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# Innovative Financial Management in Higher Education: A Multi-Scale Deep Learning Approach for Risk Reduction and Quality Enhancement

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***Abstract:* -** This paper presents a novel university financial management system leveraging multi-scale deep learning. With rising college enrollment and teaching complexities, traditional financial models require adaptation to mitigate risks and improve management quality. The system integrates hardware and software innovations: multiple sensors enhance data scanning, coordinated by a central coordinator, ensuring comprehensive financial database coverage. Software-wise, a structured database establishes attribute-based financial connections, crucial for weight assignment. Employing a multilayer perceptual network topology, a full interconnection model based on multi-scale deep learning facilitates profound data extraction. Experimental evaluations demonstrate the system's superior financial risk assessment capabilities compared to traditional approaches, extracting a broader spectrum of financial parameters for comprehensive risk warnings. By embracing multi-scale deep learning, this system promises significant advancements in university financial management, enhancing adaptability and risk mitigation in college finance departments.

***Keywords:*** Landscape gardening, Green-visibility, Deep learning, Semantic segmentation.

## I. INTRODUCTION

Financial management in higher education institutions plays a crucial role in ensuring public financial security. The advent of modern technology, particularly the Internet, has revolutionized various aspects of university operations[1-2]. Firstly, it emphasizes the need to establish a standardized financial management information system tailored to the complexities of university finances[3]. This entails systematic organization of financial workflows and the creation of standardized information protocols to enhance overall financial management quality.

Furthermore, leveraging the Internet's capabilities, universities are urged to adapt and innovate their financial management mechanisms. The Internet serves as a pivotal platform for streamlining financial processes, optimizing management mechanisms, and improving the efficiency of financial services[4]. It enables seamless integration and transmission of financial data, enhancing the quality and accessibility of financial management services.

In this context, the Internet facilitates more effective financial risk management in universities[5]. By harnessing network data and establishing financial risk models, universities can proactively identify and mitigate financial risks[6]. This includes developing comprehensive risk models tailored to specific aspects of university finances, such as fixed asset management. By utilizing relevant data to inform risk models, universities can enhance asset management quality and prevent financial risks arising from mismanagement[7-10].

In summary, this paper delves into the intricate composition of university financial risk systems and proposes scientific frameworks for early warning systems. By addressing the unique characteristics of university financial management, particularly regarding fixed asset management, the proposed models aim to bolster financial management quality and mitigate associated risks[11-14].

## II. HARDWARE DESIGN OF UNIVERSITY FINANCIAL SYSTEM

To accommodate the demands of multi-scale deep learning in the university financial system, a redesign of the system hardware is imperative. The hardware redesign aims to facilitate the fully interconnected mode required by the multilayer perceptron network in multi-scale deep learning[15-18]. Crucially, the hardware components crucial for achieving this mode include sensors and coordinators. Sensors play a pivotal role in enhancing the transmission, processing, storage, display, and recording of electrical signals within the financial system. They contribute to improving the overall functionality and efficiency of the system by enabling seamless data management and control. Meanwhile, coordinators serve as essential components for scanning financial data within the system[19]. They are

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responsible for selecting appropriate parameters necessary for constructing a multilayer perceptron network capable of supporting multi-scale deep learning[20]. The coordination process ensures that the network is equipped to handle the complexities of financial data analysis and processing.

The block diagram presented in Figure 1 illustrates the hardware design of the university financial system, depicting the integration of sensors and coordinators to enable effective multi-scale deep learning capabilities.

