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Design and Application of an Intelligent Enterprise Financial Accounting System Based on Cloud Computing

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Abstract With the widespread application of cloud computing technology, the security of financial accounting information systems has increasingly come under scrutiny. This study explores the construction of an accounting information management cloud platform based on cloud computing. By analyzing the basic operational mechanisms of online accounting cloud platforms, it designs a DaaS process for the financial early warning module, providing a technical foundation for the operation of the financial crisis early warning module. Subsequently, a financial early warning model for enterprises based on a hybrid LSTM-GRU structure is proposed. Using M Company's financial data from 2019 to 2024 as the research sample, a set of 24 potential financial indicators is established, covering five aspects: profitability, solvency, operational efficiency, cash flow capability, and growth potential. The research results show that incorporating Benford factors plays a certain role in improving the overall performance of the financial crisis early warning model. Additionally, the model enables more accurate and stable prediction results, with prediction accuracies of 95.74%, 94.83%, and 94.31% for T-1, T-2, and T-3 years, respectively, enabling accurate judgment of future corporate financial trends.

Index Terms neural network, financial warning, cloud computing, financial accounting information system

I. Introduction

Corporate financial accounting work is shaped by its historical context, reflecting the societal transformations and technological advancements of its time [1]. Over the past five years, the application of big data has revolutionized the workflows of the accounting industry. Big data processing technologies have been widely adopted across the sector, with accurate and efficient data processing techniques and backend algorithmic models significantly enhancing enterprises' comprehensive data processing capabilities [2]. The application of technologies such as big data and cloud computing enables the collection of vast amounts of data from both internal and external sources, expanding financial analysis—which was previously confined to the backend—to include frontend data collection. This achieves the goal of accurate and efficient accounting processing and forecasting. Mobile communication and internet technologies will inevitably realize the concept of a financial shared service center, breaking through spatial and temporal constraints to facilitate data exchange and information sharing across the entire platform. IoT technology digitizes physical assets, enabling interaction and collaboration between people and objects through sensors. Blockchain technology ensures the security and authenticity of accounting information data, among other benefits [3]. Under the backdrop of digitalization, informatization, and intelligence, enterprises can achieve significant improvements in data processing speed, maximize the utilization of data information value, establish a financial data sharing center, provide strong support for strategic decision-making and development, and enhance both internal and external competitive advantages through the intelligent transformation of basic financial accounting work [4]-[7].

With the development of IoT technology, cloud computing technology has emerged, offering advantages such as low cost, large storage capacity, and fast processing speed [8]. In the construction of intelligent financial accounting systems for enterprises, the use of cloud computing technology for the acquisition, clustering, and analysis of accounting big data not only overcomes the high cost issues of traditional accounting informationization models [9]-[11], but also significantly improves the efficiency of analyzing massive accounting big data, gradually unleashing the analytical value of accounting big data. This provides new insights for further developing and utilizing accounting big data, enhancing the relevance of accounting information, assisting managerial decision-making, and achieving low-cost accounting control for enterprises [12]-[14].

After more than 20 years of development, academic research in areas such as accounting informationization theory, policy, system design, internal control, and security has made significant progress and continues to deepen with the advancement of IT technology. Jiang, L studied the application of blockchain technology in enterprise financial accounting information systems, demonstrating its significant achievements in terms of efficiency, accuracy, and cost reduction [15]. Yu, W, and Hamam, H proposed a new enterprise financial management model centered on user information signal conversion, offering users a more streamlined, efficient, and intelligent financial management solution [16]. Rasid, S, et al. explored the interrelationship between financial accounting systems, enterprise risk management, and organizational performance, finding that enterprise risk management requires complex management accounting system information, and both are crucial components of decision-making and control [17].

To enhance the efficiency of accounting data utilization and assist corporate managers in making effective decisions, decision support systems have been integrated into accounting information systems to form accounting decision-making information systems. Kozlov, V., et al. focused on the application of financial decision support systems (DSS), detailing the architecture and components of DSS for financial accounting management, and emphasizing the critical role of DSS in managing financial conditions [18]. Bu, Y proposed a fuzzy decision support system (FDSS) for financial planning and management. This system significantly improves budget management, risk warning, investment decision-making efficiency, and financial health by utilizing fuzzy logic, neural networks, and genetic algorithms [19]. Bhayat, I et al. proposed a decision support model and tool aimed at selecting the optimal project portfolio based on risk tolerance and available funds to maximize financial returns and contributions to the mission [20].

Subsequently, artificial intelligence technology was introduced into the construction of accounting information systems to build intelligent accounting information systems. Tasatanattakool, P., et al. developed a digital transformation architecture framework focused on an intelligent financial management system integrated with artificial intelligence technology, aiming to improve operational efficiency and decision-making capabilities. The research results indicated that the system has high applicability and benefits, promoting organizational development and innovation [21]. Solikin, I., and Darmawan, D. explored the performance of artificial intelligence in accounting information systems. The results indicated that artificial intelligence significantly improved the effectiveness of accounting information systems, optimized audit processes, enhanced decision-making capabilities, reduced the workload of accounting personnel, and increased their work efficiency [22]. Artene, A, et al. explored the synergistic effects of artificial intelligence, digital transformation, and financial reporting systems, optimizing decision-making processes by revolutionizing traditional financial processes and enhancing financial analysis capabilities, thereby unlocking corporate value [23]. Marshall, T, and Lambert, S proposed a cognitive computing model based on artificial intelligence technology to support task automation in the accounting industry and explored the drivers and consequences of task automation [24].

With the generation of massive amounts of data and the sharing of information resources, traditional information technology could no longer handle such volumes, leading to the emergence of cloud computing technology. Fauzi, F., et al. studied the direct and indirect impacts of big data and cloud computing technologies on data processing in financial accounting systems. Their findings revealed that these technologies significantly improved data processing efficiency and promoted financial accounting management through efficient data processing [25]. Chanthinok, K, and Sangboon, K developed a financial accounting system based on cloud computing technology, which provides timely information and cost savings for small businesses, representing an improvement over traditional manual accounting systems and offering an alternative to expensive commercial software [26]. Ahmad, S., et al. investigated the application of cloud accounting information systems in Jordanian financial enterprises, identifying perceived utility, information quality, system quality, and service quality as key factors influencing adoption [27]. Given the numerous advantages of cloud computing technology, its use in financial accounting systems can significantly enhance the value of accounting data [28]. Many scholars have provided insights for constructing cloud-based accounting information systems; however, due to theoretical inadequacies, practical research progress has been slow.

This study focuses on establishing an accounting information management system based on cloud computing technology, proposing an enterprise financial early warning model based on an LSTM-GRU hybrid structure, training the financial early warning model, and inputting prediction samples into the trained model to verify its accuracy and robustness. The model fully leverages the advantages of LSTM and GRU, thereby enhancing its predictive capability and robustness. Twenty-four financial indicators across five major categories that influence corporate financial status were selected as initial variables. The financial data of Company M from 2019 to 2024 was analyzed, and a Benford factor was overlaid to provide technical support for corporate financial accounting through the application results.

II. Intelligent enterprise financial accounting system based on cloud computing

II. A. Application of Cloud Computing in Financial Accounting Information Systems

II. A. 1) Centralization of Data Storage and Processing

Through cloud computing technology, enterprises can centrally store financial data in cloud-based data centers, enabling unified management and maintenance of data. This centralized storage approach not only enhances data reliability and security but also facilitates real-time updates and sharing of data. For example, a large retail company adopted cloud computing technology to centrally store sales data from across the country in the cloud, enabling real-time aggregation and analysis of data. This not only improved the efficiency of sales data processing but also provided timely and accurate data support for business decision-making.

