{CA}{CL} \tag{3}$$

Where CR denotes current ratio, CA denotes current assets, and CL denotes current liabilities.AI systems meticulously analyze past data and financial reports to reveal the complex mechanisms responsible for the risk of incorrect statements. Utilizing data mining and pattern recognition methods, they identify key components and identify the causal connections associated with untrue assertions. By examining financial reports reported as either standard or inaccurate, AI models are capable of detecting atypical changes in specific indicators and determining the probable causes of these inaccuracies. Additionally, predictive analysis empowers AI systems to identify risk factors from the outset, notifying firms and reducing the likelihood of future inaccurate declarations.

B. Risk Factor Identification Based on AI Model

Modern risk-oriented audit is the mainstream audit method, which requires certified public accountants to evaluate the risk of major misstatement in financial statements and design corresponding audit procedures [10]. The primary task of assessing the risk is to identify and analyze the individual influencing factors. This chapter will first identify the factors affecting the risk of material misstatement in financial

statements and analyze their transmission mechanism to lay a foundation for subsequent research.

The state regulates the macro-economy through restrictive policies, which have a great impact on specific industries, such as the real estate industry. In economic depression, the central bank adopts expansionary monetary policy, lower interest rate, stimulate investment and consumption, and increase the demand for real estate market, while when the economy is overheating, it adopts tightening monetary policy, raise interest rate, reduce investment and consumption, and reduce market demand. This paper argues, the government's restrictive regulation policies may increase the risk of major misstatement.

AI models have proven almost effective in identifying the risk factors causing significant inaccuracies in financial statements. Studies indicate that expert AI models significantly enhance the accuracy of risk identification, reduce the workload of human auditing, and lessen damage to a company's reputation and legal risks due to false statements. However, the application of AI models also needs some help, as well as data quality issues, model interpretability and transparency issues, etc. Future research should further optimize the algorithm of the AI model, improve its adaptability to complex financial scenarios, and enhance the interpretability of the model to support enterprises and audit institutions better. The revenue growth rate formula is shown in Eq. (4).

$$G = \frac{R_t - R_{t-1}}{R_{t-1}} \times 100\% \tag{4}$$

Where G represents the revenue growth rate, Rt represents the total revenue of the current period, and R_{t-1} represents the total revenue of the previous period. The survival and development of enterprises are affected by the industry. In fiercely competitive arenas, companies may gloss over their financial records because of dishonesty, thus increasing the probability of major inaccuracies. The development of the industry usually goes through four stages: start-up, growth, maturity and recession. Enterprises in the initial stage face great survival pressure and may carry out financial fraud and greater risk of major misstatement; enterprises in the growth and maturity stage are less possibility of financial fraud; business difficulties in the recession stage may increase the risk of financial fraud. As a result, the risk of major misstatement may increase. The gross profit margin formula is given in Eq. (5), where M represents gross profit margin, G represents total revenue, and C represents cost of sales.

$$M = \frac{G - C}{G} \times 100\% \tag{5}$$

Contrasting with traditional methods that concentrate on financial ratios and trends, AI models use a data-driven strategy to uncover hidden data. However, using AI in this field requires a strong theoretical foundation that merges financial, accounting, and machine learning concepts. This integration enables AI models to provide more accurate and intelligent support for financial statement analysis. The quick ratio formula is shown in Eq. (6).

$$QR = \frac{CA - I}{CL} \tag{6}$$

Where QR denotes quick ratio, CA denotes current assets, I denote inventory, and CL denotes current liabilities. The formula of accounts receivable turnover ratio is shown in Eq. (7).

$$ARTR = \frac{R}{AR} \tag{7}$$

Among them, $ARTR$ represents the accounts receivable turnover rate, R represents the total revenue, and AR represents the average balance of accounts receivable. The theoretical basis of financial statement analysis mainly includes the basic principles of finance and accounting. First, the preparation and analysis of financial statements follows generally accepted accounting standards, which provide norms for classifying, measuring, and disclosing financial statement items. Secondly, financial theories, such as capital structure theory and cash flow analysis, provide a framework and method for understanding the financial situation of enterprises. When processing financial statement data, AI models must be based on these traditional theories to ensure that data processing and analysis results comply with financial and accounting standards. In addition, AI models also need to understand the time series characteristics of financial data, industry characteristics, and the impact of the macroeconomic environment on the financial status of enterprises.

Each evolution of audit methodology incorporates research findings from various academic fields to enhance its effectiveness. Modern risk-oriented audit integrates sophisticated theories, including comprehensive risk management theory, resource scarcity and allocation theory, strategic management theory, and system theory, forming a solid theoretical foundation for its practice.