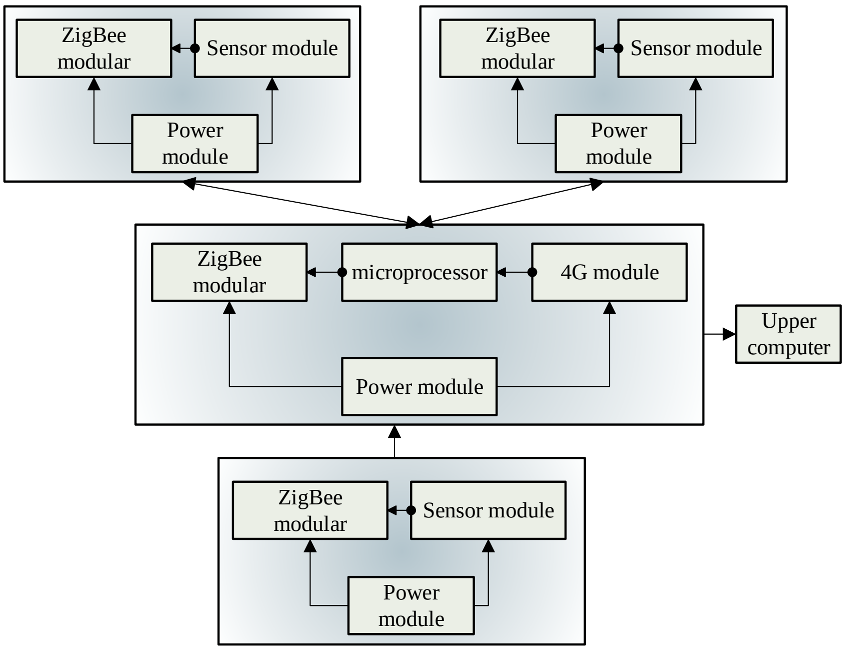


Figure 1 Hardware design framework of financial system in higher education

## III. Software design of university financial system

### *A. Create database form to set connection weights*

In the financial system of higher education, the financial information covered is of various types, complex contents, and refined subjects may appear at three or four levels, and the system wants to carry out multi-scale deep learning by designing a database form with a sharp, clear objective and distinct type division, and by setting a weight value to connect the same attribute information. The basic information of college users and college workers are shown in Table 1 and Table 2.

Table 1 Basic information of users

| Yuduan name | Data type | length | Remarks | Crux |
|---|---|---|---|---|
| EID | varchar | 10 | Customer number | yes |
| Name | varchar | 10 | full name | no |
| Tel | varchar | 10 | contact information | yes |
| DID | varchar | 20 | Affiliated unit | no |
| Area | varchar | 50 | Place of residence | yes |
| DName | varchar | 10 | Unit type | no |

Table 2 Basic information of employees

| Yuduan name | Data type | length | Remarks | Crux |
|---|---|---|---|---|
| EID | varchar | 10 | Employee number | yes |
| Name | Varchar | 10 | Employee name | yes |
| Sex | Varchar | 10 | Gender | no |
| Birthday | Date | 10 | date of birth | no |
| Hometown | Varchar | 10 | Native place | no |
| Adress | Varchar | 50 | Current residence | Yes |
| Tel | Varchar | 10 | contact number | Yes |
| ID_number | Varchar | 10 | ID number | Yes |
| Department | Varchar | 20 | Department | Yes |

With Table 1 and Table 2 as the two major categories for financial information retrieval, the financial information of universities in terms of customers and employees is recorded and updated in real time. Set up information such as customer payment items, drug categories and charge numbers connected with Table 1; set up information such as basic salary, job salary, seniority salary, employee benefits, incentive salary and social insurance connected with Table 2. And so on, according to all the financial information of the university, set the weights of the connected financial information, and the equation of the change of the weights, as in equation (1).

$$\Delta q_{ij} = -\mu \frac{\partial D}{\partial q_{ij}} = -\mu \frac{\partial}{\partial q_{ij}} \left( \sum_{m=1}^{m} D_m \right) = \sum_{m=1}^{m} \left( -\mu \frac{\partial D_m}{\partial q_{ij}} \right) \quad (1)$$

Where $q_{ij}$ denotes the connection weights between financial information; $\Delta q_{ij}$ denotes the change of weights; i and j denote two random financial information; μ denotes the learning rate of the system; m denotes the same attribute financial information; and $D_m$ denotes the global error value. According to the information of the established database form, the weights that can connect the financial information of universities are set.

*B. Designing a fully interconnected model*

It is known that the perceptron has a single-layer computing capability and belongs to a kind of feed-forward network, and according to the set weights, bottom-up information transmission can be performed for each layer of the network. Therefore, according to this function of the perceptron, a multilayer perceptual network is constructed, and in this way, the full interconnection pattern of the system information is set, and the connections between neurons in different layers are used to mine the financial information of the university.

The perceptron is used as each node in the neural network, and a dynamic connection weight is set according to the result of equation (1), and then the perceptron is used to learn this weight, and the topology of the multilayer perceptual network is schematically shown in Figure 2.

