# Research on Accounting Information Quality Evaluation Model of Listed Companies from the Perspective of Differentiated Machine Learning

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## Abstract

**Developing quantitative tools to evaluate the accounting information quality of listed companies is of great value for in- vestors' risk prevention. Based on the selection of multi-dimensional factors affecting the accounting information quality , the random forest model is used to screen the importance , and then the accounting information quality evaluation system is built. At the same time , based on convolutional neural netowrk long short-term memory (CNN-LSTM) method , the evaluation model of accounting information quality is constructed , and the good performance of the model in the evaluation of accounting informa- tion quality is proved.**

## Keywords

**Listed company; accounting information quality; random forest; convolutional neural network; long short-term memory network.**

## 1. Introduction

Capital markets are highly sensitive to information dynamics, where the quality of listed companies 'accounting disclosures directly impacts investor decision-making. To address this, developing quantitative analytical tools for evaluating accounting information quality is crucial. Such tools enhance the comprehensibility of corporate financial reporting, which is vital for investor protection and the sustainable development of capital markets [1]. By leveraging machine learning algorithms' robust analytical capabilities to assess systematically disclosed accounting information, we can establish user-friendly evaluation methodologies. These methods not only satisfy stakeholders' need for operational transparency but also guide them in making informed investment decisions [2].

In recent years, scholars have conducted extensive research on quantifying accounting information quality, analyzing its influencing factors, and examining economic consequences [3]. However, existing studies still suffer from limitations in comprehensive evaluation perspectives and low precision, with their application scope constrained by research objectives [4-5]. Machine learning models demonstrate superior performance in processing multidimensional data. To address this, this paper selects potential influencing factors of accounting information quality across multiple dimensions, employs random forest (RF) for indicator importance screening, and establishes an evaluation system for accounting information quality metrics. Furthermore, based on the convolutional neural network-long short-term memory (CNN-LSTM) approach, we develop an accounting information quality evaluation model to conduct empirical research on sample corporate data. Through multi-angle performance assessments, the study demonstrates the model's excellent adaptability in evaluating accounting information quality for listed companies.

## 2. Model and Data

### 2.1. Design of the Evaluation Model Construction Process

After thorough evaluation of scientific rigor and methodological soundness, the experimental framework is structured as follows:

(1) The modified Jones model is applied to calculate adjusted controllable accrued interest (DA), with its absolute negative value serving as both an proxy for accounting information quality (AIQ) and the model's output data.

(2) Multidimensional analysis identifies latent factors influencing AIQ; the Gini coefficient is computed using a random forest model, with threshold values applied to prioritize key indicators.

(3) An AIQ evaluation model is developed via CNN-LSTM architecture, empirically validated with sample corporate data. Comparative tests across three models (XGBOOst, BP neural network, and LSTM) demonstrate the superior performance of the CNN-LSTM approach in accounting information quality assessment.

### 2.2. Output Layer Data Metrics

Building on Huang Hui-ping et al.'s [6] research, this paper adopts the absolute value of modified DA as a proxy variable for accounting information quality in listed companies. A higher absolute value indicates greater earnings disclosure adjustments, suggesting poorer accounting information quality. DA is measured using the modified Jones model, with the calculation process as follows.

$$\frac{TA_{i,t}}{A_{i,t-1}} = \mu_t \times \frac{1}{A_{i,t-1}} + \beta_t \times \frac{\Delta REV_{it}}{A_{i,t-1}} + \beta_t \times \frac{PPE_{i,t}}{A_{i,t-1}} + e_{i,t} \tag{1}$$

$$\mathrm{NDA}_{i,t} = \hat{\beta}_t \times \frac{1}{A_{i,t-1}} + \hat{\beta}_t \times \frac{\Delta \mathrm{REV}_{i,t} - \Delta \mathrm{REC}_{i,t}}{A_{i,t-1}} + \hat{\beta}_t \times \frac{\mathrm{PFE}_{i,t}}{A_{i,t-1}} \tag{2}$$

$$\mathrm{DA}_{4,i} = \frac{\mathrm{T}A_{i,t}}{A_{i,t-1}} - \mathrm{NDA_{i,t}} \tag{3}$$