Amazon Web Services (AWS) offers powerful cloud computing services to many businesses, including the storage and processing of financial accounting data. Through AWS, businesses can easily store financial data in the cloud and utilize AWS's various services for data analysis and processing. For example, a large multinational corporation uses AWS's S3 storage service to store its global financial accounting data and leverages EC2 computing services for data processing and analysis. This not only improves data processing efficiency but also reduces the company's IT costs.

II. A. 2) Optimization of Business Processes

The introduction of cloud computing technology has optimized financial accounting business processes. In traditional financial accounting processes, data entry, review, and bookkeeping require a significant amount of manpower and time. However, with cloud computing combined with artificial intelligence and other technologies, these processes can be automated and intelligentized, greatly improving work efficiency and accuracy. For example, through automated bookkeeping systems, enterprises can automatically enter and record financial data, reducing manual errors and tedious operations.

II. B. System Architecture Design

II. B. 1) System Cloud Architecture

This study is based on cloud technology to build an enterprise accounting information management system, which essentially involves the cloudification of information management systems. Combining the inherent characteristics of various information management software on the cloud platform with the results of the analysis of the development requirements for accounting information management systems, this study deploys a multi-level, multi-application architecture, as shown in Figure 1.

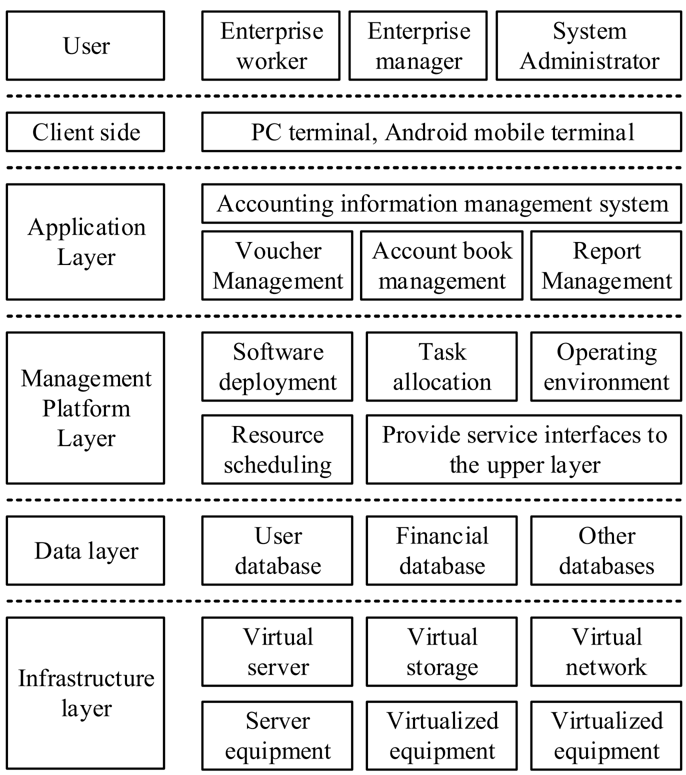

Figure 1: System cloud platform architecture

As shown in Figure 1, the architecture of the accounting information management system comprises four layers: the infrastructure layer, the data layer, the management platform layer, and the application layer. System users access the system via computers or mobile devices to utilize its functionalities. Users are primarily categorized into three groups: enterprise staff, enterprise management, and system administrators, with the latter holding the highest system privileges. The infrastructure layer provides the components and equipment necessary for the system's operation. the data layer provides data resource support for the operation of the accounting information management system; the management platform layer can be understood as the maintenance center for the accounting information management system; and the application layer can be understood as the service provider for the accounting information management system. This section provides a detailed introduction to the functional scope of the data layer, management platform layer, and application layer.

II. B. 2) System Physical Architecture

The physical architecture of the accounting information management system is shown in Figure 2. It can be seen that the system port devices include the master control platform and client terminals. The master control platform connects to the system through a virtual private network. Client terminals are divided into two types, namely PC terminals and Android terminals, which connect to the system through Ethernet. The system uses Web Services to achieve data transmission and communication between servers, enabling rapid response and providing users with an excellent experience. In addition, since permissions are set to allow only administrators to access the database server, the security of system data can be effectively guaranteed to a large extent.

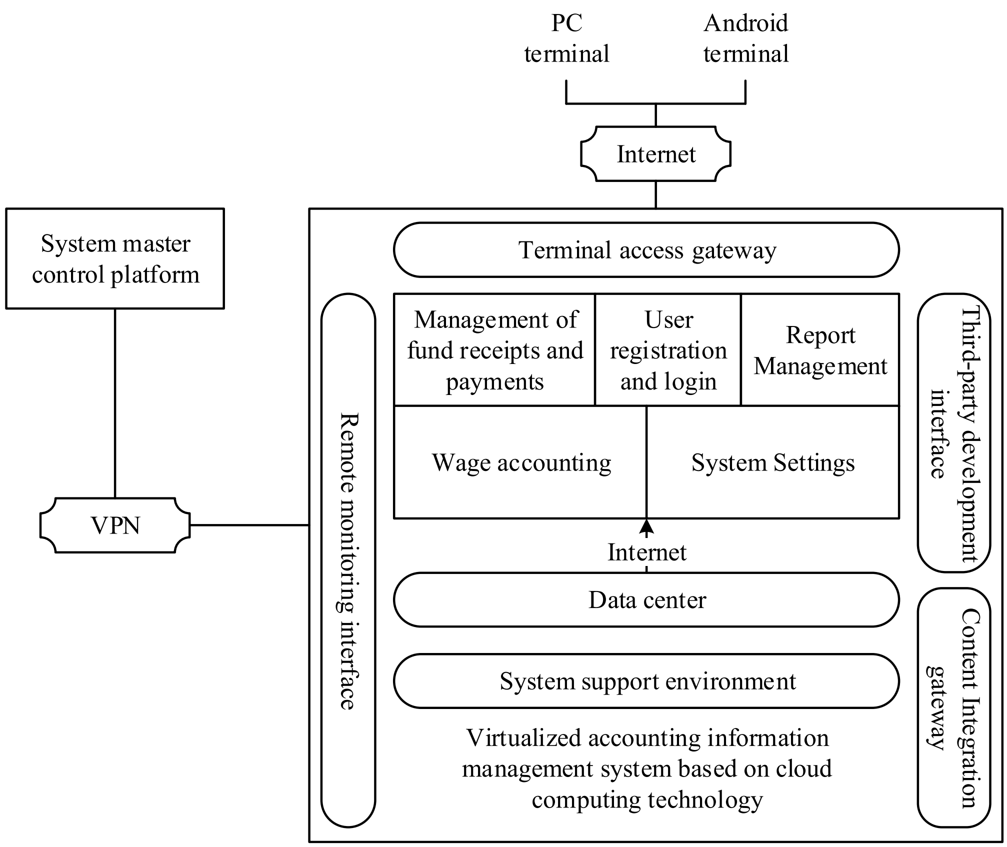

Figure 2: System physical architecture diagram

II. B. 3) System Cloud Platform Architecture Implementation

(1) Data Sharing SaaS Model

To address the issue of data extraction efficiency in the system, a persistence layer was introduced. Its role is to leverage the mapping functionality of its internal ORM to accelerate read/write speeds. The ORM of the persistence layer is a critical component of the entire system, built upon the DAO architecture to process and manage data, serving as an interaction hub between the business logic layer and the database layer. By leveraging the persistence layer, the system analyzes incoming and outgoing data during enterprise accounting information processing, optimizes processing workflows, and handles redundant or unnecessary data transmission, thereby significantly enhancing overall data interaction efficiency.