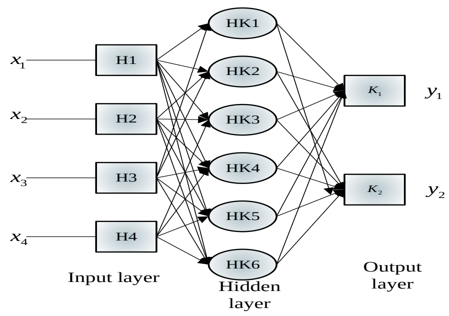


Figure 2 Topology of multi-layer sensing network

In Fig. 2, X denotes the random financial information; H denotes the input layer unit; hk denotes the hidden layer unit; K denotes the output layer unit; and Y denotes the final result. According to Figure 2, neurons in the same layer are not connected to each other, and neurons in two adjacent layers are fully connected to each other, and the data transmitted from the input to the output are calculated layer by layer through directional information transfer. The multilayer perceptual network set up contains not only input and output layers, but also one or more hidden layers, allowing the system to extract financial data features with associated properties within the system during deep learning, which is the forward propagation system interconnection. In contrast, the reverse system interconnection of the perception network is designed using the back propagation algorithm, which is a secondary assignment of weights, feeding the input pattern into the system from the input side, and adjusting the weights of the previous layer using the error between the output value and the target output value, thus realizing the full interconnection pattern of the multilayer perception network.

It is known that the input layer of the perceptual network has a input neurons, the output layer has b output neurons, the hidden layer has e hidden neurons, $q_{ij}$ plus the formula (1) sought, is the connection weights between the output hidden layer and the output layer, $p_{ij}$ is the connection weights , then the output results of the hidden neurons, the output layer neurons under forward propagation, as in equation (2).

$$\begin{cases} K = f_1\left(\sum_{i=0}^{a} p_{ij} X_n\right) \\ Y = f_2\left(\sum_{i=0}^{e} p_{ij} - K\right) \end{cases} \quad (2)$$

Using the above equation, the multi-layer perception network completes the forward propagation and establishes the spatial mapping from a dimension to b dimension. And under the definition of back propagation algorithm, let the input data be c, denoted by $x_1, x_2 \ldots x_c$ , and the output value is calculated after the cth data is input to the network. Assuming that the error function is squared, the error between the cth output value and the target output value is calculated as in equation (3).

$$\Delta Y = \frac{1}{2}\sum_{c=1}^{n}\left(X_c - Y_c\right) \quad (3)$$

Where ΔY is the error; $X_c$ denotes the original input and also the desired output. Adjusting the connection weights $q_{ij}$ between the input layer and the output hidden layer according to this result, the equation of change of $p_{ij}$ , as in equation (4).

$$\Delta p_{ij} = \sum_{i=1}^{c}\sum_{j=1}^{n} \mu\left(X_c - Y_c\right) f_2'\left(S_{HK}\right) q_{ij} f_1'\left(S_K\right) q_{ij} \quad (4)$$

Where $f_2'\left(S_{HK}\right)$ is the partial differential of the hidden layer transfer function and $f_1'\left(S_K\right)$ is the partial differential of the output layer transfer function. Add $p_{ij}$ to the result of equation (4), and similarly $q_{ij}$ to the result of equation (1), and use the connection weights of the two directions to realize the data analysis of positive and negative directions, and complete the setting of the full interconnection mode of the multilayer perception network, so that the design of the university financial system based on multi-scale deep learning is completed.

## IV. Results

### A. Model Evaluation

Constructing a financial reporting fraud identification model with good out-of-sample prediction ability is crucial to the research in this paper. For both the deep learning model and the benchmark model, three types of evaluation metrics, Precision, Recall, and F1-score, are used to measure the classification performance of the model on the test set.

### B. Empirical Results and Analysis

Tables 3 and 4 present the prediction outcomes of the deep learning model and the benchmark model, respectively, on the out-of-sample dataset using MD&A texts from university periodic reports. The deep learning model architecture incorporates a word embedding model and a character-level convolutional neural network. Meanwhile, the benchmark model includes two statistical models (logistic regression and plain Bayesian models) and three shallow models (support vector machines, random forests, and gradient boosting decision trees).

