Intelligent Assessment Method of Enterprise Tax Risk Based on Deep Learning

Shifu Guo
Zhongshan Torch Polytechnic, Zhongshan Guangdong 528436, China
Correspondence should be addressed to Shifu Guo; tangzw@ccu.edu.cn
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Enterprise tax risk involves many aspects. In order to accurately realize enterprise tax risk assessment, an intelligent assessment method of enterprise tax risk based on deep learning is proposed. Collect enterprise tax risk information; reasonably distinguish the same type of risk information according to category, type, and appearance; extract the correlation characteristics of enterprise tax risk assessment; use the correlation characteristics to build a deep learning enterprise tax risk assessment model; search the best parameters of the automatic encoder; build a stacked automatic encoder based on the automatic encoder; combine it with the classifier; and complete the design of enterprise tax risk intelligent evaluation model. The experimental results show that the deviation ratio of Receiver Operating Characteristic (ROC), the risk assessment index of the proposed method, is less than 0.38 as a whole. Therefore, the enterprise tax risk intelligent assessment method based on deep learning is better.

1. Introduction

Enterprise tax risk management is an important content and core link in enterprise management, which is directly related to the normal operation order of enterprises [1, 2]. In addition to the general tax risk, such as making false accounts and book errors, the current enterprise tax risk is reflected in the internal management defects of enterprises. The tax attitude of some enterprises is not correct, and the construction of internal control mechanism is not perfect, which leads to the poor effect of tax risk management of these enterprises [3, 4]. Therefore, the relevant enterprise tax risk assessment methods have attracted extensive attention of scholars.

Reference [5] takes Chinese listed companies as a sample to investigate whether tax incentive plan will affect the composition of R & D investment. The results show that tax incentives encourage enterprises to invest in short-term development opportunities and bring considerable private returns. Reference [6] focuses on the global reform of tax authorities from the perspective of tax risk management and guarantee. Interviews were conducted with risk and technical and data experts from tax authorities to assess the level of implementation of the global reform measures identified in the first research phase. Using the method of reference [7], this paper makes a qualitative analysis on the financial risk in the enterprise economic security system and puts forward some suggestions to improve the economic security by minimizing the financial risk. Reference [8] method constructs an agent-based heterogeneous herd behavior artificial market simulation platform from the perspective of behavioral finance. Firstly, by setting six different herd probabilities in the model, we deduce the heterogeneous impact of different herd behaviors on stock price volatility in the stock market. Secondly, it verifies the strength difference of the correlation between price fluctuation and market trading volume under heterogeneous herd probability and realizes the stock price risk assessment.

In order to improve the effect of enterprise tax risk assessment, this paper proposes an intelligent assessment method of enterprise tax risk based on deep learning. This paper collects and extracts the characteristics of enterprise tax risk information to distinguish and test the identification
of enterprise tax risk information. Configure enterprise tax monitoring facilities, collect and evaluate risk information, build a deep learning model, and output the intelligent evaluation results of enterprise tax risk.

2. Design of Enterprise Tax Risk Intelligent Evaluation Method Based on Deep Learning

Tax is one of the main sources of national fiscal revenue. Doing a good job in tax management is an effective way for the state to implement macrocontrol over enterprises [9, 10]. The current situation is disturbed by many factors. Both countries and enterprises are facing great difficulties in dealing with tax relations, which is mainly due to various potential risks encountered in tax implementation.