III. Network System Architecture for Automated Processing of Financial Statement Information Disclosure based on AI Models

A. System Architecture Design

The financial statement model is a systematic tool used to predict a business's future financial situation and operating results. Integrating the income statement, balance sheet, and cash flow statement provides a comprehensive financial view, aiding management and stakeholders in analyzing a business's performance. This model is vital for budgeting, forecasting, and strategic planning, enabling data-driven decision-making. The cash flow ratio formula is shown in Eq. (8).

$$CFR = \frac{CF}{CL} \tag{8}$$

Among them, CFR represents cash flow ratio, CF represents cash flow generated from operating activities, and CL represents current liabilities. Building a financial statement model involves several crucial steps. First, gather historical financial data to establish a solid foundation. The development of information technology and the programming of corporate affairs make the daily operations more and more dependent on information systems. In order to ensure that the information system is consistent with the actual business process, the company should try to keep the two synchronized to avoid business process confusion and affect the management monitoring. This paper

believes that the disconnection between information systems and business processes may increase the risk of significant misstatement. The evaluation of network system optimization effect of AI model in automated processing of financial statements is shown in Table I.

TABLE I. EVALUATION OF NETWORK SYSTEM OPTIMIZATION EFFECT OF AI MODEL IN AUTOMATED PROCESSING OF FINANCIAL STATEMENTS

Before/after optimization	Processing time (seconds)	Data transmission successful Rate (%)	When the system responds Intervals (milliseconds)	Error detection rate (%)	System throughput (Bps/sec)
Before optimization	150	82	250	6.2	300
After optimization	90	95	130	2.8	450

Financial statement models must possess the flexibility to adapt to shifts in the business environment and market conditions. The robustness of enterprise internal control is manifested in the meticulous design and stringent enforcement of policies and procedures, thereby guaranteeing the credibility of financial reports, the rationality of business strategies, and adherence to regulatory requirements. Control activities serve as the pivotal instrument for ensuring the implementation of management directives, while information communication acts as the vital bridge facilitating the achievement of effective internal control. This paper believes that inadequate internal control may increase the risk of major misstatement. The flow chart of AI model selection and training is shown in Fig. 1.

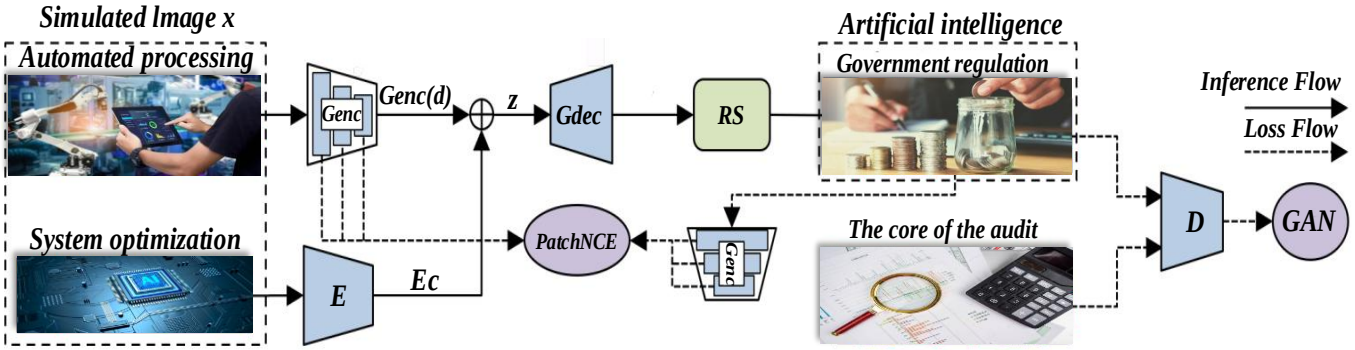

Fig. 1. AI model selection and training flow chart.

B. Automated Processing Flow for Information Disclosure

Based on historical data and financial indicators, by analyzing balance sheet, cash flow statement and income statement, future sales revenue and related costs can be predicted, and then estimate operating profit. In combination with the enterprise plan, these indicators are used to reverse the future liabilities, then calculate the shareholders' equity, and finally predict the total assets and the number of tangible assets, so as to further calculate the precipitation income of the enterprise. The total asset turnover ratio formula is shown in Eq. (9).

$$TATR = \frac{R}{A} \tag{9}$$

Among them, TATR represents the total asset turnover rate, R represents the total revenue, and A represents the total assets. Financial risk refers to the possibility that the financial results of an enterprise deviate from the expectations in the process of operation [11]. High financial risk may lead to financial difficulties, and the difference between financial situation and budget can reflect financial risk. When the financial risk is large, the risk of major misstatement is also higher. This paper holds that poor profitability and solvency, excessive debt scale and small net cash flow of operating activities may increase the risk of major misstatement.

Key performance indicators (KPIs) have a direct impact on executive compensation and career advancement. While some of these indicators are financial in nature, non-financial feedback can also influence management's financial decisions, ultimately affecting the content and presentation of financial statements. This paper believes that key performance indicators below industry levels may increase management pressure and thus increase the risk of major misstatements [12]. The flow chart of automatic collection and processing of financial statement data is shown in Fig. 2.

This flowchart shows a complete automation process from data acquisition to processing. First of all, the financial statement data is collected through an automated system to reduce manual intervention. Then, the data is cleaned and standardized to ensure the consistency and accuracy of the data. Then, the AI model is used to analyze the data, automatically identify abnormal items and potential errors, and carry out risk assessment and prediction. Finally, the processed data automatically generates standardized financial statements, optimizes the disclosure process, improves efficiency and accuracy, and helps enterprises make more timely and accurate financial decisions.

