Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
 Volume 25, Issues 4, pp. 3100–3113, DOI 10.12694/scpe.v25i4.2894

# A MULTI-LEVEL DEEP NEURAL NETWORK-BASED TOURISM SUPPLY CHAIN RISK MANAGEMENT STUDY

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**Abstract.** With the rapid advancement of the tourism, the capital demand of tourism enterprises has gradually risen, but the confusion of market management has increased the difficulty of risk assessment of tourism enterprises by financial institutions, which has led to difficulties in financing tourism enterprises and seriously hindered their development. On this basis, this research first analyses the risk structure of the tourism supply chain (TSC) from the financial aspect and establishes a relevant risk assessment system. After confirming the assessment indexes, the data is dativized and normalized, and finally a multi-level deep neural network (DNN) is used to construct a TSC risk prediction model to calculate the transformed indexes and assess the risk degree of the enterprise according to the results. The experimental results indicate that the model has the best performance when the H-Net hidden layer is 3 layers and the L-Net hidden layer is 4 layers, and its accuracy reaches 93.35%, sensitivity reaches 84.13%, convergence starts at 25 iterations, the final loss value is only 0.8, and the predicted and the real value error is within 2.5%. Therefore, the multi-level DNN model constructed in this experiment has certain application value in TSC risk management.

**Key words:** Multilevel Deep Neural Networks; Tourism; Risk Management; Finance

**1. Introduction.** As people's living standards improve, the domestic tourism market is developing more and more rapidly, and the rapid development of the tourism market also demonstrates the country's growing economic strength [9]. Although the domestic tourism industry is currently thriving, small and medium-sized tourism enterprises still have some obstacles for development, mainly the lack of capital due to financing difficulties, which makes it difficult for enterprises to develop on a large scale. The difficulty of financing is mainly due to the complexity of the SME management system which makes it difficult for financial institutions to predict the risk level of the business and therefore prevents them from investing in it [11]. The TSC is the main investment of financial institutions. Although many studies have been explored on this issue, it is still difficult to cope with the complexity of the tourism industry. The field of deep learning is developing rapidly, replacing traditional mathematical and statistical methods as an important form of computing, and has led to many industries entering the age of intelligence [1]. DNNs, an important algorithm in the field of deep learning, can synthesize a wide range of input features and characterize the results. However, the current application of deep learning technology in the tourism industry is relatively rare. To address the above issues, this study proposes to construct a multi-level DNN model based on improving the risk assessment index of tourism enterprises to predict and assess the risk level of enterprises.

**2. Related Works.** With the development of information technology, DNN, a core technology for deep learning models, is widely used in various fields. lee et al. designed a heterogeneous floating point computing architecture using DNN. The architecture uses bfloat16DNN to train the processor to optimize the exponential computation and to improve energy efficiency and reduce memory consumption. The resulting computational architecture achieves an energy efficiency of 13.7 TFLOPS/W when processing data [6]. Wang C et al. developed a DNN-based optimized read voltage value strategy for expressing the relationship between voltage distribution and read voltage threshold. The strategy first analyses the channel coding rate for error probability, then uses cross iterative search to optimize the read voltage threshold, and finally uses DNN to optimize it. The results of this simulation experiment indicate that the optimization strategy using DNN improves the stability of the programming and slows down the read time delay [15]. Manoharan V et al. proposed a hybrid DNN-SHO algorithm for the performance measurement of an ECDM process for zirconia. The process starts with input