ORM, as the core component of the persistence layer, accesses and retrieves data from the database based on mapping principles. Its data read/write process differs from using SQL statements to perform data read/write functions, significantly improving data read/write speeds while simplifying the data retrieval process. This has greatly improved the overall system's operational efficiency.

(2) System Cloud Storage Solution

On an established cloud platform, enterprises can adopt distributed storage for massive financial data and documents. Traditional accounting information systems typically use centralized storage servers to store all financial data, which cannot meet large-scale storage requirements and only allow extraction of local data, providing services and operations only to local users. This results in regional and limited system data utilization, significantly reducing user satisfaction. Distributed storage breaks through geographical restrictions, enabling user location-based storage. Financial data from different branches can be stored according to geographical location, thereby improving system storage efficiency while enhancing system security performance and operational effectiveness.

II. C. DaaS Process Design for Financial Early Warning Module

II. C. 1) Process Design

There are many ways to connect to a database. The DaaS design in this article provides two methods for accessing the database: JDBC direct connection and object access. JDBC has three main functions: establishing a connection with the database, sending and executing database statements, and processing results. The management system establishes a connection pool for the application, and the financial early warning model can access the connection pool to obtain data.

(1) The specific process for the DaaS direct connection access method is as follows:

a) The DaaS client establishes the corresponding connection pool based on the database information provided by the management system.

b) After receiving the operation request from the financial early warning model, DaaS performs route selection and obtains the connection via JDBC to execute data operations in the corresponding database.

c) DaaS merges the operation results from the backend database cluster and returns them to the application.

(2) The specific process for the object access method is as follows:

a) DaaS establishes a connection pool connected to the database cluster during initialization.

b) The application initiates a request, undergoes authentication, performs OR conversion, maps to the corresponding operation, selects a route, and selects the database and corresponding connection.

c) DaaS executes data access via the JDBC interface, performs OR conversion on the returned results, and then returns the results to the application.

II. C. 2) Component Design

The main components of DaaS and their functional definitions are as follows: The data access component provides data access services and is responsible for user access authentication. The persistence component participates in routing distribution and is primarily responsible for model mapping and conversion. The database sharding component is primarily responsible for routing distribution and conversion. The database cluster module provides support for routing distribution and conversion, as well as data replication. The connection pool component provides an access interface for relational databases and has connection management capabilities.

The management component group includes a large number of components, primarily the runtime monitoring component, management agent component, logical database management component, and routing and model mapping management component. The runtime monitoring component is responsible for collecting, analyzing, and presenting status metrics for physical databases, clusters, DaaS services, and other components; the management agent component is responsible for management tasks required by the PaaS platform; The logical database management component is responsible for maintaining application subscription relationships; the routing and model mapping management component is primarily responsible for configuring and managing routing and OR information.

Through an analysis of the DaaS construction scheme for the online accounting financial warning module, it was found that by leveraging existing mature technologies and implementing a reasonable architecture, a practical and flexible DaaS system can be built to support online accounting and achieve financial warning functionality, providing reliable data support services for financial warning analysis. Of course, such services still require validation through actual application.

III. Intelligent Early Warning Model for Corporate Financial Accounting

III. A. Recurrent Neural Networks

Financial risk warning is essentially a classification problem. The results of financial risk warning are generally divided into two categories: those with financial risks and those without financial risks. At its core, this is a classification problem, making it an ideal application scenario for neural networks. Therefore, using neural network methods for financial risk warning analysis is feasible.

Corporate financial data exhibits temporal continuity. For general neural networks, the datasets they process do not exhibit time-series characteristics. However, corporate financial data exhibits temporal continuity, with not only interdependencies between report items but also the influence of previous year's financial information on the following year, particularly ratio information such as year-over-year growth rates and growth rates compared to the beginning of the period, which are also important financial data. Therefore, it is necessary to incorporate time-series information into neural networks, and the emergence of recurrent neural networks (RNNs) was specifically designed to better handle sequence information.

Recurrent neural networks (RNNs) are a type of neural network in the field of neural networks where neurons within the same hidden layer are internally connected. This enables them to learn complex samples with time series characteristics [29]. The key feature of RNNs is their ability to handle sequence information. In general, neural networks process each set of feature values as independent input values, with no connection between the previous and subsequent inputs. However, in certain scenarios, there is a connection between the preceding and subsequent feature value inputs, necessitating a type of neural network that can better handle sequence information. This led to the development of RNNs. Its primary application is when the data in the samples contains sequential information. The self-connections between neurons in the same hidden layer of an RNN can store the memory of the previous input, making it a neural network model for sequential data.

The learning process of neural networks is similar to the Logistic method, both using gradient descent to minimize the loss function and obtain the optimal parameters. However, the learning process of recurrent neural networks differs from the Logistic learning process due to the inclusion of time series. The learning process of recurrent neural networks is as follows:

Assuming that the loss function is E, at time t, the partial derivative of net_t can be obtained as follows:

$$\frac{\partial E_t}{\partial net_t} = \frac{\partial E_t}{\partial o_t}\frac{\partial o_t}{\partial net_t} \tag{1}$$

First, take the partial derivative of V. The error at each time t is related to the error at the current time, so

$$\frac{\partial E_t}{\partial V} = \frac{\partial E_t}{\partial net_t}\frac{\partial net_t}{\partial V} = \frac{\partial E_t}{\partial net_t}s_t \tag{2}$$

Secondly, take the partial derivative of W. For a training sample, the sum of the error values at all time points is the overall error value of the sample, because the partial derivative of W at time t can be obtained as follows:

$$\frac{\partial E_t}{\partial W} = \frac{\partial E_t}{\partial net_t}\frac{\partial net_t}{\partial s_t}\frac{\partial s_t}{\partial W} \tag{3}$$

As mentioned above, the value of s_t actually depends on the previous moment, because of $s_t = \sigma(Ux_t + W\sigma(Ux_{t-1} + Ws_{t-2}))$, so we need to continuously calculate the partial derivative of s_t at a certain moment until it propagates to t=0:

$$\frac{\partial E_t}{\partial W} = \sum_{k=0}^{k=t}\frac{\partial E_t}{\partial net_t}\frac{\partial net_t}{\partial s_t}\frac{\partial s_t}{\partial s_k}\frac{\partial s_k}{\partial W} \tag{4}$$

Finally, differentiate with respect to U:

$$\frac{\partial E}{\partial U} = \frac{\partial E}{\partial h_t}\frac{\partial h_t}{\partial U} = \frac{\partial E}{\partial U}x_t \tag{5}$$

III. B. Benford's factor

III. B. 1) Benford's Law

Benford's Law states that any natural data that has not been deliberately designed by humans has a certain pattern in the distribution of its first digits [30]. That is, the probability distribution of the digits 1 to 9 is monotonically decreasing. The mathematical formula for Benford's Law is as follows. Let d = 1, 2, 3, ···, 9, and the probability of the first digit D being d is:

$$f_{B.d} = \log_{10}(1 + \frac{1}{d}) \tag{6}$$

In a set of data, count the frequency of the first digit of each sample. If the above formula is satisfied, it indicates that the data quality is good. The general method for determining whether the distribution law of the first digit satisfies Benford's law is the χ^2 goodness-of-fit test, as shown in the following formula:

$$\chi^2 = N\sum_{d=1}^{9}\left[\frac{(f_d - f_{B,d})^2}{f_{B,d}}\right] \tag{7}$$

In formula (7), N is the sample size, f_d is the observed frequency of d, and $f_{B,d}$ is Benford's law. If the value of χ^2 exceeds the significant threshold of 10%, the original hypothesis is rejected, and the frequency of the first digit of the financial data is considered inconsistent with Benford's law. However, this method can only evaluate the overall quality of the data set, but cannot locate a specific sample point.