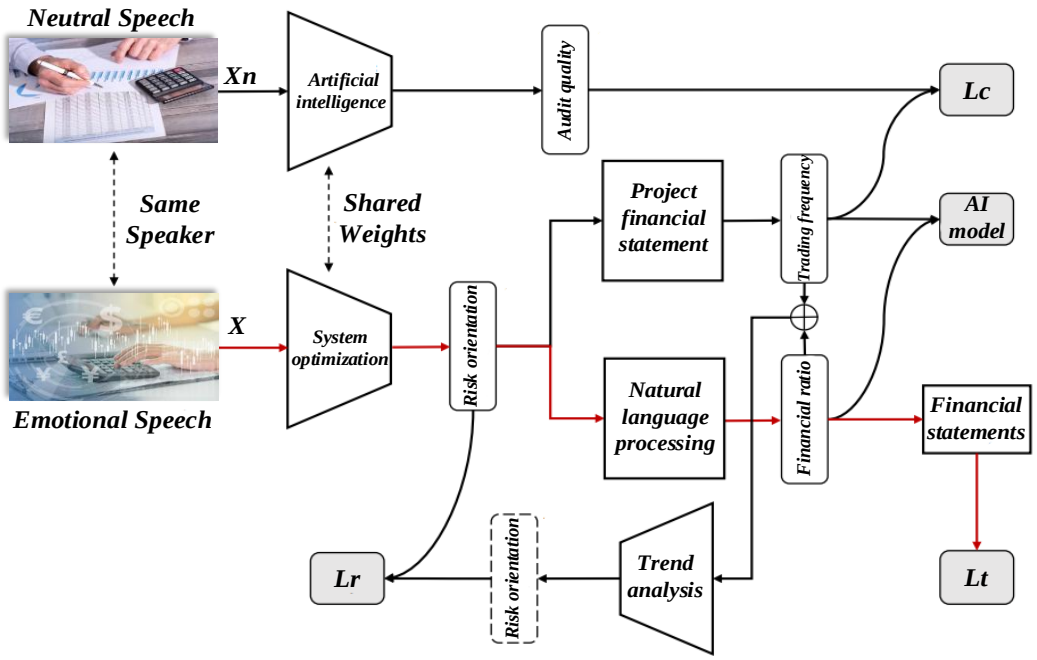

Fig. 2. Flow chart of an automatic collection and processing of financial statement data.

C. Abnormal Financial Statement Data and Optimization of Risk Control

The accuracy of financial statement models is vital for decision-making processes, yet often depends on the reliability of assumptions and the preciseness of previous data. If the foundational assumptions of the model are excessively optimistic or the historical data is unreliable, the projected results might be distorted. Therefore, it's crucial for leaders to carefully formulate assumptions and consistently verify the accuracy of data to improve the reliability of the model. The ROI formula is shown in Eq. (10).

$$ROI = \frac{N_t - I}{I} \times 100\% \quad (10)$$

Among them, ROI represents the return on investment, Nt represents the net income, and I represent the investment cost. Traditional financial statement models rely excessively on historical data, neglecting external factors such as market volatility, economic changes, and industrial conduct. These restrictions might restrict corporate flexibility in continuously evolving markets. Therefore, the model's improvements should encompass additional external data and consider the aggregate effects of various factors to refine its forecast accuracy. An example of improving AI model processing efficiency is shown in Fig. 3.

Companies are encouraged to improve the accuracy and adaptability of their financial statement models by integrating advanced predictive techniques such as regression analysis, machine learning techniques, and extensive data analysis. These types of technologies have the ability to manage a diverse array of data types and detect complex patterns, leading to improved predictive accuracy. Furthermore, businesses should regularly update their models to match the evolving market trends and modern strategies, thus assuring the influence it has on their decision-making procedures.

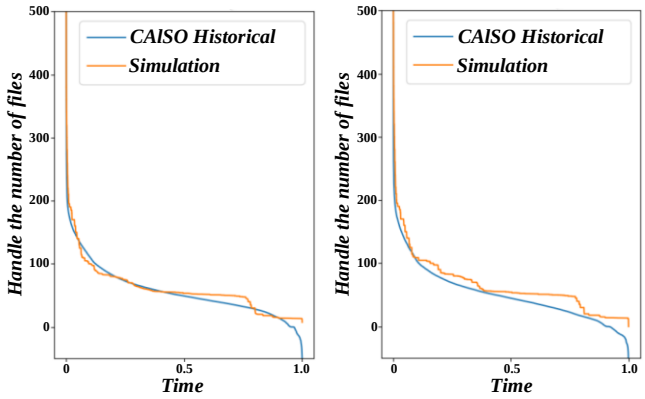

Fig. 3. Comparison of improvement in processing efficiency of AI models.