In equations (1) to (3): i denotes the company βsequence number; t represents the year; β and are the parameters to be evaluated; εWhere TA denotes total profit, NDA represents non-manipulated accrued profit, A stands for total assets at the end of the period, ΔREV and ΔREC are the changes in operating revenue and accounts receivable respectively, and PPE is the net fixed assets. As DA is a negative indicator, this paper adopts the absolute negative value of DA as the measurement of accounting information quality (AIQ) in the model, i.e.:

$$\mathrm{AIQ} = -|\mathrm{DA}| \tag{4}$$

## 2.3. Selection of Potential Influencing Factors

Based on the research of Li Qing et al. [3], this paper selects 25 potential influencing factors of accounting information quality from five dimensions, such as solvency, operating ability, profitability, risk level and development ability, including current ratio, as shown in Figure 1.

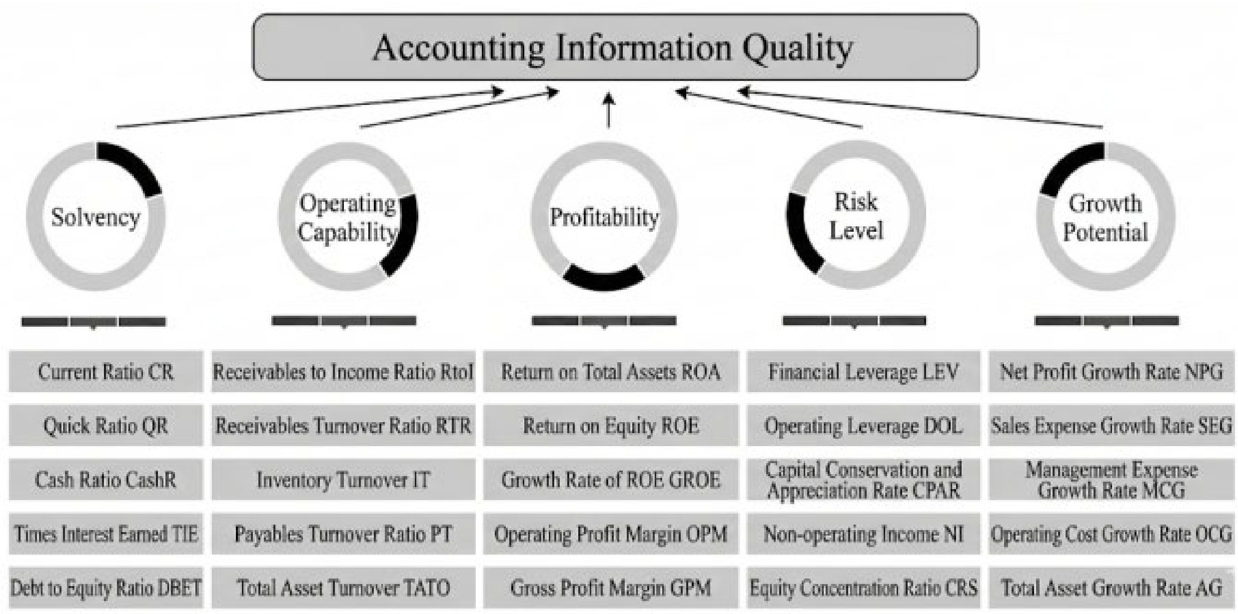


**Figure 1.** Selection of Potential Factors Affecting Accounting Information Quality

At the same time, considering that the dimension difference of the potential influencing factors will affect the precision of the model, the paper normalizes the data of each index, that is, the data is converted into the number of [0,1], in order to eliminate the dimension difference and improve the performance of the model.

$$f_i = \frac{f_i - f_{\text{abs}}}{f_{\max} - f_{\text{abs}}} \tag{5}$$

In Equation (5), fi* is the normalized value of the indicator, fi is the actual value of the indicator, and fmin and fmax are the minimum and maximum values in the indicator sequence, respectively. Thus, the initial feature vector for accounting information quality assessment constructed in this paper is as follows.