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parameters such as electrolytic concentration, duty cycle and voltage, followed by measurements of the output parameters, i.e., material removal rate, overcutting and tool wear rate, and finally performance determination based on the measured results. The research results indicate that the final material removal rate is 0.371 mg/min, the overcut is 162.2 µm and the tool wear rate is 0.26 mg/min. This determination is fully consistent with the experimental values and therefore the DNN-SHO algorithm is feasible [10]. A DNN accelerator was proposed by Jia et al. to solve the dynamic timing margin problem for PE arrays. First, a two-dimensional PE array with 16 clock domains is created, the clock period is dynamically adjusted according to the running instructions and operations, and finally a global clock bus is used for data transfer. The measurement results show that the performance conversion rate of the dynamic timing margin data stream under this DNN accelerator is improved by 34% and the effective operating frequency is increased by 19%, so this DNN accelerator can effectively solve the dynamic timing margin problem of PE arrays [3]. Kwon et al. define the concept of flexibility of DNN accelerators and propose flexion as a quantitative metric. Different accelerator flexions were tested and the experimental results showed that the Eyeriss-like accelerator was 2.2 times more flexible than the NVDLA-based accelerator, which is in line with the actual value, so the proposed quantitative metric has some application value [5]. Kariyappa et al. proposed drift regularization and multiplication in order to solve the situation of unstable DNN weight values caused by noise sources of PCM devices. noise training two techniques. The proposed techniques were used for image classification and language modelling experiments and performance evaluation, and the experimental results indicated that the proposed techniques raise the accuracy of DNN models by 12% [4]. Sun et al. proposed a DNN-based PDF security detector for epidemic documents in order to protect the security of PDF documents. Experiments on security detection of PDF files using this detector showed that the accuracy of the determination was 99.3% [14]. Ravindran R et al. applied DNNs to the field of self-driving cars. The technique of fusing sensors and DNNs to achieve multi-target detection and tracking of self-driving cars is proposed to optimize the perception model of self-driving cars [13].

As mentioned above, DNN, as a key technology of deep learning, has been well utilized in different fields, and many scholars have optimized and developed the performance of DNN. However, not many studies have applied DNN to the tourism industry, especially to the risk assessment of the TSC. With the gradual increase in the value of the tourism market, the use of deep learning algorithms to establish risk assessment models for the supply chain is an inevitable development trend, so this study discusses and analyses the application of DNN in the risk assessment management of the TSC.

## 3. Research on the application of multi-level DNNs in TSC risk assessment.

**3.1. Construction of a TSC risk assessment system incorporating financial risk forecasting.** With the rapid development of the global tourism industry, TSC is faced with increasing risks, which mainly include market demand fluctuation, supply chain disruption, information asymmetry and policy and legal changes. These risks not only threaten the operational efficiency of tourism enterprises, but also affect the profitability and sustainable development of enterprises. Although a variety of risk management tools and strategies have been proposed, these methods often rely on traditional statistical analysis and empirical judgment, which are difficult to deal with large-scale and high-dimensional data, resulting in inaccurate risk assessment and lagging response. In this context, this study aims to address two main issues. The first is how to accurately and quickly assess multiple risk factors in TSC, especially in a dynamic and changing market environment. The second is how to come up with an effective risk management framework that can respond in real time and adapt to changing risks. To this end, a risk assessment model based on Multi-level DNN is proposed, which utilizes deep learning technology to comprehensively analyze and process large amounts of data to discover potential risk patterns and associations, thereby improving the accuracy and efficiency of risk prediction.

The amount of capital invested needs to be determined by the value of the enterprise, however, the industry currently lacks a valuation system that can objectively reflect the market value of the enterprise [8]. In addition, as the TSC is relatively new, financial institutions are unable to objectively assess the transaction risk of tourism companies. This study aims to develop an objective and valid assessment system for risk prediction in the TSC [2].

Figure 3.1 shows the pyramid risk structure of the TSC. As shown in Figure 3.1, supply chain risks can be analyzed by viewing them as a pyramid structure [12]. The bottom level is the irresistible risk, which is the least likely to occur and the least damaging, and includes mainly policy risk and black swan risk. The