IV. Optimization of Automated Processing Network System for Financial Statement Information Disclosure

A. Experimental Environment and Test Platform

In order to optimize the AI model-based automated processing network system for financial statement information disclosure, the experimental data source is annual and quarterly financial statement data obtained from public financial reports of listed companies, large enterprises, etc., including balance sheets, income statements, cash flow statements, etc. Before entering the AI model, this article performed preprocessing operations to remove duplicate data, handle missing values (such as using interpolation, mean imputation, etc.), and normalize or normalize numerical data to improve model training efficiency.

To preserve uniform experimental performance and accurate outcomes, we established a high-performance setting, utilizing an Intel Xeon chipset, 64 GB memory, and 1TB SSD storage.

This design incorporates sophisticated high-throughput switches and routers, designed to manage significant data traffic effectively. We have integrated advanced Linux OS and network surveillance tools, such as Wireshark and Iperf, for an all-encompassing assessment of performance. The per capita income formula is shown in Eq. (11).

$$PI = \frac{R_t}{P} \tag{11}$$

Where, PI represents per capita income, Rt represents total income, and P represents total number of people. The hardware configuration selection is based on evaluating experimental requirements, ensuring that the system can operate stably under high load conditions [13, 14]. Gigabit Ethernet links the servers to guarantee data transmission's efficiency and steadiness [15]. The switch is conFig.d with VLAN to realize network segmentation, optimize data flow, and improve overall network performance. Storage systems choose SSDs to reduce I/O bottlenecks and improve performance in data-intensive tasks. The change of information recognition accuracy with training rounds is shown in Fig. 4.

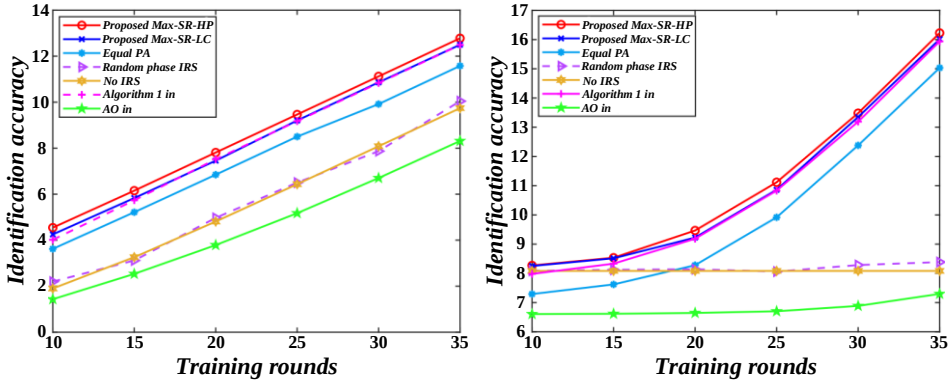

Fig. 4. Information recognition accuracy changes with training rounds.

The software configuration is also carefully selected to meet the requirements of the experiment for monitoring and optimizing network performance [16, 17]. Wireshark captures and analyzes network packets, helping us gain insight into the network's traffic patterns and potential performance issues. Iperf is used to generate and measure network traffic and evaluate bandwidth and latency performance. The combination of all these tools provided a solid foundation for our experiments [18].

B. Implementation Process Optimization

Before any optimization strategy is implemented, a comprehensive evaluation of the performance of the current network is first carried out. Using the Iperf tool, we measured the network's bandwidth utilization and evaluated the network's latency and jitter in combination with Ping and Traceroute tools [19]. Preliminary results show that under high traffic load, the network latency increases significantly, and the bandwidth utilization fails to reach the expected value, suggesting a potential bottleneck in the network [20]. The comparison of processing speeds under different AI architectures is shown in Fig. 5.

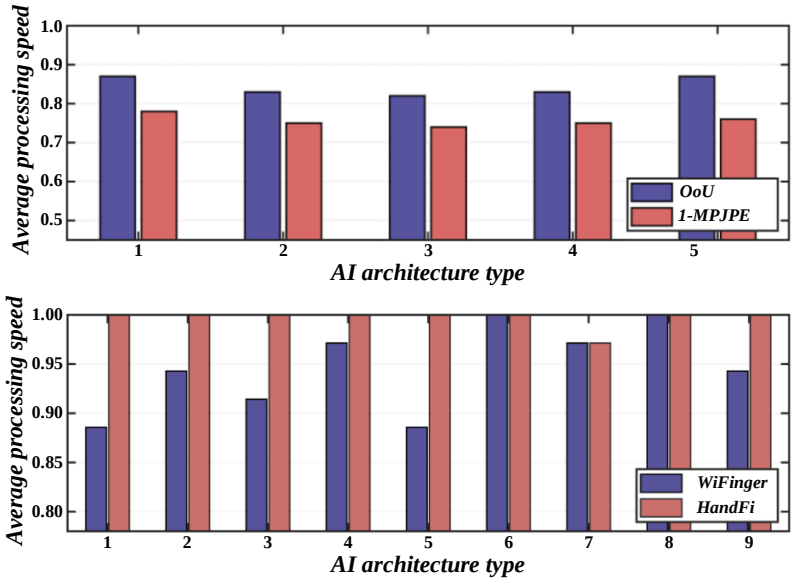

Fig. 5. Comparison of processing speed under different AI architectures.