$$\mathbf{AIQ} = \begin{bmatrix} \text{CR, QR, CashR, TIE, DBET, Rml, RTR, IT, PT,} \\ \text{TATO, ROA, ROE, GROE, OPM, GFM, DFL,} \\ \text{DOL, CPAR, NI, CRS, NPG, SEG, MCG, OCG, AG} \end{bmatrix} \tag{6}$$

## 2.4. Random Forest Model

If all 25 influencing factors mentioned above were used as input values for the evaluation model, the model would become extremely complex, and the training time would be significantly increased. Therefore, it is necessary to screen out factors with strong representativeness to simplify the model and reduce training time. The RF model is an integrated machine learning method that can be used to analyze complex interactive features [7]. In this paper, the RF model is employed to calculate the Gini index (Gini index) and rank the importance of indicators [8]. The specific steps are as follows.

$$G_L = \sum_{n=1}^{c} \sum_{p \neq p\prime} p - p' = 1 - \sum_{n=1}^{c} p_n^2 \tag{7}$$

In Equation (7): GIx denotes the Gini index of feature Fi at node x; C represents the number of categories; pxc indicates the proportion of samples belonging to category c in the sample at node x. Furthermore, Six signifies the importance of feature Fi at node x, with the calculation process as follows.

$$Six = GIx - GIi - GIr \tag{8}$$

In Equation (8), GIi and GIr represent the Gini indices of the i-th and r-th subnodes after branching, respectively. Assuming there are J trees in the RF, the importance scores of feature Fi are as follows.

$$S_i = \sum_{j=1}^{I} \sum_{\sigma \in M} S_\sigma \tag{9}$$

In Equation (9): M denotes the set of nodes where the feature Fi appears in decision j, and is standardized. The final importance score is thus obtained:

$$S_i = \frac{S_t}{\sum_{i=1}^{n} S_t} \tag{10}$$

In Equation (10), k is the eigenvalue index; Sk is the importance of the eigenvalue with index k; n is the number of features.

## 2.5. LSTM model

LSTM is a specialized recurrent neural network that enables memory units to retain information through gate control mechanisms. The LSTM model employs three gate structures to process nodes, allowing learning based on continuously changing signals [9]. In practical applications, LSTM can rapidly process large volumes of input data while retaining relevant information. Its strong generalization ability and enhanced learning capacity make it particularly suitable for the accounting information quality evaluation tasks discussed in this paper. The study first utilizes the multi-layer neural architecture of the LSTM model to extract features of influencing factors, thereby capturing correlations between indicator data. Subsequently, memory operations are performed to establish connections between input data, enabling data prediction and output, ultimately achieving the analytical objectives. Figure 2 illustrates the specific architecture of the LSTM model.

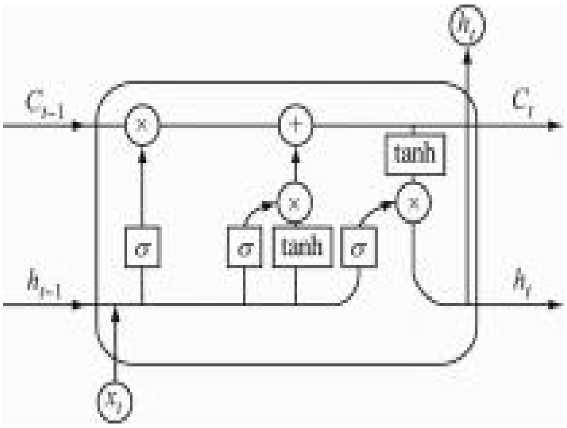


**Figure 2.** LSTM Model Architecture

Figure 2 illustrates the architecture of a single LSTM. After the input data is processed, it first enters the model's forgetting gate, where σ determines how much data from the previous time step (ht−1) is retained, thereby achieving information forgetting and retention. Subsequently, the input gate controls the flow of input information, selecting which data should be fed into the memory unit. The data from ht−1 and the current time step (xt) enter the input gate, undergo a series of computations, and are then combined with the output of the forgetting gate for final processing. Finally, the output gate governs the flow of information from the memory unit, determining which data should be output. The LSTM model's input-to-output process is described by equations (11) to (14).

$$zt = \sigma(Wz \times [ht - 1, xt]) \tag{11}$$

$$rt = \sigma(Wr \times [ht - 1, xt]) \tag{12}$$

$$h_t = \tanh( W \times [r_t \times h_{t-1}, x_t]) \tag{13}$$

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times h_t \tag{14}$$

In equations (11) to (14): zt denotes the state of the forgetting gate; Wz is the weight matrix of the forgetting gate; σ is the activation function; rt represents the state of the input gate; Wr is the weight matrix of the input gate; t indicates the state of the candidate ħelement; W is the weight matrix; tanh is the activation function; htis the output at time t, i.e., the evaluation value.