III. B. 2) Methods for constructing data quality factors

Assume that $X_i(i=1,2,3,...n)$ is variable data with quality issues that does not comply with Benford's law, let the difference between the observed frequency f_d of the first digit d of X_i and the theoretical frequency $f_{B,d}$ of Benford's law be e_d^i :

$$e_d^i = f_d^i - f_{B,d}^i, i=1,2,...n \tag{8}$$

Since the sum of the frequencies of the two distributions is 1, the constraints $\sum_{d=1}^{9} f_d^i$ and $\sum_{d=1}^{9} f_{B,d}^i = 1$ are satisfied.

Based on the principle of significance testing under Benford's Law, if the observed frequency of a leading digit of the indicator $X_i(i=1,2,3,...n)$ differs significantly from the theoretical frequency, there is a high likelihood of fraudulent activity, and such activity often exhibits a certain bias, manifesting as the observed frequency of the leading digit being significantly higher than the theoretical frequency. Therefore, this paper defines the largest leading digit with an observed frequency higher than the theoretical frequency as the risk value. Let the first digit with the largest positive difference be u_i and the first digit with the smallest negative difference be n_i, with the following formula:

$$u_i = \arg\max e_d^i, i=1,2,3,...n \tag{9}$$

$$n_i = \arg\min e_d^i, i=1,2,3,...n \tag{10}$$

Considering the positive and negative values of the differences, there are two ways to construct the Benford quality factor for the two indicators $X_i(i=1,2,3,...n)$. These are denoted as C_s^i and C_s, as shown in formulas (11) and (12):

$$C_s^i = \begin{cases} 1, X_{i,s}\text{The first digit is } u_i \\ 0, \text{other} \end{cases} \tag{11}$$

$$C_s = \begin{cases} 1, X_{i,s}\text{The first digit is } n_i \\ 0, \text{other} \end{cases} \tag{12}$$

In Equations (11) and (12), if the first digit of the indicator $X_{i,s}$ of the observed sample point S satisfies u_i, then C_s^i takes the value 1, otherwise it takes the value 0. The same applies to C_s.

III. C. Model Construction

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are both widely used deep learning models in sequence data modeling and prediction. Unlike traditional Recurrent Neural Networks (RNN), LSTM employs more advanced memory units and gating mechanisms, while GRU is a simplified version of LSTM. Both LSTM and GRU optimize prediction results by minimizing the loss function and learn to adapt to the patterns and rules of sequence data based on the characteristics of the training data.

The parameters of the LSTM model are trained using the backpropagation algorithm and gradient descent. The model optimizes prediction results by minimizing the loss function and learns to adapt to the patterns and rules of sequential data based on the characteristics of the training data.

The computational process of each LSTM unit can be described by the following formula:

Input gate value:

$$i = \sigma(x_t W_x^{(i)} + h_{t-1} W_h^{(i)} + b^{(i)}) \tag{13}$$

The value of the Forgetfulness Gate:

$$f = \sigma(x_t W_x^{(f)} + h_{t-1} W_h^{(f)} + b^{(f)}) \tag{14}$$

Memory unit update:

$$c_t = f^* c_{t-1} + g^* i \tag{15}$$

$$g = \tanh(x_t W_x^{(g)} + h_{t-1} W_h^{(g)} + b^{(g)}) \tag{16}$$

Output door value:

$$o = \sigma(x_t W_x^{(o)} + h_{t-1} W_h^{(o)} + b^{(o)}) \tag{17}$$

Hidden status:

$$h_t = o \cdot \tanh(c_t) \tag{18}$$

GRU does not have memory units; it only has a hidden state that propagates temporally. The structure of GRU includes several key elements: the update gate, the reset gate, and the hidden state.

The LSTM-GRU hybrid structure is a hybrid recurrent neural network architecture that combines LSTM and GRU. The design draws inspiration from the unique features and advantages of LSTM and GRU. LSTM effectively controls the flow of information through its gating mechanism, enabling real-time memory updates. In contrast, GRU has a simpler structure, consisting of only two key gating units—the update gate and reset gate—reducing the number of parameters and computational complexity. Enterprise financial risk diagnosis data typically has a short time series but involves complex relationships and dependencies. By combining LSTM and GRU, the hybrid structure can fully leverage their respective memory units and gating mechanisms to better capture long-term dependencies in sequence data. Additionally, models can be selected based on the characteristics of enterprise financial data to meet specific requirements. The enterprise financial risk diagnosis model consists of a three-layer neural network, which flexibly adjusts the proportion and position of LSTM and GRU within the structure to learn financial features. Finally, the model outputs a binary classification prediction result for financial risk through a fully connected layer. The output result indicates whether the enterprise is facing potential financial risks. During the training and prediction process, a large amount of corporate financial data is first input to train the hybrid structure. Through the backpropagation algorithm and gradient descent optimizer, the weights and parameters of each layer are updated to continuously optimize the model's performance. After sufficient training, the model can extract key features from the input data and use them for financial risk diagnosis. Once the model is trained, the hybrid structure model can be used for prediction.

IV. Application of Intelligent Financial Accounting Systems in Enterprises

IV. A. Sample Data Collection

M Company is a manufacturing company based in Hubei Province. Established in November 2007, the company specializes in the production of automated mechanical equipment, focusing on research and development, design, manufacturing, and installation and commissioning of intelligent automated equipment systems. It relies on high-tech innovation, centers on independent R&D, and leverages unique management practices to provide customers with comprehensive products and services, including product design, project management, and technical support.

M Company has a registered capital of 613,928,715 yuan. In October 2013, M Company submitted its initial public offering (IPO) application to the Growth Enterprise Market (GEM). On December 27, 2013, M Company successfully listed on the Shenzhen Stock Exchange, issuing 87,530,000 shares. The total number of shares issued was 87.53 million, with 22.74 million shares issued in the initial public offering, accounting for 26.31% of the total share capital.

The annual financial statements of M Company for the past five years from 2020 to 2024 are shown in Table 1, while the balance sheet and cash flow statements are shown in Tables 2 and 3. As shown in Tables 1, 2, and 3, in 2023, M Company's main business revenue was 1.37 billion yuan, a decrease of 13.4% compared to the same period last year. At the same time, due to the reduction in investment scale, the company's operating performance and net profit both declined significantly.