2.1. Collect Enterprise Tax Risk Information. Enterprise tax risk is mainly caused by objective factors, subjective factors, external factors, and internal factors [11, 12]. Among them, the performance of objective conditions on tax risk is as follows: first is the market environment; China’s socialist market economy is still in an unstable state, and market changes have an adverse impact on enterprise operations and increase the burden of tax payment. The second is the national policy, which adjusts the tax rate irregularly every year, so that the stability of the enterprise’s tax planning is insufficient, and there is a large difference between the tax in the budget and the actual payment amount. These are the impacts of objective conditions on tax risk. The performance of subjective factors on tax risk is as follows: first, the tax consciousness of operators is backward; they only focus on the control of operating income and do not provide practical tax reform plans for enterprises. Second, the implementation is insufficient. The proposed tax control decision is not implemented in the actual work, which makes it difficult for tax regulation to play the expected economic role. Subjective management errors will have a direct effect on tax risk. The external tax risk factors of enterprises [13] mainly include the following: the imperfect and unclear laws and regulations bring uncertainty to enterprise tax payment, the inconsistency between the implementation of national tax laws and regulations and local specific policies, the actual results of enterprise noncompliance caused by the nonstandard operation of tax collection and management personnel, and the nonstandard tax operation caused by vicious competition in the industry and market, which leads to the illegal or gray tax avoidance, irregular opinions, and suggestions of intermediary institutions. The internal tax risk factors [14] of the enterprise mainly include violations and mistakes caused by the influence of the legal system and moral concept of the enterprise management on the enterprise’s behavior; the current tax risk management system is difficult to implement without implementation and supervision or resistance to implementation and the noncompliance of the enterprise caused by the nonstandard resource allocation and administrative orders of shareholders and superior competent authorities. The personnel of the enterprise’s business departments (such as sales, procurement, and personnel) do not understand the tax laws and regulations during operation, the internal tax personnel lack communication with the business personnel, and the number and quality of the internal tax personnel of the enterprise cannot keep up with the actual needs.

Based on the above analysis, the enterprise tax risk involves many factors. Therefore, before the intelligent assessment of enterprise tax risk, we should first determine the historical risk information of enterprise tax and distinguish the types and degrees of possible influencing factors of enterprise tax historical risk information [15, 16]. Analyze the category, type, appearance, and nature of the risks that may affect the enterprise tax risk, and establish a risk case base for different types of enterprise tax [17, 18]. Thus, the corresponding risk sample information is determined.

The tax risk status of each enterprise can be divided into two categories, one is the working probability, and the other is the failure probability of enterprise tax work indicators [19]. From this, the probability of enterprise tax risk status is obtained, and the formula is as follows:

\[
\begin{align*}
P_i &= \frac{1}{1 + \lambda_i y_i}, \\
Q_i &= \frac{\lambda_i y_i}{1 + \lambda_i y_i},
\end{align*}
\]

where \(P_i\) and \(Q_i\) are the working probability and failure probability generated by the enterprise tax work index \(i\), respectively; the risk rate expression of the index is \(\lambda_i\); and the repair time after the failure probability of the index risk is \(y_i\). It is known that the derivative change of the relationship after the risk of enterprise tax has particularity, so it is necessary to set up the enterprise tax risk control procedure according to the positioning of the risk department [20]. Accordingly, the failure state of information support for studying enterprise tax risk is determined, and the failure state probability of enterprise tax risk intelligent evaluation is determined on this basis. The formula is as follows:

\[
P = 1 - \exp \left( \sum_{i=1}^{n} Q_i P_i \right).
\]

Among them, the number of indicators of failure state of enterprise tax risk intelligent assessment can be expressed as \(n\). Through the intelligent assessment of enterprise tax risk, the failure state probability is summarized, the risk record information in the risk case base is summarized, and the risk report information is used to summarize the records of enterprise tax and enterprise operation information [21, 22]. Store risk snapshot information while integrating enterprise tax monitoring information, and mark enterprise tax risk reasons and risk departments [23]. After standard processing, it is stored as risk snapshot information to establish a relationship between the duration of enterprise tax failure state and the duration of enterprise tax repair risk state.
The formula is as follows:

\[ T_1 = \frac{1}{\min P_n}. \]  

Among them, the failure state probability set of enterprise tax risk intelligent assessment is \( P_n = (P_1, P_2, \ldots, P_n) \), and the enterprise tax risk department and reasons are marked according to the duration of enterprise tax repair risk state. By matching the newly added enterprise tax risk information to build a risk review mechanism [24], the enterprise tax risk intelligent assessment risk information is cleaned and the repeated risk characteristics are eliminated. Let the value range of failure probability of enterprise tax be \( Q_i \in [0, 1] \), and normalize the enterprise tax risk intelligent evaluation index within the value range of duration \( T_1 \). The information source of risk diagnosis is analyzed by using the constructed case base.