## 2.6. CNN-LSTM Model

CNN is a classic and crucial model in deep learning. Since using LSTM models alone for constructing accounting information quality evaluation models often fails to fully capture the characteristics of indicator data, this paper combines CNN with LSTM models to enhance the performance of the evaluation model. The CNN model constructed in this paper includes an input layer, convolutional layers, pooling layers, and fully connected layers. Convolutional and pooling layers are used to extract data features, while activation functions and loss functions are added to improve training efficiency. These features are then fed into the fully connected layer to complete the regression task [10].

The CNN-LSTM model implemented in this study consists of five core components: an input layer, convolutional layers, pooling layers, an LSTM recurrent layer, and an output layer. The CNN's primary role is to extract distinctive features from the influencing factor indicators, which are then fed into the LSTM model to assist in accounting information quality assessment. After the RF model screens out the most significant indicators, the multidimensional data affecting accounting information quality is fed into the CNN-LSTM model. The convolutional layers perform convolution operations to extract high-dimensional features, ultimately yielding Feature C. The convolution operation formula is as follows.

$$C = f\left(\sum_{n=0}^{2}\sum_{k=-1}^{2} w_{n,k} \times x_{l+m,n,k} + w_b\right) \tag{15}$$

In Equation (15), wm, n, and xi+m, j+n represent the weights of the convolution kernel and a local region, respectively, while wb denotes the bias value of the convolution kernel. The model first performs pooling operations to aggregate features without redundant information. Subsequently, it transforms the data dimensions and inputs the high-dimensional features into the LSTM model for selective memory and prediction, then passes the results to the output layer. Finally, the output layer normalizes and inverse-normalizes the results from the LSTM recurrent layer, yielding the final evaluation value of the CNN-LSTM model.

## 2.7. BP Neural Network Model

(1) Principle of Factor Analysis

Factor analysis is primarily used to identify and extract latent unobservable variables in data that explain correlations among multiple observed variables. Its main function is to reduce data dimensionality, simplify data structures, decrease dimensions, and enhance interpretability. This method assumes that each observed variable Xi can be expressed as a linear combination of latent factors plus an error term, i.e., Xi= λi1F1 + λi2F2 +... + λimFm + εi. Here, λij denotes the factor loading, representing the contribution of factor Fj to variable Xi; Fj is the latent factor; εi is the error term. The factor extraction process involves eigenvalue decomposition and principal component analysis. By identifying the eigenvalues and eigenvectors of the covariance matrix Σ or correlation matrix R, factors corresponding to eigenvectors with larger eigenvalues are selected. Eigenvalues represent each factor's contribution to total variance, expressed as ∑ei= λiei. Given that the eigenvalues and eigenvectors of covariance matrix Σ are λi and ei respectively, the magnitude of eigenvalues reflects each factor's explanatory power for the overall economic system. Larger eigenvalues indicate stronger explanatory power for the economic system, and vice versa.

(2) Principles of the GA-BP Neural Network Model

The quality of corporate social responsibility (CSR) accounting information disclosure is influenced by multiple factors including legal requirements, stakeholder pressures, and industry practices. This complexity makes it challenging to express evaluation results through simple mathematical formulas, representing a classic nonlinear problem. Current solutions primarily employ methods such as multiple regression analysis, structural equation modeling, and BP neural networks. Among these, BP neural networks are artificial neural network models that mimic the neural information processing characteristics of biological brains, possessing strong nonlinear mapping capabilities to handle complex relationships among influencing factors. However, this method may easily fall into local optima during training, limiting the model's accuracy and generalization ability. Genetic algorithms (GA), as global search and optimization algorithms based on biological mechanisms like natural selection and genetic variation, can effectively identify global optimal solutions. Integrating GA into traditional BP neural network models for optimization addresses inherent limitations of both BP networks and genetic algorithms, thereby enhancing the model's research accuracy in related fields.