Table 1: M Company's profit statement for 2020-2024

Year	2020	2021	2022	2023	2024
Total operating income (ten thousand yuan)	224809.84	294804.5	271558.88	137941.7	158215.6
Total operating cost (ten thousand yuan)	211279.44	284798.2	266724.98	174523.6	17647.31
Operating profit (ten thousand yuan)	12063.11	10907.23	5137.99	-9526.5	-51872.9
Total profit (ten thousand yuan)	12735.4	9422.17	5156.75	-127931	-57473.2
Income tax (ten thousand yuan)	1132.33	2886.75	2721.83	4186.23	-873.11
Net profit attributable to the parent company (ten thousand yuan)	10183.51	5301.46	1935.49	-149783	-57967

Table 2: M Company balance sheet 2020-2024

	Name	2020	2021	2022	2023	2024
Asset classes	Monetary funds (ten thousand yuan)	50334.21	49455.12	29461.3	18499.62	49391.43
	Current assets (ten thousand yuan)	274430.52	285038.8	276053.28	170964.3	164533
	Non-current assets (ten thousand yuan)	160870.42	169879.3	175878.08	128268.4	99324.2
	Total assets (ten thousand yuan)	436532.72	456316.3	453408.08	301105.8	265430.4
Liabilities	Current liabilities (ten thousand yuan)	265284.42	232810.5	226831.88	192721.1	214418.7
	Long-term borrowing (ten thousand yuan)	8142.48	3435.09	948.64	33825.98	33728.06
	Non-current liabilities (ten thousand yuan)	12480.89	57992.53	53440.54	77230.82	80655.42
	Total liabilities (ten thousand yuan)	278997.12	292201.2	281749.08	271825.1	296647.3
Shareholder equity	Paid-up capital (ten thousand yuan)	53272.56	53106.14	58369.62	57845.14	58145.14
	Undistributed profit (ten thousand yuan)	33300.46	38034.61	40380.3	-101273	-167215
	Owners' equity (ten thousand yuan)	156303.82	162716.9	170182.28	27407.51	-29783.4

Table 3: M Company's cash flow statement for 2020-2024

	2020	2021	2022	2023	2024
Net cash flow from operating activities (ten thousand yuan)	-8220.64	2045.43	10483.93	-2192.12	18211.29
Net cash flow generated by investment activities (ten thousand yuan)	-25638.47	-8620.48	-4584.85	2797.21	858.31
Net cash flow generated by financing activities (ten thousand yuan)	49430.12	-5919.64	-12902.55	-5652.8	16186.17

IV. B. Selection of Financial Accounting Prediction Characteristics

IV. B. 1) Initial variables

Feature selection is a crucial step in constructing a financial distress warning model, and it is essential to establish a quantitative financial indicator system. Previous scholars typically consider comprehensiveness, generality, sensitivity, measurability, and prior knowledge when selecting financial indicators. Building on this foundation, this paper initially selected 24 candidate financial indicators from the CSMAR database, covering five aspects: profitability, solvency, operational efficiency, cash flow capacity, and growth potential. The corresponding indicator names, types, and codes are shown in Table 4.

Table 4: Alternative indicators

Type	Number	Name of index
Profitability	S1	Total net profit margin
	S2	Return on assets
	S3	Pre-tax profit to total assets ratio
	S4	Operating margins
	S5	Cost to profit margin
Debt paying ability	S6	Current ratio
	S7	Quick ratio
	S8	Cash ratio
	S9	Asset-liability ratio
	S10	Interest protection multiple
Operation capacity	S11	Inventory turnover ratio
	S12	Average accounts receivable turnover ratio
	S13	Turnover of current assets
	S14	Turnover of total capital
	S15	Working capital turnover
	S16	Cash and cash equivalents turnover ratio
Cash flow capacity	S17	Net cash content of net profit
	S18	Net cash content of operating income operating index
	S19	Capital expenditure to depreciation and amortization ratio
	S20	Cash is a good ratio
Growth ability	S21	Total asset growth rate
	S22	Net profit growth rate
	S23	Increase rate of business revenue
	S24	Sustainable growth rate

IV. B. 2) Overlay Benford factor construction method

If a certain indicator x_j fails the χ^2 test, it indicates that there is a certain degree of data quality issue with that feature indicator, and there is a possibility that some samples have been financially manipulated or tampered with. And note:

$$r_N^j = | f_N^j - P_{B,N}^j |, j = 1, 2, ...d, N = 1, 2, ..., 9 \tag{19}$$

In equation (19), f_N^j is the frequency of the first digit being N in indicator x_j, $P_{B,N}^j$ is the theoretical probability of the first digit being N in indicator x_j, d is the total number of feature indicators, and r_N^j is the risk factor for the j th indicator x_j whose first digit is N.

Theoretically, if there is a possibility that the data of indicator x_j has been tampered with or modified, then the value of risk factor r_N^j will be larger. The larger the value of risk factor r_N^j, the greater the risk of modification for that indicator, and the more likely it is that the data of that indicator with the first digit being N has been beautified, and marked as follows:

$$r^j = \arg\max r_N^j, j = 1, 2, \ldots, d \tag{20}$$

$$B_{i,j} = \begin{cases} 1, \text{The first digit of the detailed data } x_{i,j} \text{ is } r^j \\ 0, \text{other} \end{cases} \tag{21}$$

In Equations (20) and (21), let $B_{i,j}$ denote the constructed Benford factor, and r^j denote the most significant risk digit of the j th indicator x_j, which is also the most significant risk factor. The maximum risk leading digit r^j refers to the leading digit most likely to be involved in fraud under the indicator x_j, which has the highest risk. To ensure the comparability of data across quarters, this paper constructs corresponding Benford factors for each indicator on a quarterly basis. The results of the chi-square goodness-of-fit test based on Benford's law are shown in Table 5.

As shown in Table 5, the characteristic indicators that passed the x^2 goodness-of-fit test are: total asset growth rate in the fourth quarter of 2023, cash adequacy ratio in the first quarter of 2024, sustainable growth rate in the third quarter of 2024, and cash adequacy ratio data. It can be concluded that the first digit of the indicator data in this quarter follows Benford's law distribution, and there is no reason to doubt the data quality, so no further processing is required.

Table 5: Chi-square goodness of fit test based on Benford's law

Metric	P values for the fourth quarter of 2023	P value for the first quarter of 2024	P value for the second quarter of 2024	P value for the third quarter of 2024
Current ratio	6.77E-58	1.51E-33	1.65E-53	3.253E-93
Quick ratio	2.24E-27	3.29E-32	1.39E-41	9.31E-61
Cash ratio	0.00049542	0.02187612	0.000591724	7.14E-01
Asset-liability ratio	2.27E-117	4.09E-89	7.89E-118	1.03E-237
Total asset growth rate	**0.231953022**	0.003851274	0.009719452	0.017571183
Sustainable growth rate	2.29E-02	3.83E-05	3.87E-06	**0.11831782**
Net cash content of net profit	1.01E-77	4.19E-115	2.62E-73	253E-89
Net cash content of operating income	3.15E-22	1.49E-25	2.82E-19	4.83E-11
Cash is a good ratio	0.000158752	**0.311085723**	0.029157103	**0.15782917**
Return on assets	6.15E-08	9.31E-11	3.05E-03	1.43E-07
Total net profit margin	4.29E-01	5.65E-11	7.67E-03	0.012378427
Pre-tax profit to total assets ratio	4.05E-13	2.69E-05	2.23E-09	0.00331189
Operating margins	8.41E-05	3.39E-05	4.11E-04	0.001489141
Cost to profit margin	0.001147853	1.35E-23	0.00226573	3.27E-01
Average accounts receivable turnover ratio	1.01E-24	7.26E-21	1.21E-26	3.01E-27
Inventory turnover ratio	1.15E-16	1.08E-28	3.85E-17	2.24E-06
Working capital turnover	1.95E-137	9.83E-114	9.62E-41	1.87E-228
Cash and cash equivalents turnover ratio	5.09E-12	1.57E-29	3.04E-13	6.53E-09
Turnover of current assets	3.24E-89	2.68E-94	1.41E-89	6.85E-85
Turnover of total capital	3.83E-157	3.51E-191	9.11E-151	3.29E-124

It is not difficult to see that most feature indicators fail the goodness-of-fit test based on the Benford's law distribution of

x^2, indicating that most feature indicator data are relatively scattered, and there may be instances of artificial data manipulation or fraud. It should be noted that feature indicators whose leading digits do not follow the Benford's law distribution do not necessarily indicate data fraud or manipulation; this may be influenced by factors such as limited sample data volume or data missing. However, it can be said that for feature indicators that do not follow the Benford's Law distribution, we have sufficient reason to question the authenticity of some of the sample data in these feature indicators. Therefore, it is necessary to construct Benford factors for feature indicators that do not conform to the Benford's Law distribution. This can also be understood as a possible marker of the data quality of the indicator, i.e., marking the sample data where the leading digit is the highest-risk leading digit in the indicator data. The maximum risk factor values and maximum risk leading digits for each indicator data under each year and quarter are shown in Tables 6 and 7.