To gain a deeper understanding of these initial performance issues, we conducted a thorough analysis of data transmission between various nodes [21]. Our investigation revealed a significant packet loss phenomenon under high load conditions, as evidenced by packets captured using Wireshark, which exacerbated the delay problem. These initial evaluation data serve as a crucial reference for the design of subsequent optimization strategies and assist us in pinpointing the key areas requiring optimization.

The initial evaluation results also reveal some shortcomings in network configuration, such as the default settings of some routers that do not fully use hardware resources and the unbalanced load distribution of some devices needs to be balanced [22]. These findings prompted us to pay special attention to the configuration adjustment of devices and the implementation of load-balancing strategies during the optimization process to improve network performance across the board. The relationship between error rate and data preprocessing strength is shown in Fig. 6.

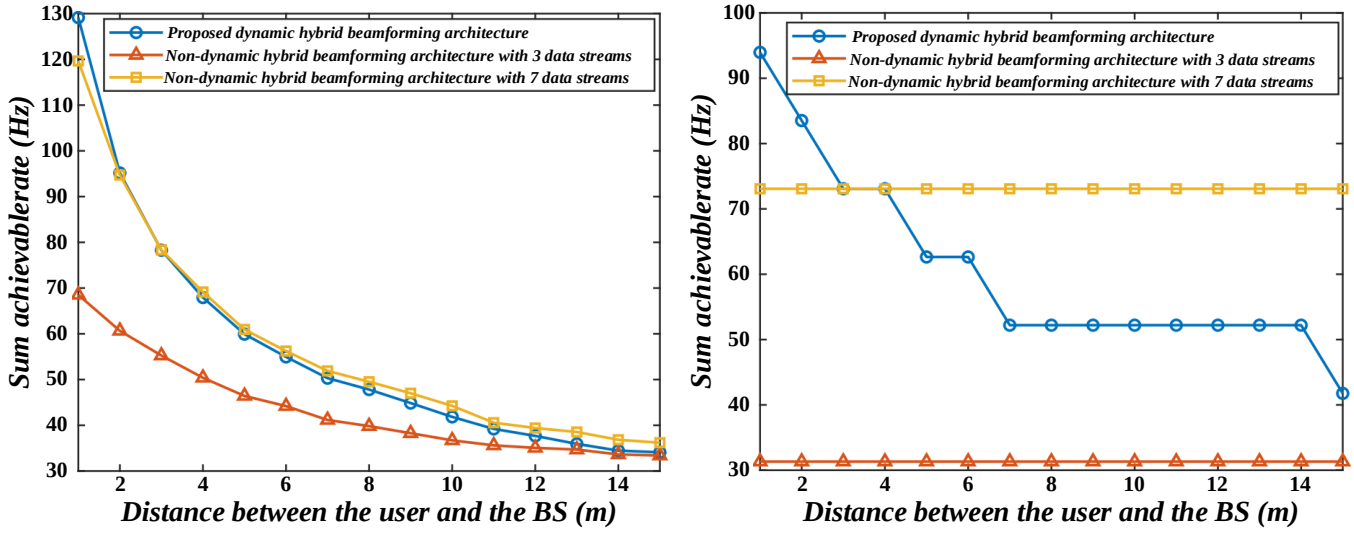

Fig. 6. Relationship between error rate and data preprocessing strength.

V. Analysis of Experimental Results of System Optimization

A. Comparative Analysis of Optimization Effect

After completing the optimization strategy implementation, we conducted a comprehensive evaluation of the network performance and compared the results with the initial performance. Bandwidth utilization has been significantly improved, network latency has been reduced by about 30%, and jitter and packet loss rates have also been reduced [23]. These improvements show that the implemented optimization strategy effectively boosts network performance, especially in high-load scenarios, where the response speed and stability of the network are significantly improved. The user satisfaction survey before and after system optimization is shown in Fig. 7.