The evaluation process for the GA-BP neural network model is illustrated in Figure 3. First, determine the hierarchical structure of the BP neural network, including the number of nodes in the input layer, hidden layers, and output layer. The number of input layer nodes depends on the quantity of input features, while the output layer nodes are determined by the number of output targets. The hidden layer nodes are typically determined empirically or through experimentation. Second, calculate the weights of all connections in the neural network and the number of thresholds per node. Assuming the network has L layers, the weight matrix for the l-th layer is W(l), and the bias vector is b(l), the total number of parameters is Σ[n(l)×n(l+1)+n(l+1)], where n(l)is the number of nodes in the l-th layer. Third, initialize the GA algorithm population. Use the genetic algorithm to initialize a population, where each individual represents a set of weights and thresholds for the BP neural network. The initial state of each individual is usually randomly generated. Fourth, define the fitness function. Typically, the sum of squared errors of the BP neural network is chosen as the fitness function to measure the quality of each individual (i.e., a set of network parameters). Smaller sum of squared errors indicate higher fitness. Fifth, perform genetic operations such as selection, crossover, and mutation on the current population to simulate natural selection and genetic evolution, continuously generating new potential optimal solutions. Sixth, after each round of genetic operations, check whether the current iteration count has reached the preset maximum iteration count. If not, return to the steps of selection, crossover, and mutation to continue the next iteration. When the maximum number of iterations or other stopping conditions are reached, the fittest individual in the population is selected as the optimal individual. The optimal initial weights W* and threshold b* of the BP neural network are decoded from this individual's genes. These parameters are then fed into the BP neural network for training, with continuous adjustments to the network parameters to minimize the error between the network's output and the actual evaluation results.

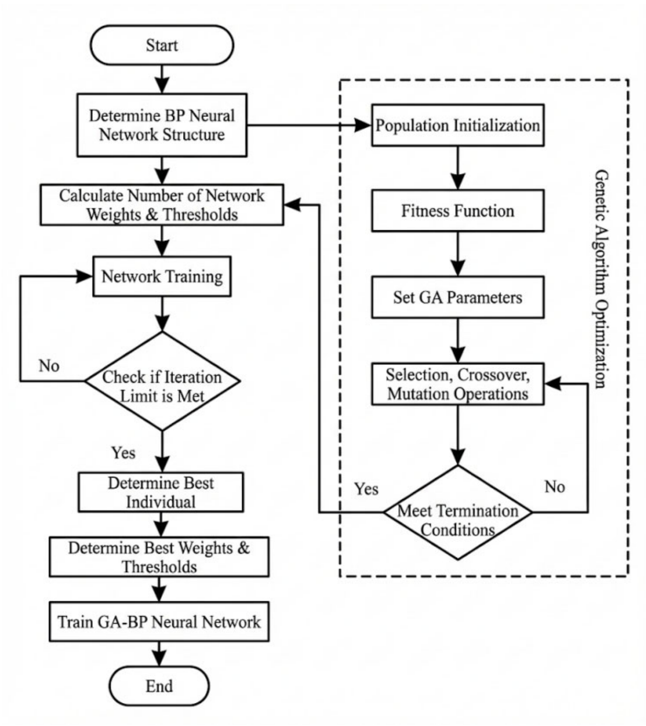


**Figure 3.** GA-BP Neural Network Model Flow

## 2.8. Sample Selection and Data Sources

This study examines A-share listed companies on the main board of the Shanghai and Shenzhen stock exchanges from 2015 to 2021, with the following processing: excluding newly listed, delisted, or suspended companies; excluding financial sector firms; and removing data with missing values. The dataset was sourced from Juchao Information Network and Guotai An CSMAR Database, processed using Excel and Python, yielding a final dataset of 4,595 numerical entries. The data was then randomly divided into a test set and a training set in a 3:7 ratio for subsequent analysis.