For the fourth quarter of 2023 to the first quarter of 2024, corresponding maximum risk factors and maximum risk numbers were constructed for feature indicators that did not pass the χ^2 goodness-of-fit test. In Table 6, it was found that the number 1 accounted for a high proportion of the maximum risk numbers for each feature indicator, indicating that the data for indicators with the first digit as 1 may have been manipulated or fraudulent. For example, the current ratio had a maximum risk first digit of 1 in both quarters, with maximum risk factor values of 0.13659 and 0.13923, respectively. As shown in Table 7, the proportion of the digit 1 in the maximum risk numbers remains high, but the distribution of maximum risk numbers during this period is more balanced compared to the previous period.

Table 6: The Maximum Risk Factor from the Fourth Quarter of 2023 to the First Quarter of 2024

Metric	P value for the fourth quarter of 2023		P value for the first quarter of 2024	
	Maximum risk factor value	Maximum risk number	Maximum risk factor value	Maximum risk number
Current ratio	0.13659	1	0.13923	1
Quick ratio	0.07628	1	0.07478	1
Cash ratio	0.01296	3	0.01647	2
Asset-liability ratio	0.06861	4	0.06320	5
Total asset growth rate	0	0	0.01099	3
Sustainable growth rate	0.01248	6	0.02568	2
Net cash content of net profit	0.17895	1	0.21934	1
Net cash content of operating income	0.09476	1	0.08491	1
Cash is a good ratio	0.01597	1	0	0
Return on assets	0.00347	5	0.04409	4
Total net profit margin	0.00659	4	0.0308	3
Pre-tax profit to total assets ratio	0.01131	5	0.05268	1
Operating margins	0.04635	1	0.02505	1
Cost to profit margin	0.02379	1	0.04795	8
Average accounts receivable turnover ratio	0.04289	3	0.04134	2
Inventory turnover ratio	0.03322	3	0.04962	4
Working capital turnover	0.10503	9	0.12628	5
Cash and cash equivalents turnover ratio	0.00928	3	0.04848	7
Turnover of current assets	0.11587	1	0.12864	1
Turnover of total capital	0.06174	6	0.09615	6

Since all feature indicators for the residual rejection distribution fitting test require the establishment of corresponding Benford factors, this leads to an increase in feature dimension, similar to the data sparsity caused by one-hot encoding, and may even increase memory usage. For example, if Benford factors are constructed for each of the 24 feature metrics, this results in a 48-dimensional feature space, with each original feature metric accompanied by its corresponding Benford factor. To reduce memory usage and better reflect the data quality of each enterprise sample, this paper combines the constructed Benford factors.

$$B_i = \sum_{j=1}^{d} B_{i,j} \tag{22}$$

The stacked Benford factor B_i breaks through the landmark structure of the original Benford factor. This is because the original Benford factor only takes values of 0 or 1, while the stacked Benford factor adds together the Benford factors of indicators with problematic characteristics, resulting in values that can be any integer between [0,24]. The larger the value of the aggregated Benford factor B_i is, the more reason there is to suspect the data quality of the enterprise sample x_i; conversely, the smaller the value, the better the data quality of the enterprise sample x_i is.

Table 7: The Maximum Risk Factor from the Second Quarter to the Third Quarter of 2024

Metric	P value for the fourth quarter of 2024		P value for the third quarter of 2024	
	Maximum risk factor value	Maximum risk number	Maximum risk factor value	Maximum risk number
Current ratio	0.14488	1	0.19172	1
Quick ratio	0.08457	1	0.09457	1
Cash ratio	0.01987	3	0.02614	2
Asset-liability ratio	0.06378	5	0.09681	5
Total asset growth rate	0.07655	3	0.08329	5
Sustainable growth rate	0.00301	5	0.00524	7
Net cash content of net profit	0.02073	4	0	0
Net cash content of operating income	0.11885	3	0.20185	1
Cash is a good ratio	0.05602	1	0.05498	1
Return on assets	0.00301	5	0	0
Total net profit margin	0.00972	6	0.01762	5
Pre-tax profit to total assets ratio	0.00618	8	0.01008	3
Operating margins	0.02488	4	0.00933	5
Cost to profit margin	0.03669	1	0.00802	1
Average accounts receivable turnover ratio	0.03346	1	0.01026	7
Inventory turnover ratio	0.03927	3	0.04317	4
Working capital turnover	0.03501	2	0.0114	4
Cash and cash equivalents turnover ratio	0.08012	4	0.15108	8
Turnover of current assets	0.01867	7	0.01693	4
Turnover of total capital	0.10575	1	0.11391	1

IV. B. 3) Feature selection based on the Boruta algorithm

This paper uses the Boruta algorithm for feature selection, as previously introduced. Boruta is a feature selection algorithm based on random forests. In simple terms, features that consistently achieve high importance scores in a single random forest run are identified as important features. After multiple iterations using the Boruta algorithm, 13 important features were identified, as shown in Table 8. This table includes statistical information on the importance of each feature: the first column (MeanImp) represents the mean value of feature importance, the second column (MedianImp) represents the median value of feature importance, the third column (MinImp) represents the minimum value of the feature importance scores, the fourth column (MaxImp) represents the maximum value of the feature importance scores, the fifth column (NormHits) represents the percentage of random forest runs where the feature is more important than its most important shadow feature, and the last column (Decision) represents the decision made by the Boruta algorithm for the feature: important/non-important. "Confirmed" indicates that the feature is an important feature.

Table 8: Results of boruta feature selection

Index	MeanImp	MedianImp	MinImp	MaxImp	NormHits	Decision
S1	2.709	2.766	-0.141	4.34	0.711	Confirmed
S2	3.093	3.067	1.658	4.078	0.842	Confirmed
S3	2.884	2.914	1.256	3.834	0.691	Confirmed
S5	2.882	2.949	0.903	4.245	0.721	Confirmed
S7	2.783	2.836	0.959	4.047	0.701	Confirmed
S11	2.753	2.744	1.394	4.486	0.66	Confirmed
S14	5.499	5.513	3.981	7.626	1	Confirmed
S16	2.937	2.884	1.46	5.083	0.691	Confirmed
S20	2.784	2.773	0.064	3.955	0.721	Confirmed
S22	5.012	4.966	3.567	7.399	1	Confirmed
S24	4.911	4.926	3.25	6.937	1	Confirmed
S25	3.62	3.624	2.028	5.207	0.883	Confirmed

IV. C. Corporate Financial Accounting Evaluation and Analysis

IV. C. 1) Analysis of model training results

Figure 3 illustrates the accuracy of the training. The horizontal axis represents the number of iterations of the training samples, while the vertical axis denotes the training error rate. The red solid line represents the loss curve of the training samples, and the blue solid line represents the loss curve of the prediction samples. As can be seen from the figure, during training, as the number of iterations increases, the error values of the samples gradually decrease. Although there are local fluctuations within a small range, the overall trend is a gradual decrease. Additionally, at the beginning of training, the error rate changes rapidly, indicating that the model is continuously fine-tuning itself during training. After 400 iterations, the trend of error value reduction becomes more gradual, indicating that the model is gradually approaching the optimal process, ultimately stabilizing around 0.26, indicating that the model has good fitting performance.