From the evaluation metrics provided in Tables 3 and 4, several key points emerge: Firstly, both the deep learning model and the benchmark models exhibit classification performance greater than 0.7, indicating their effectiveness in utilizing MD&A textual information for financial reporting fraud detection. Secondly, the classification performance of the deep learning model surpasses that of the benchmark models significantly. The framework established in this study demonstrates superior capability in identifying fraudulent financial reports compared to traditional intelligent financial reporting fraud detection methods. Lastly, the evaluation index values of the deep learning models on both types of MD&A text sets exceed 0.82, highlighting their enhanced fraud identification ability across different datasets.

Table 3 Classification performance of deep learning models and benchmark models on MD&A text dataset

| Model | Macro_Precision | Macro_Recall | Macro_F1-score |
|---|---|---|---|
| Word embedding + character level CNN | 0.89 | 0.850 | 0.851 |
| logistic regression | 0.80 | 0.81 | 0.801 |
| Naive Bayes | 0.795 | 0.795 | 0.795 |
| Support vector machine | 0.811 | 0.82 | 0.812 |
| Random forest | 0.767 | 0.768 | 0.768 |
| XGBoost | 0.734 | 0.734 | 0.734 |
| LightGBM | 0.769 | 0.769 | 0.769 |

Table 4 Classification performance of deep learning models on two types of MD&A text datasets

| Sample category | Precision | Recall | F1-score |
|---|---|---|---|
| Fraud | 0.87 | 0.83 | 0.84 |
| Non fraud | 0.84 | 0.86 | 0.85 |

### C. Financial System Performance Testing

Based on the experimental data obtained, the system undergoes black-box testing to evaluate its functions and operations. Upon logging into the system, users access the dynamic income statement interface to analyze detailed data correctness in the financial multi-dimensional analysis table, review income and expense reports, and verify graphical representations of year-on-year comparisons. Subsequently, users navigate to the financial trend analysis page to validate parameter settings and conduct analyses, such as setting the year of salary withdrawal and selecting department sections for query submission. Results include financial trend analysis charts, equipment yield tracking, and future growth and cost management trend analyses. Efficiency testing of the financial system operation is depicted in Figure 3.

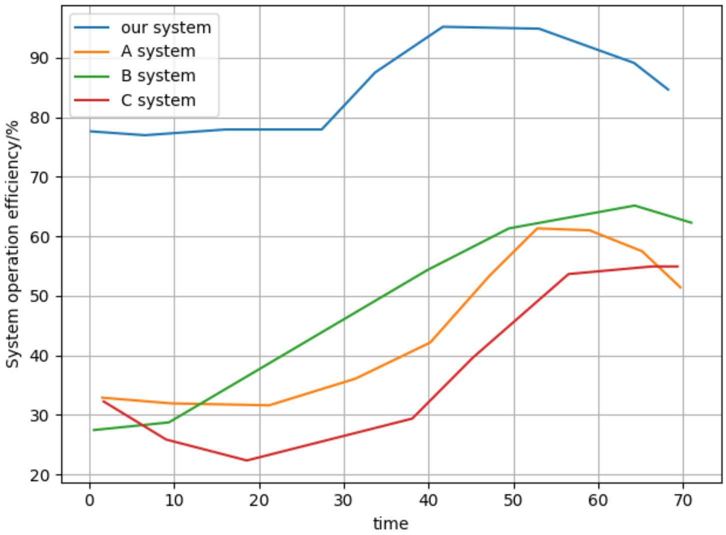


Figure 3 Efficiency testing diagram of financial system operation

As can be seen from Figure 3, the operating efficiency of the system designed in this paper is significantly higher than that of the system used in the control experiment conducted by the three groups, and the highest operating efficiency of the system designed in this paper is close to 96%, indicating that the performance of the university financial system designed in this paper is superior.

## V. Conclusion

This paper introduces a character-level CNN model for detecting fraudulent financial reports in universities, leveraging advancements in NLP within deep learning technology. By analyzing MD&A text from financial reports, the model demonstrates superior classification performance, even on smaller datasets where shallow models excel, without the need for complex textual feature extraction. This underscores the potential of deep learning techniques in enhancing existing fraud identification methods. Moreover, the study highlights the improved prediction performance of the models on MD&A texts, showcasing the value of publicly disclosed university texts. The accessibility and reliability of financial report disclosures serve as valuable data sources for further research in the field.

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