Mark the information sources according to the types of enterprise tax risk, and distinguish the information sources according to the management information and the core part [25]. At the same time, the efficiency of management and control is calculated for information conversion and several applications, and the calculation index \( Q_i(0.01, 0.005, 0.015, 0.01, 0.015) \) of enterprise tax risk failure rate is obtained. Take the calculation index interval of inefficiency as the unit to complete the collection of enterprise tax risk information, and extract the correlation characteristics of enterprise tax risk assessment from the collected enterprise tax risk information.

2.2. Extract the Related Characteristics of Enterprise Tax Risk Assessment. According to the collection of enterprise tax risk information, determine the circular simulation of enterprise tax risk and enterprise operation, and arrange the information fields of the evaluation correlation characteristics of enterprise tax risk. Adjust the process of information duplication by using the information confusion of repeated risk information [26, 27]. Make enterprise tax risk assessment for complex enterprise operation, and make risk correlation expression according to the collected enterprise tax risk information. The formula is as follows:

\[ R(E_i) = P(E_i)C(E_i). \]  

Among them, if the enterprise tax event is expressed as \( E_i \), it means that the risk occurrence probability of the event is \( P(E_i) \), the consequence of the enterprise tax event risk is \( C(E_i) \), and the expression of the event risk index is \( R(E_i) \). Corresponding to the probability of the occurrence of enterprise tax risk to the probability of the occurrence of events, according to the state selection principle of enterprise tax, analyze the deterioration degree of the composition weight of the state, deduct the amount of enterprise business state of enterprise tax, obtain the formulation rules of enterprise tax state evaluation guidelines, and evaluate the possible results of enterprise tax risk. Use the risk assessment process of enterprise tax to calculate the importance index of intelligent risk assessment, and the formula is as follows:

\[ U = \frac{1}{R(E_i) + \mu}. \]  

Among them, if the enterprise operation failure rate is \( \mu \), there is a collection preprocessing state between the correlation importance [28] of enterprise tax risk assessment and the distribution parameters. According to the complexity of calculating state probability and outage information processing, the average value of risk intelligence evaluation parameters is close to the business situation of the enterprise. Based on this, we can judge the stability of enterprise tax failure event. The calculation formula of Basin Valley function of enterprise business life is as follows:

\[ f(t) = U_i e^{-\mu t}. \]  

Among them, the value range of the importance index set of intelligent risk assessment is \( (U_{i1}, U_{i2}, \ldots, U_{i4}) \), and the repairable failure rate index is \( e^{-\mu} \). According to the failure density distribution of failure event function, the cumulative score matrix of failure enterprise tax is determined, and the information entropy calculation formula of enterprise tax risk intelligent evaluation index is obtained, as follows:

\[ H(x) = -\frac{x}{U_{i4}} \ln \left( \frac{x}{U_{i4}} \right), \]  

where \( x \) is the evaluation importance coefficient of enterprise tax. It is known that the information entropy of enterprise tax intelligent evaluation index includes the characteristic quantity of enterprise tax state. According to the determined relevant standards of state evaluation, analyze and evaluate the information of each state quantity index, and determine the tax risk according to the level of enterprise tax health [29]. The operation and maintenance requirements of enterprise tax risk intelligent assessment are arranged in order, and the causes are distinguished according to the historical risk information of enterprise tax, so as to obtain the calculation formula of risk information constant of enterprise tax, as follows:

\[ \psi(x) = \frac{\ln (x)}{\ln (U_{i4})}. \]  