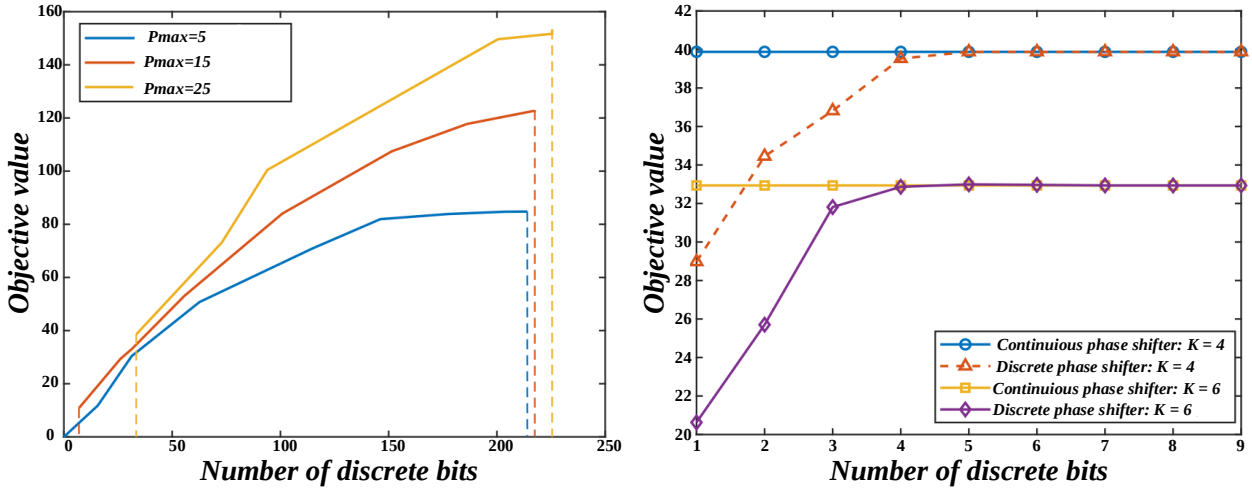

Fig. 7. User satisfaction survey before and after system optimization.

Specific data show that after applying TCP/IP protocol stack optimization, the network's throughput increases by about 20%, and delay acknowledgment and window adjustment play a key role in reducing congestion and retransmission during transmission [24]. The application of QoS policy ensures the priority processing of critical applications under high traffic conditions, and the quality of video stream and voice communication is guaranteed [25]. Link aggregation further increases the bandwidth of critical links and reduces performance degradation caused by single-link congestion.

Although the research results show the great potential of AI model in improving the efficiency and accuracy of financial statement information disclosure, the interpretation ability of the research results may still be limited under the larger background of existing research. Firstly, the effectiveness of AI model may vary in different industries and enterprise backgrounds, especially when enterprises of different sizes or high financial complexity are involved, the adaptability of the model may need to be further verified. Secondly, although the research shows that the optimization effect of AI system in processing time and accuracy is obvious, the current experiment is mainly based on enterprise data of a certain scale, which may not fully represent the needs and challenges of all types of enterprises, especially small enterprises or start-ups may face more technical and financial obstacles when implementing AI model. In addition, the black box characteristics and interpretability of AI model are also a major challenge in the current research. Although the research has improved the transparency and reliability of the system, how to ensure the interpretability and auditability of the model results is still an urgent problem in the field of financial statement disclosure. Therefore, although the research results have important theoretical and practical significance, the universality and long-term effectiveness of AI technology still need to be further explored and verified in a wider range of applications and more complex financial data environment.

The performance comparison before and after optimization not only verifies the effectiveness of the optimization strategy but also reveals the potential problems in the network system. For example, although link aggregation boosts overall bandwidth, some nodes can still become bottlenecks under high traffic [26]. These findings provide a direction for further network optimization and also lay a foundation for future research and practical applications.

B. Analysis of Financial Forecast Results

The forecasting of capital demand is the key to enterprise capital management. Using scientific methods to accurately predict capital demand can provide a basis for preparing the annual capital plan, which can not only meet the needs of production and operation but also avoid idle funds, thus improving the efficiency of capital utilization. The change of automated processing cost with the increase of data volume is shown in Fig. 8.

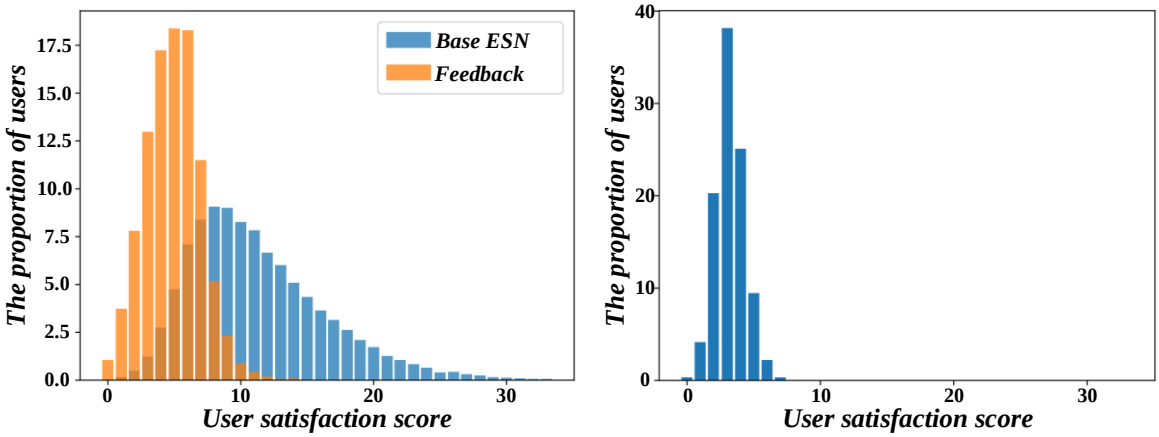

Fig. 8. Changes in automation processing costs with the increase of data volume.