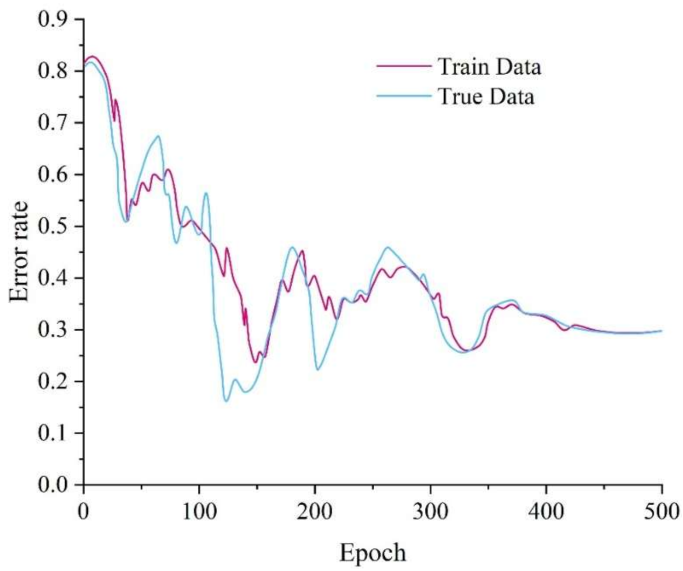

Figure 3: Training results figure

IV. C. 2) Corporate Financial Accounting Forecasts

In terms of model evaluation, this paper uses the root mean square error (RMSE) to evaluate the model. The principle of RMSE is as follows:

The range of RMSE is $[0, +\infty]$. If the error between the actual value and the predicted value increases, the RMSE value also increases. In this study, the RMSE of the LSTM-GRU financial warning identification model was calculated to be 30.2, indicating that the error between the actual value and the predicted value is small, and the model has a high degree of fit.

In terms of training results, this paper introduces prediction samples into the trained deep neural network model for financial prediction. To distinguish between financial health and financial distress, this paper adds a "status" column to the normalized data, where 0 indicates financial health and 1 indicates financial distress. When the output result is greater than 0.5, it is adjusted to 1; when it is less than 0.5, it is adjusted to 0. This is used to determine the company's financial status. The final results are shown in Table 9. As shown in the table, the closer to the predicted year, the higher the prediction accuracy. In the LSTM-GRU financial warning identification model prediction, using data from T-1 and T-2 years to predict the financial status of year T yields higher accuracy.

Table 9: Predictions results table

Predictive dimension	Year	Prediction accuracy
Single step dimension	T-1	95.74%
	T-2	94.83%
	T-3	94.31%

IV. D. Application Results and Analysis

(1) Collect data on 18 financial indicators for Company M for each year.

Collect data on Company M based on the indicators required to construct a financial crisis early warning model. The data collected is on 18 financial indicators for each year from 2019 to 2024, as shown in Table 10.

Table 10: Financial indicators of Company M from 2019 to 2024

Type	Name of index	2019	2020	2021	2022	2023	2024
Profitability	S1	3.66	4.07	3.31	1.29	0.39	−39.11
	S2	4.79	5.49	5.12	4.03	2.85	−35.2
	S4	11.43	5.98	5.4	2.03	0.75	−95.18
	S5	15.08	8.09	8.44	6.17	4.86	−87.22
Growth ability	S21	106.22	300.74	29.59	30.91	−8.25	−43.79
	S22	183.87	128.93	20.1	−18.01	−44.97	−1648.1
	S23	186.06	105.21	15.45	−43.85	−62.88	−6123.8
	S24	13.87	91.26	9.65	−49.77	−62.11	−34104.2
Operation capacity	S11	2.57	4.36	3.39	3.42	2.87	2.5
	S12	0.69	1.36	1.23	0.89	0.83	0.4
	S13	0.49	0.89	0.86	0.49	0.46	0.37
Debt paying ability	S6	30.48	54.76	64.28	63.97	62.12	88.27
	S7	56.08	60.64	63.24	62.41	60.87	56.48
	S8	44.28	39.8	37.3	37.25	38.85	41.84
	S9	9.68	8	7.73	10.88	11.51	13.29
Cash flow capacity	S18	82.92	84.01	79.18	99.16	106.8	137.57
	S19	−4.77	−1.49	−3.53	1.01	3.59	−1.05

(2) Standardize the financial indicator data for each year of Company M.

Financial indicators have different dimensions and units of measurement, which can affect the results of model analysis and prediction. Therefore, in order to unify the dimensions of the financial indicator data, this paper uses the Z-score standardization method to standardize the financial indicator data. The following formula shows how to calculate the mean and standard deviation of each financial indicator:

$$\overline{X}_j = \sum_{i=1}^{n} x_{ji} \tag{23}$$

$$S_j = \sqrt{\frac{\sum_{i=1}^{n}(x_{ji} - \overline{X}_j)^2}{n-1}} \tag{24}$$

In the above equation, $\overline{X}_j$ is the average value of the financial indicators for the j-year period, s_j is the standard deviation of the j-year data, x_{ji} is the value of the x_i th financial indicator data point in the j-year period, n is the number of financial indicators, which is 18, and j represents the year in which the financial indicator data was calculated.

Using the mean and standard deviation calculated from the financial indicator data for each year, the financial indicator data for each year is standardized. The specific standardization formula is as follows:

$$x_{ji}^* = \frac{x_{ji} - \overline{X}_j}{S_j}, (j \in [2014, 2019], i = 1, \cdots, 18) \tag{25}$$

In the above equation, x_{ji}^* is the standardized value of the i th financial indicator data for the j th year.

The results of standardizing M Company's annual financial indicator data using the above standardization formula are shown in Table 11.

(3) Analyzing M Company's data using the model

Using LSTM-GRU to analyze M Company's standardized financial indicator data for each year, the data in the table was input into the established financial crisis prediction model in two groups of five-year data sets: 2018–2023 and 2019–2024. The results are shown in Table 12. As shown in the table, the probability of M Company experiencing a financial crisis in 2026, predicted using the 2018–2023 data, is 94.79%, while the probability predicted using the 2019–2024 data is 96.85%. It can thus be concluded that the two LSTM models established using the five-year data from 2018 to 2023 and the five-year data from 2019 to 2024 can both accurately predict that Company M is highly likely to experience a financial crisis in 2026.

Similarly, the closer the time to the possible occurrence of a financial crisis, the higher the probability of a financial crisis predicted by the established LSTM model.