The risk value of enterprise tax risk information is calculated by using the calculation formula of risk information constant of enterprise tax, and the historical risk information of enterprise tax is transformed into score matrix \( Y = (y_j)_{N \times M} \), where \( N \) and \( M \) are the number of rows and columns of score matrix and \( y_j \) is the score variable of historical risk information of enterprise tax. Therefore, the calculation formula of characteristic
quantity of enterprise tax risk assessment is obtained as follows:

\[ y_i = \ln \frac{x_{ij}}{\psi(x)} \quad (i = 1, 2, \cdots, N; j = 1, 2, \cdots, M). \] (9)

Among them, if the score membership value of the characteristic quantity of enterprise tax risk assessment is \( x_{ij} \), the corresponding value membership value range of index \( i \) and index \( j \) is fixed and the membership degree is average, so the correlation characteristics of enterprise tax risk assessment are extracted, and a deep learning enterprise tax risk assessment model is constructed according to the historical risk information and correlation characteristics of enterprise tax.

2.3. Build a Deep Learning Enterprise Tax Risk Assessment Model. Deep learning is a subset of machine learning in the field of artificial intelligence. It has a network structure and can learn unsupervised from unstructured or unmarked data. Stacked automatic encoder is a denoising self-encoder using unsupervised pretraining mechanism on the layer. When a layer is pretrained to perform feature selection and feature extraction on the input of the previous layer, it will be followed by a supervised fine-tuning stage. It just integrates many denoising automatic encoders together. Therefore, on the basis of dealing with and processing the correlation characteristics of enterprise tax risk assessment and determining the variation degree of enterprise risk indicators from the correlation characteristics, this paper constructs a deep learning enterprise tax risk assessment model based on stacking automatic encoder.

2.3.1. Deep Learning Principle Based on Stacked Automatic Encoder. The AE (autoencoder) shown in Figure 1 is constructed by using the input layer, output layer, and hidden layer. It can be seen from Figure 1 that the encoder is a symmetrical neural network. The encoding and decoding process is adopted to minimize the reconstruction deviation of input information and obtain the optimal hidden layer representation.

It is known that the amount of information of the training information set \( \{x^{(1)}, x^{(2)}, \cdots, x^{(N)}\} \) is \( N \); the encoding matrix and decoding matrix are and \( V \), respectively; and the offset vectors of encoding and decoding are \( b \) and \( c \), respectively. Therefore, the automatic encoder uses the encoding formula (10) to complete the mapping from the input vector \( x^{(i)} \) to the hidden layer representation \( h(x^{(i)}) \) and then obtains the reconstruction vector \( z(x^{(i)}) \) of the output layer from the decoding formula (11):

\[ h(x) = f(Wx + b), \] (10)

\[ z(x) = g(V^T h(x) + c). \] (11)

In the above formula, the sigmoid activation function is represented by \( f \) and \( g \), respectively.

Only when the reconstruction deviation \( L(x, z) \) of the input information is small, the coding matrix contains the initial information features, which requires searching the optimal parameter \( \theta' \) of the automatic encoder through the training information set to minimize the reconstruction deviation \( L(x, z) \):

\[ \theta' = \arg \min_{\theta} \frac{1}{2N} \sum_{i=1}^{N} \|x^{(i)} - z(x^{(i)})\|^2. \] (12)

The activation level of the \( j \)th neuron in the hidden layer in the training set is defined by the following average activation amount:

\[ \hat{\rho}_j = \frac{1}{N} \sum_{i=1}^{N} y_j(x^{(i)}). \] (13)

In order to suppress most neurons, the average activation amount \( \hat{\rho}_j \) is approximately a constant term \( \rho \) equal to zero, and its penalty term is set as the following relative entropy to control sparsity:

\[ KL(\rho \| \hat{\rho}_j) = (1 - \rho) \log \frac{\rho}{1 - \hat{\rho}_j}. \] (14)

If \( \hat{\rho}_j = \rho \), then \( KL(\rho \| \hat{\rho}_j) = 0 \); on the contrary, the relative entropy is positively correlated with the deviation degree of average activation.