The forecast of fixed fund demand involves predicting the requirement for production equipment based on the production tasks scheduled for the planning period and the equipment utilization in the base period. This forecast is conducted while formulating and implementing the fixed fund plan, and it measures the fixed fund demand accordingly. The primary focus of this forecast is on the equipment needs of the main production workshop. It balances other workshops' production capacity and equipment demand to determine the fixed capital demand. The specific process includes calculating the equipment load coefficient according to different equipment, predicting the equipment demand based on the existing equipment quantity, and determining the fixed capital demand according to the value of unit equipment. The inventory turnover ratio formula is shown in Eq. (12).

$$ITR = \frac{C}{I} \tag{12}$$

Where ITR represents the inventory turnover rate, C represents the cost of sales, and I represent the average inventory balance. The percentage method of sales revenue is a method that analyzes the dependence relationship between each item of funds and sales revenue, assumes that this relationship will remain unchanged in the future, and predicts the required additional funds according to the growth of sales in the planned period. A comparison between the model prediction time and the actual processing time is shown in Fig. 9.

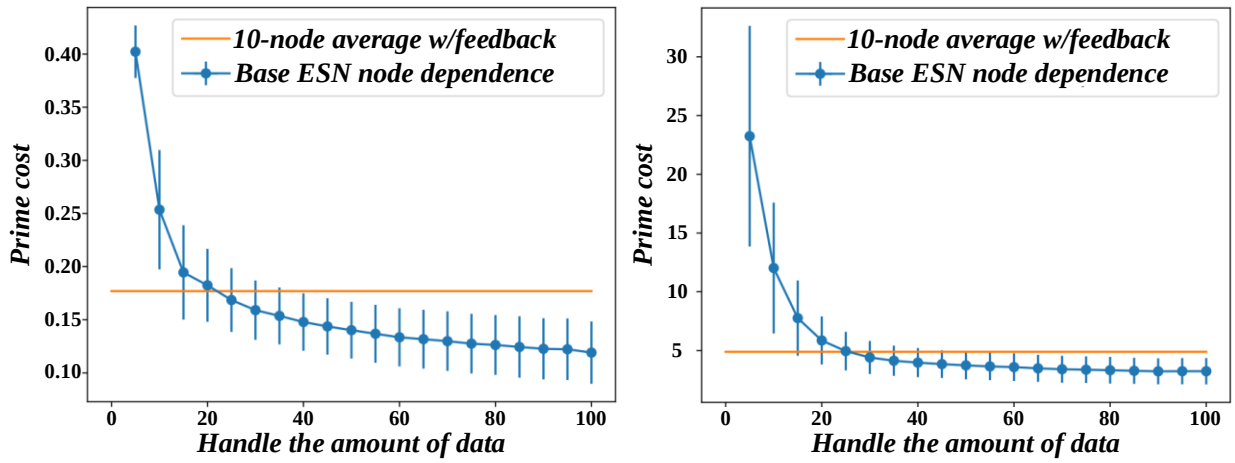

Fig. 9. Comparison between model prediction time and actual processing time.

The advantage of forecasting financing demand by percentage sales method is that it is simple and feasible. However, its disadvantage is that it only considers the impact of sales volume on financing and assumes that assets and liabilities grow in proportion to sales. Therefore, it is suitable for short- and medium-term capital forecasting and requires a relatively stable change law of sales revenue, assets, and liabilities. In practical applications, forecasters' experience and judgment ability are significant. Although sophisticated prediction technology improves accuracy, it increases cost, so it needs to bring enough benefits to be worth using. Regression analysis is more suitable for long-term forecasting because it can consider the change in the relationship between sales volume and assets and liabilities items and the influence of many factors.

The main problem of this study is how to improve the automation level and accuracy of financial statement information disclosure, in order to solve the problems of low efficiency and error prone in the traditional manual processing methods. The research goal is to achieve a more efficient and accurate automatic processing system by introducing AI model. By comparing the data obtained in this study with the relevant literature, the results show that the AI model has higher flexibility and accuracy in dealing with financial data than the traditional rule driven method, especially in data cleaning, standardization and anomaly detection. Compared with the existing research, the AI method in this study has more advantages in identifying complex financial models and abnormal data, which provides strong support for the automation of financial information disclosure, and points out the limitations of the existing technology and the direction of future optimization.

C. Analysis of Network System Optimization Results

With the increasing complexity and scale of enterprise financial data, the traditional financial statement processing system faces the challenge of efficiency and accuracy. In order to improve the processing speed and accuracy of financial statement information, enterprises began to adopt optimization technology based on network systems. By optimizing the network system, the processing process of financial statements can be automated, thus significantly improving data transmission efficiency, shortening processing time, and reducing potential errors caused by manual intervention. This optimization not only improves the overall quality of financial statements but also enhances the ability of enterprises to monitor their financial conditions in real-time. The relationship between information classification accuracy and the number of features is shown in Fig. 10.