Table 11: Standardization results of financial indicators of Company M from 2019 to 2024

Type	Name of index	2019	2020	2021	2022	2023	2024
Profitability	S1	0.845	−0.516	−0.577	−0.134	−0.121	0.3638
	S2	−0.609	−0.496	−0.503	−0.156	−0.131	0.3642
	S4	−0.501	−0.489	−0.491	−0.313	−0.182	0.3571
	S5	−0.442	−0.46	−0.366	0.094	−0.081	0.3581
Growth ability	S21	1.04	3.583	0.507	0.704	−0.414	0.3637
	S22	2.303	1.209	0.115	−0.685	−1.306	0.1665
	S23	2.338	0.882	−0.077	−1.573	−1.346	−0.3953
	S24	−0.461	0.689	−0.316	−1.878	−1.427	−3.9842
Operation capacity	S11	−0.645	−0.512	−0.574	−0.174	−0.131	0.3689
	S12	−0.676	−0.553	−0.663	−0.195	−0.18	0.3687
	S13	−0.679	−0.56	−0.678	−0.157	−0.132	0.3687
Debt paying ability	S6	−0.191	0.185	1.937	1.639	1.326	0.3793
	S7	0.225	0.266	1.894	1.595	1.295	0.3754
	S8	0.033	−0.022	0.824	0.883	0.754	0.3737
	S9	−0.53	−0.462	−0.395	0.137	0.082	0.3704
Cash flow capacity	S18	0.661	0.589	2.551	2.935	2.424	0.3853
	S19	−0.765	−0.593	−0.859	−0.144	−0.113	0.3685

Table 12: Predict the probability of financial crisis in company M in 2026

Data set	Predict the probability of a financial crisis in 2026
2018-2023	94.79%
2019-2024	96.85%

V. Conclusion

This paper leverages cloud computing technology to establish a financial accounting information system and proposes an enterprise financial crisis early warning model based on a hybrid LSTM-GRU structure. Company M was selected as the data sample, and financial data from 2019 to 2014 over a consecutive five-year period was statistically analyzed. Based on the constructed financial indicators, predictions were made regarding the financial crisis situation of Company M. The results show that the financial early warning model, when applied to the construction of a financial crisis identification system, can achieve higher accuracy and stability in prediction results. The prediction accuracy of the model for years T-1, T-2, and T-3 is 95.74%, 94.83%, and 94.31%, respectively; After processing the financial indicator data published by Company M for the periods 2018–2023 and 2019–2024, the probability of a financial crisis occurring in 2026 was calculated to be 94.79% and 96.85%, respectively. Both sets of financial indicator data from different time periods predict a high probability of a financial crisis occurring in 2026.

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References

[1] Bhimani, A., & Willcocks, L. (2014). Digitisation,'Big Data'and the transformation of accounting information. Accounting and business research, 44(4), 469-490.

[2] Gao, J. (2022). Research on the corporate financial transformation with big data technologies. International Journal of Progressive Sciences and Technologies, 32(2), 08-12.

[3] Fang, B., Liu, X., Ma, C., & Zhuo, Y. (2023). Blockchain technology adoption and accounting information quality. Accounting & Finance, 63(4), 4125-4156.

[4] Liu, X. (2021, December). Transformation from Financial Accounting to Management Accounting in the Age of Artificial Intelligence. In International conference on Big Data Analytics for Cyber-Physical-Systems (pp. 1185-1195). Singapore: Springer Singapore.

[5] Zheng, M. (2022). Advanced artificial intelligence model for financial accounting transformation based on machine learning and enterprise unstructured text data. Mobile Information Systems, 2022(1), 5708652.

[6] Zhu, Y. (2023). The Digital Transformation of Enterprise Accounting: Big Data, AI and Financial Sharing. Advances in Economics, Management and Political Sciences, 31, 187-192.

[7] Chen, Y. (2021). Framework of the smart finance and accounting management model under the artificial intelligence perspective. Mobile Information Systems, 2021(1), 4295191.

[8] Al-Zoubi, A. M. (2017). The effect of cloud computing on elements of accounting information system. Global Journal of Management And Business Research, 17(3), 1-9.

[9] Sun, L. (2024). Management research of big data technology in financial decision-making of enterprise cloud accounting. Journal of Information & Knowledge Management, 23(01), 2350067.

[10] Huang, N. (2016, August). Discussion on the application of cloud accounting in enterprise accounting informatization. In 2016 International Conference on Economics, Social Science, Arts, Education and Management Engineering (pp. 136-139). Atlantis Press.

[11] Deng, Y. (2022). Optimising enterprise financial sharing process using cloud computing and big data approaches. International Journal of Grid and Utility Computing, 13(2-3), 272-281.

[12] Dai, Q. (2022). Designing an accounting information management system using big data and cloud technology. Scientific Programming, 2022(1), 7931328.

[13] Li, X. (2023). Data protection of accounting information based on big data and cloud computing. Scientific Programming, 2023(1), 8387441.

[14] Feng, J. (2015, December). Cloud accounting: The transition of accounting information model in the big data background. In 2015 International Conference on Intelligent Transportation, Big Data and Smart City (pp. 207-211). IEEE.

[15] Jiang, L. (2024). The use of blockchain technology in enterprise financial accounting information sharing. Plos one, 19(2), e0298210.

[16] Yu, W., & Hamam, H. (2024). Architecting an enterprise financial management model: leveraging multi-head attention mechanism-transformer for user information transformation. PeerJ Computer Science, 10, e1928.

[17] Rasid, S. Z. A., Isa, C. R., & Ismail, W. K. W. (2014). Management accounting systems, enterprise risk management and organizational performance in financial institutions. Asian Review of Accounting, 22(2), 128-144.

[18] Kozlov, V. V., Tomashevska, T. V., & Kuznetsov, N. I. (2020). Using of optimization models in financial decision support systems. Statistics of Ukraine, 88(1), 75-83.

[19] Bu, Y. (2024). Fuzzy Decision Support System for Financial Planning and Management. Informatica, 48(21).

[20] Bhayat, I., Manuguerra, M., & Baldock, C. (2015). A decision support model and tool to assist financial decision-making in universities. Journal of Higher Education Policy and Management, 37(1), 69-82.

[21] Tasatanattakool, P., Pradit, K., Nilsook, P., & Wannapiroon, P. (2025). Digital transformation of organizations: Intelligence financial management system. International Journal of Innovative Research and Scientific Studies, 8(1), 773-783.

[22] Solikin, I., & Darmawan, D. (2023). Impact of artificial intelligence in improving the effectiveness of accounting information systems. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 14(2), 82-93.

[23] Artene, A. E., Domil, A. E., & Ivascu, L. (2024). Unlocking Business Value: Integrating AI-Driven Decision-Making in Financial Reporting Systems. Electronics (2079-9292), 13(15).

[24] Marshall, T. E., & Lambert, S. L. (2018). Cloud-based intelligent accounting applications: accounting task automation using IBM watson cognitive computing. Journal of emerging technologies in accounting, 15(1), 199-215.

[25] Fauzi, F., Effendi, R., & Basrowi, B. (2024). Utilization of big data and cloud computing platforms for the smooth processing of financial ac-counting system data and its implications for the success of village development. International Journal of Data and Network Science, 8(3), 2015-2028.

[26] Chanthinok, K., & Sangboon, K. (2021). The development of digital accounting system on cloud computing. Journal of Computer Science, 17(10), 889-904.

[27] Ahmad, S., Ghidan, E., & Yousef, S. (2022). The adoption of cloud accounting information system in Jordanian financial firms: Influencing factors. Uncertain Supply Chain Management, 10(4), 1315-1322.

[28] Nguyen Phu, G., Hoang Thi, T., & Tran Nguyen Bich, H. (2025). The impact of cloud computing technology on cloud accounting adoption and financial management of businesses. Humanities and Social Sciences Communications, 12(1), 1-14.

[29] Fahd N. Al Wesabi,Abeer A. K. Alharbi & Ishfaq Yaseen. (2025). An advanced fire detection system for assisting visually challenged people using recurrent neural network and sea-horse optimizer algorithm. Scientific Reports,15(1),21493-21493.

[30] Xiankun Hao,Xu Li,Jingying Wu,Baoguo Wei,Yujuan Song & Bo Li. (2024). A No-Reference Quality Assessment Method for Hyperspectral Sharpened Images via Benford's Law. Remote Sensing,16(7).