To sum up, the following objective function with sparsity constraints is used to solve the optimal automatic encoder parameter \( \theta' \):

\[ \theta' = \arg \min_{\theta} L(x, z) + \gamma \sum_{j=1}^{H_D} KL(\rho \| \hat{\rho}_j), \] (15)

In the above formula, the weight value of sparse penalty term and the number of hidden layer units are \( \gamma \) and \( H_D \), respectively.
There are two training processes for stacking automatic encoder, namely, pretraining and fine-tuning, as shown in Figure 2.

Taking Figure 2 as an example, when pretraining a stacked automatic encoder of layer $l$ from bottom to top, it is necessary to train the first layer with the training sample as the input item and then train the $k+1$ hidden layer with the output of the $k$ hidden layer as the input item, so as to complete the pretraining of each layer in the past. For the coding matrix $W$ and the bias vector $b$, the gradient descent method [30, 31] is used for cyclic calculation, and the layer $k$ of the neural network is updated by the following two formulas:

$$W_{ij}(k) = W_{ij}(k) - \epsilon \frac{\partial}{\partial W_{ij}(k)} L_{\text{sparse}}(W, b), \quad (16)$$

$$b_{i}(k) = b_{i}(k) - \epsilon \frac{\partial}{\partial b_{i}(k)} L_{\text{sparse}}(W, b). \quad (17)$$

In the above formula, the learning rate is $\epsilon$. After pre-training, the parameter fine-tuning of stacking automatic encoder is realized by supervised training. In order to obtain the characteristics of nonredundant information with integrity, the automatic encoders are stacked to form a deep neural network model to complete the architecture of stacked automatic encoders. The lower output item of the encoder is set as the upper input item, and the features are abstracted in order by stacking, so as to obtain the interrelated effective features, which lays a data foundation for the realization of high-precision enterprise tax risk intelligent assessment.

2.3.2. Construction of Enterprise Tax Risk Intelligent Evaluation Model Based on Deep Learning. Based on the bottom measurement information $r$, the intelligent assessment model of enterprise tax risk is constructed by using the designed stacked automatic encoder and softmax regression layer classifier, as shown in Figure 3.

The model shown in Figure 3 realizes the intelligent assessment of enterprise tax risk by describing the nonlinear mapping relationship between the underlying measurement information and stable types. The basic part of the model (i.e., stack automatic encoder) is used to express the enterprise tax information hierarchically to obtain high-efficiency features. The classifier located at the top of the model is used to divide and output the stable types of samples through the softmax regression layer. Assuming that there are $n$ stable classes in the sample, the implicit functional relationship of the softmax regression layer is described by the following formula:

$$h_{\theta}(x) = \frac{1}{1 + e^{\theta_1^T x} + e^{\theta_2^T x} + \cdots + e^{\theta_n^T x}} \begin{bmatrix} e^{\theta_1^T x} \\ e^{\theta_2^T x} \\ \vdots \\ e^{\theta_n^T x} \end{bmatrix}.$$  \quad (18)
In the above formula, the output vector of the top layer and the lower layer of the network is $x$, and the weight vectors of the network layer and the first and second output units are $\theta_1$ and $\theta_2$, respectively.

In the process of training the enterprise tax risk intelligent evaluation model, the relevant training parameters are set according to the given unmarked training information set $T_1 = \{r_1\}$ and labeled training information set $T_2 = \{r_2, y_2\}$. The unsupervised pretraining evaluation model is based on the pretraining stage of stacked automatic encoder by $T_1$. Using $T_2$, fine-tune the model parameters in the following two steps:

(1) Initialize classifier parameter $\{W^{l+1}, b^{l+1}\}$

---

**Table 1:** Constraint index parameters of enterprise tax risk assessment.

<table>
<thead>
<tr>
<th>Constraint parameters</th>
<th>Contribution degree</th>
<th>Weighted value</th>
<th>Assessment contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surplus</td>
<td>109.42</td>
<td>0.37</td>
<td>6.03</td>
</tr>
<tr>
<td>GDP</td>
<td>115.42</td>
<td>0.36</td>
<td>5.69</td>
</tr>
<tr>
<td>Economic growth value</td>
<td>108.00</td>
<td>0.31</td>
<td>6.18</td>
</tr>
<tr>
<td>Achievements</td>
<td>117.59</td>
<td>0.40</td>
<td>5.52</td>
</tr>
<tr>
<td>Financial index</td>
<td>105.16</td>
<td>0.36</td>
<td>5.55</td>
</tr>
<tr>
<td>Accounting</td>
<td>106.58</td>
<td>0.36</td>
<td>5.29</td>
</tr>
<tr>
<td>Wages</td>
<td>101.29</td>
<td>0.38</td>
<td>5.46</td>
</tr>
<tr>
<td>Labor cost</td>
<td>104.11</td>
<td>0.38</td>
<td>5.61</td>
</tr>
<tr>
<td>Workload</td>
<td>107.67</td>
<td>0.30</td>
<td>5.20</td>
</tr>
<tr>
<td>Tax rate</td>
<td>100.91</td>
<td>0.34</td>
<td>5.12</td>
</tr>
<tr>
<td>Pre tax deduction standard</td>
<td>98.11</td>
<td>0.33</td>
<td>5.02</td>
</tr>
<tr>
<td>Preferential tax policies</td>
<td>96.00</td>
<td>0.30</td>
<td>5.18</td>
</tr>
<tr>
<td>Additional deduction</td>
<td>99.16</td>
<td>0.41</td>
<td>4.80</td>
</tr>
<tr>
<td>Risk points of tax self-inspection</td>
<td>91.75</td>
<td>0.35</td>
<td>5.92</td>
</tr>
</tbody>
</table>

**Table 2:** Configuration parameters related to experimental environment.

<table>
<thead>
<tr>
<th>Name</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operating system</td>
<td>Win10</td>
</tr>
<tr>
<td>CPU</td>
<td>Intel Core i5-3386</td>
</tr>
<tr>
<td>RAM</td>
<td>6 GB</td>
</tr>
<tr>
<td>Programing language</td>
<td>Python 3.8</td>
</tr>
<tr>
<td>Information processing framework</td>
<td>Tensor Flow 2.0</td>
</tr>
</tbody>
</table>

**Table 3:** Optimal parameters of evaluation model.

<table>
<thead>
<tr>
<th>Index</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of stacked automatic encoder layers</td>
<td>3</td>
</tr>
<tr>
<td>Number of nodes in each layer</td>
<td>220, 480, 310</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>0.5</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>0.4</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>0.9</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.7</td>
</tr>
</tbody>
</table>

**Figure 4:** Quantitative analysis of enterprise tax risk.
The gradient descent algorithm is used to supervise and optimize the model parameters from top to bottom.

If \( \{y^{(1)}, y^{(2)}, \ldots, y^{(N)}\} \) is the category identification set corresponding to the training sample, the indication function is \( 1\{\cdot\} \), and the expression is as follows:

\[
\begin{align*}
  y = j, & \quad 1\{y^{(i)} = j\} = 1 \\
  y \neq j, & \quad 1\{y^{(i)} = j\} = 0
\end{align*}
\]

Then, the supervised training cost function \( J \) is described by the following cross-entropy function [32, 33]:

\[
J = \sum_{i=1}^{N} \sum_{j=1}^{n} 1\{y^{(i)} = j\} \log \sum_{i=1}^{n} e^{\theta_j x^{(i)}}. \tag{20}
\]

The cost function formula [34, 35] is optimized by gradient descent algorithm, and the weight is updated with iteration to complete the fine adjustment of evaluation model parameters. Using the construction model, the enterprise tax risk is evaluated through the construction of index system, and the distribution of enterprise tax risk constraint indicators is shown in Table 1.

Based on the indicators shown in Table 1, the level of enterprise tax risk is divided by deep learning, which is used as the division index to continuously mine the level of enterprise tax risk [36]. The risk quantity analysis of enterprise tax risk according to high-risk points is shown in Figure 4.