# 3. Experimental Results and Analysis

## 3.1. Screening Results of Potential Factors

Based on the RF model, the paper evaluates the importance of each potential factor and sets 0.05 as the threshold to exclude factors with importance below 0.05. Thus, 11 indicators are obtained, and the strong representative factors affecting accounting information quality are screened out. The screening results are shown in Table 1.

**Table 1.** Factors Influencing Accounting Information Quality Selected by Random Forest

| Importance Ranking | Factor name | degree of importance |
|---|---|---|
| 1 | CRS | 0 . 0888 |
| 2 | DBET | 0 . 0865 |
| 3 | GPM | 0 . 0836 |
| 4 | RtOI | 0 . 0780 |
| 5 | TATO | 0 . 0656 |
| 6 | DOL | 0 . 0627 |
| 7 | OPM | 0 . 0619 |
| 8 | ROA | 0 . 0564 |
| 9 | CR | 0 . 0534 |
| 10 | QR | 0 . 0530 |
| 11 | AG | 0 . 0513 |

The evaluation model is simplified and the training time is shortened by eliminating the potential factors that have little influence on the quality of accounting information.

$$\mathrm{AIQ} = \begin{bmatrix} \mathrm{CRS, DBET, GPM, Rto, TATO,} \\ \mathrm{DOL, OPM, ROA, CR, QR, AG} \end{bmatrix} \tag{16}$$

## 3.2. Model Performance Evaluation Metrics

To fully demonstrate the evaluation effectiveness of the model, drawing on the research findings of Li Mei et al. [11], this paper selects three evaluation indicators: root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R2). The calculation formulas for each indicator are as shown in the equation(17) to (19).

$$E_{\max} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_0)^2} \tag{17}$$

$$E_{\mathrm{MAX}} = \frac{1}{n}\sum_{i=1}^{n} | Y_i - Y| \tag{18}$$

$$R^2 = 1 - \frac{\sum(\hat{g}_i - x_i)^2}{\sum(\bar{g}_i - x_i)^2} \tag{19}$$

In equations (17) to (19), Y and y represent observed values, n denotes the sample size, andYy̌.

### 3.3. Comparative Analysis

To validate the effectiveness of the CNN-LSTM model proposed in this study for accounting information quality assessment, we referenced Zhao Qicheng et al.'s [12] research and employed three models: XGBOOst, BP neural network, and LSTM. The experimental results were compared with the performance of the CNN-LSTM model. All three models (BP neural network, LSTM, and CNN-LSTM) were trained 200 times with a batch size of 16, using Adam optimization and cross-entropy loss function. The evaluation metrics of each model are presented in Table 2.

**Table 2.** Comparison of Evaluation Indicators for Various Prediction Models

| model | XGBOOst | BP | LSTM | CNN-LSTM |
|---|---|---|---|---|
| RMSE | 0 . 047 21 | 0 . 046 12 | 0 . 041 24 | 0 . 037 89 |
| MAE | 0 . 033 65 | 0 . 033 28 | 0 . 031 31 | 0 . 028 24 |
| R2 | 0 . 829 94 | 0 . 817 41 | 0 . 870 61 | 0 . 902 42 |

Figure 4 presents the evaluation metrics in a more intuitive bar style pie chart.

As shown in Figure 4, the CNN-LSTM model outperforms both the XGBOOst and BP neural network models in all selected evaluation metrics, with RMSE, MAE, and R2 values of 0.037 89 ,0.028 24 , and 0.9024, respectively. Under the same data volume, the CNN-LSTM model significantly improves model accuracy compared to a single LSTM model by incorporating CNN for feature extraction of the metrics. The CNN-LSTM model achieves an 8.12% reduction in RMSE, a 9.81% decrease in MAE, and a 0.031 81 increase in R2 compared to a single LSTM model. This demonstrates that the CNN-LSTM model exhibits excellent fitting performance in evaluating accounting information quality, enabling a relatively accurate assessment of corporate accounting information quality.