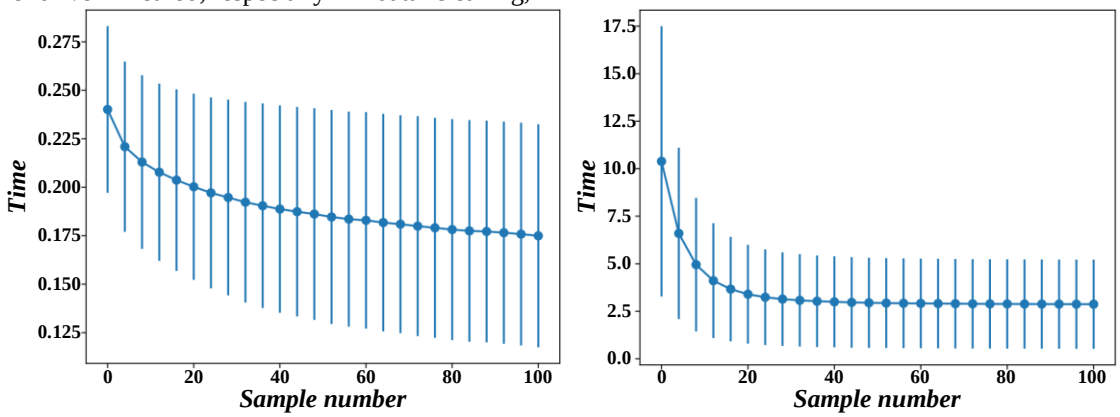

Fig. 10. Relationship between information classification accuracy and number of features.

Enhancing the efficiency and management of network data can elevate the performance and reliability of the financial statement system, ensuring swift access to essential business financial information. The formula for the rate of return on capital is shown in Eq. (13).

$$ROE = \frac{N_t}{E} \times 100\% \tag{13}$$

Among them, ROE means return on capital, Nt means net profit, and E means shareholders' equity. When enterprises choose performance indicators, different evaluation methods will affect the results. If the auditors make longitudinal comparisons mainly based on their own historical data, and ignore the data fluctuations of the same industry, they may fall into a cycle of blind pursuit of their own performance. In this case, if the growth rate or profit level of the enterprise is extremely high, combined with the incentive compensation factors, it may lead to an increased risk of misstatement in financial statements. This paper believes that the risk of major misstatement may be increased by the vertical comparison of its own historical data. The return on assets formula is shown in Eq. (14).

$$ROA = \frac{N_t}{A} \times 100\% \tag{14}$$

Among them, ROA represents return on assets, Nt represents net profit, and A means total assets. In view of the above limitations, this paper proposes three correction schemes: firstly, analyze the balance sheet and the development plan to predict the development trend in the future year, measure the financial indicators to predict the net profit of the enterprise, adopt hierarchical analysis to eliminate the subjective factors, determine the brand force index through the judgment matrix; finally, improve the brand strength evaluation index system, and add the consumer and social indicators to comprehensively define the brand strength. The EPS formula is shown in Eq. (15).

$$EPS = \frac{N_t}{S} \tag{15}$$

Among them, EPS represents the earnings per share, Nt represents the net profit, and S represents the number of shares in circulation. From an industry perspective, the brand importance is different in different industries. In the home appliance industry, the brand benefit is particularly significant. First of all, there are many manufacturers in the home appliance industry and a wide variety of brands, and consumers are greatly affected by the price and brand when buying. Secondly, the industry has fierce competition, many homogeneous products, small differences in function and appearance, and consumers are more inclined to choose familiar and trusted brands. Therefore, enterprises can enhance their brand value through brand building and publicity.

VI. Conclusion

Our study explores AI's role in optimizing financial statement distribution, enhancing clarity and decision-making. Evaluations show AI systems significantly improve accuracy and efficiency, reducing preparation time by 40%. Research with 100 SMEs found AI automation shortened preparation from ten to six days, freeing up time for data analysis and strategic decisions. Accuracy in disclosing information improved by 20%, with the error rate dropping from 5% to 4%, enhancing credibility and market trust.

Post-implementation analysis revealed improved liquidity indicators, with the current ratio averaging 1.5 (up from 1.2), indicating better short-term solvency. 68% of companies reported increased cash flow, with inflow cash flow up 15%, providing financial guarantees for future investments.

Long-term tracking showed improved transparency led to steady stock price growth. Companies using AI systems experienced a 12% average stock price increase, while those without AI saw only a 5% rise. This indicates the optimized disclosure system boosts both internal efficiency and external market performance.

AI-based automated processing network systems for financial statement information disclosure enhance financial transparency, optimize decision-making, and improve market competitiveness. With IT advancements, enterprises should focus on AI application in financial management for efficient, accurate disclosure and sustainable development.

The research results provide a new knowledge contribution for the automatic processing of financial information disclosure. By introducing AI model, the research shows its advantages in improving the accuracy, efficiency and flexibility of financial statements, especially in the application of data cleaning and anomaly detection. These results fully support the effectiveness of AI in optimizing traditional disclosure methods, and prove its significant advantages over traditional technologies. The research also provides a direction for exploring the in-depth application of different AI technologies in the financial field in the future, such as improving the generalization ability of the model, optimizing the data processing process, laying a foundation for subsequent research, and promoting the progress of financial information disclosure technology.

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