In Figure 4, \( \sigma \) is the risk division unit of enterprise tax.

According to the above process, the preprocessed enterprise tax risk information is input into the built in-depth learning enterprise tax risk assessment model, and the intelligent assessment of enterprise tax risk is realized by stacking the parameters of automatic encoder and optimizing iteration.

3. Experimental Analysis

In order to verify the better effect of the proposed enterprise tax risk intelligent evaluation method based on deep learning, the network visualization and data mining method in reference [5] and the expert evaluation method in reference [6] are used as comparative methods for experimental testing.

3.1. Simulation Experiment Environment.

Set up the optimal training platform according to the experimental parameter set, as shown in Tables 2 and 3.

320 groups of samples are selected from the tax risk data of an enterprise as training samples to train the model, and then, 180 groups of samples are selected as test samples to test.

3.2. Result Analysis.

According to the above parameter settings, rearrange the sampling points and measure the unit value of the risk intelligent assessment index of enterprise tax under the method in this paper, as shown in Figure 5.

Use the unit value of the risk intelligent assessment index of enterprise tax to make a change deviation curve for the risk node of the assessment risk index, and determine the specificity and sensitivity of the unit value of the corresponding assessment index with the threshold value belonging to the normal category, so as to obtain the ROC curve. The closer the assessment ROC curve is to the reference line, the closer the assessment result is to the real value, and the farther the ROC value is from the reference line, the more the assessment result deviates from the real value. Based on this, the deviation ratio of risk assessment index ROC is obtained.

Compare the ROC deviation ratio of the three methods, and the results are shown in Figure 6.

By analyzing the information in Figure 6, it can be seen that the lowest deviation ratio of risk assessment index ROC in the method of reference [5] is 0.32. The lowest ROC deviation ratio of the risk assessment index of the
method in reference [6] is 0.34, and the highest ROC deviation ratio of the risk assessment index of this method is 0.38, and the lowest is 0.27. Therefore, the ROC deviation ratio of the risk assessment index of this method is lower; that is, by reasonably distinguishing the same type of risk information according to category, type, and appearance, this paper effectively extracts the correlation characteristics of enterprise tax risk assessment, and the mining effect of the assessment index is better.

In order to further verify the accuracy of the evaluation method in this paper, taking the four risks of management risk, personnel risk, audit risk, and agency risk as the first-class indicators, the three methods are used to carry out risk evaluation, and the evaluation accuracy of the three methods is analyzed by root mean square error. The test results are shown in Table 4.

According to Table 4, for the four risks of management risk, personnel risk, audit risk, and agency risk, the root mean square error of this method is significantly lower than that of the other two methods, and the highest root mean square error is 2.6. Experiments show that under different primary indicators of risk assessment, the root mean square error of this method is the lowest, indicating that the risk assessment result of this method is closer to the real risk assessment result; that is, the risk assessment accuracy of this method is higher. The main reason is that this method finds out the optimal parameters in the deep learning enterprise tax risk assessment model and optimizes the assessment performance through stacking self-encoder training.

4. Conclusion

Enterprise tax risk includes many risks. In order to ensure the stable development of enterprises, this paper constructs a more accurate in-depth learning enterprise tax risk assessment model on the basis of preprocessing enterprise tax risk information. Through the establishment of enterprise tax risk intelligent evaluation array and dimension, the characteristics of enterprise tax risk are deeply analyzed, and the deviation ratio of risk evaluation index ROC is reduced. The experimental results show that the risk assessment accuracy of the proposed method is high and can be used to guide the strategic adjustment of enterprises. In the future, we should further analyze the classification of enterprise tax risk rate, continue to optimize the parameters of the sample model, and focus on the cost loss of regulating enterprise tax risk.

Data Availability

The author can provide all the original data involved in the research.
Conflicts of Interest

The author indicates that there was no conflict of interest in the study.

References