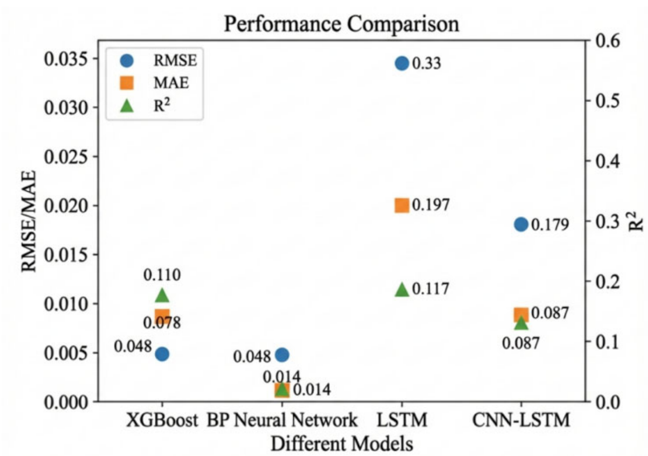


**Figure 4.** Presents the evaluation metrics in a more intuitive bar style pie chart.

### 3.4. Robustness Test of Experimental Results

To evaluate the robustness of the CNN-LSTM model constructed in this study, we refer to the research findings of Zhou Jingyang et al. [13]. The most significant influencing factor derived from the Gini index calculated by the RF method in the previous section—equity concentration—was selected as the classification criterion. Subsequently, the 4,595 experimental data points were divided into five levels: 0–0.2 as Level 1, 0.2–0.4 as Level 2, 0.4–0.6 as Level 3, 0.6–0.8 as Level 4, and 0.8–1 as Level 5. The LSTM and CNN-LSTM models selected earlier were then applied to evaluate these five-level data, with the results presented in Table 3.

**Table 3.** Robustness test results of experimental data

| model | CNN-LSTM | | | LSTM | | |
|---|---|---|---|---|---|---|
| metric | RMSE | MAE | R2 | RMSE | MAE | R2 |
| Level 1 | 0.039 | 0.029 | 0.934 | 0.041 | 0.032 | 0.916 |
| Level 2 | 0.031 | 0.028 | 0.823 | 0.033 | 0.026 | 0.641 |
| Level 3 | 0.030 | 0.027 | 0.823 | 0.039 | 0.030 | 0.633 |
| Level 4 | 0.032 | 0.028 | 0.868 | 0.040 | 0.032 | 0.842 |
| Level 5 | 0.029 | 0.029 | 0.936 | 0.032 | 0.022 | 0.880 |

As shown in Table 3, the evaluation metrics of the CNN-LSTM model demonstrate significantly lower fluctuations compared to the single LSTM model across different equity concentration categories, particularly in the R2 metric. This demonstrates that the CNN-LSTM model developed in this study exhibits robustness and transferability in accounting information quality assessment.

## 4. Summary

To build a machine learning model to improve the operability of the accounting information quality evaluation of listed companies is of great significance for investors' risk prevention and the sustainable and healthy development of the capital market. Therefore, this paper selects the multi-dimensional factors affecting the accounting information quality, establishes an accounting information quality evaluation model based on the differentiated machine learning method, and draws the following conclusions through the research.

The paper calculates the index importance by the method of RF model to calculate the Gini index, and sets the threshold to screen the strong representative influence factors. It can be considered that the equity concentration, asset-liability ratio and other 11 indicators are the main factors affecting the quality of accounting information of enterprises, which need investors to pay special attention.

(2) This paper constructs an evaluation model of accounting information quality of enterprises by integrating CNN model and LSTM model, which can combine the advantages of CNN and LSTM models.

(3) Through comparative analysis of three models—CNN-LSTM, XGBOOst, and BP neural network—this study concludes that the CNN-LSTM model demonstrates superior applicability and robustness in evaluating accounting information quality of listed companies, making it suitable for practical applications in investor decision analysis.

(4) The research methodology employed in this study primarily analyzes financial statements disclosed by listed companies, with limited attention to off-balance-sheet factors such as debt guarantees and pending lawsuits. Future research will incorporate more off-balance-sheet

factors and integrate techniques like text mining to develop a more rigorous framework for evaluating the quality of accounting information in listed companies.

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