Fig. 3.1: The Pyramid Risk Structure of the Travel Supply Chain

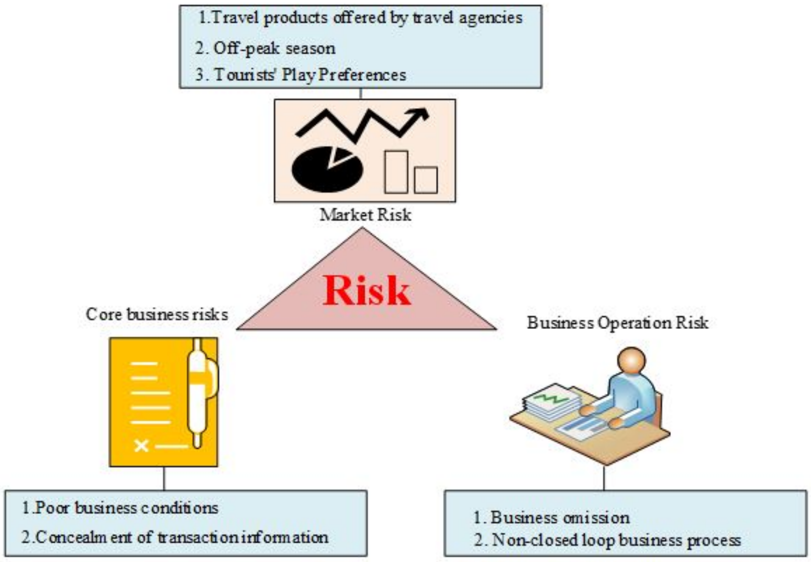


Fig. 3.2: Types of risk occurrence in the TSC

middle level of risk is transaction risk, which determines whether the TSC can run smoothly and requires a quantifiable model to dynamically predict the level of risk when assessing transaction risk. This risk is mainly tourism operational risk, for example. At the highest level is customer risk, where customer level risk is mainly assessed using financial institutions' intelligent risk control models, which are generally static and qualitative in nature. The probability of occurrence of this type of risk is the highest and is the most damaging.

The information flow of TSC mainly includes three aspects: market information flow, enterprise core information flow and operation information flow. The market information flow covers the dynamic changes of the tourism market, the uncertainty of tourism preference and other factors, which is helpful to accurately predict the market risk. Core businesses act as information hubs in TSC, holding visitor billing and transaction data. The integrity and transparency of information directly affect the trust of financial institutions and the financial stability of the entire supply chain. Operational information flow involves the monitoring of capital flow and financial information, which requires real-time, closed-loop management to ensure the effectiveness of risk control. Effective information flow management not only reduces the probability of risk occurring, but also protects the health of the entire TSC by responding quickly when it does occur. After analyzing the risk structure of the supply chain, different types of risk can be distinguished according to the characteristics of their occurrence.

Table 3.1: Supply chain risk assessment index system for tourism enterprises

| Primary indicators | Secondary indicators | Third level indicators |
|---|---|---|
| Corporate profitability | Return on Net Assets | Net income divided by owner's equity |
| | Operating Margin | Net income divided by operating income |
| Corporate debt repayment ability | Gearing ratio | Total liabilities divided by total assets |
| | Current Ratio | Total current assets divided by total current liabilities by total current liabilities |
| Business Operation Capability | Accounts Receivable Turnover Ratio | Ratio of operating revenues to average accounts receivable balance |
| Business Growth Capability | Total operating revenue | Growth for the period divided by total operating income for the previous period by total operating income for the previous period |
| | Total Assets | Increase in total assets for the period divided by total assets for the previous period |
| Corporate Capital Strength | Operating income | Net cash flow from operating activities and operating income |
| | Loan recovery rate | Loans recovered during the period |
| Corporate Cash Flow | Other receivables divided by assets as a percentage | Other receivables divided by total assets |

Figure 3.2 shows the types of risk occurring in the TSC. As shown in Figure 3.2, the types of risk are mainly divided into three categories, firstly, market risk, market risk is mainly due to the off-peak season, the uncertainty of tourists' touring preferences and other factors, so it leads to the inability of financial institutions to make accurate predictions on the tourism market. The second is core enterprise credit risk. The core enterprises in the tourism industry hold most of the information on visitor billing transactions in the industry, which could easily lead to the disruption of most of the financial supply chain in the industry in the event of a breach of trust by the core enterprises. Finally, the business operation risk, because the tourism industry needs to monitor the flow of funds and other financial information in real time, and closed-loop management, so the tourism industry's financial business operation process must be interlocked, up and down to take over, one of the problems will lead to the failure of risk management. TSC risk assessment indicator validation refers to the process of determining which indicators effectively reflect the level of risk in the TSC. These indicators are a key element in assessing the various potential risks faced by tourism enterprises, including market risk, operational risk and customer risk. The selection of evaluation indicators is based on the following criteria. The first indicator should be directly related to TSC's operations and risks. The second indicator should be quantifiable and can be clearly expressed through data. The third indicator should be sensitive to changes in the supply chain and can reflect changes in risk in a timely manner. Fourth, in the process of data collection, indicators should be easily obtained to ensure the real-time and accuracy of risk assessment. On this basis, a risk assessment system can be constructed based on the risk characteristics of the TSC.

Table 3.1 shows the supply chain risk assessment index system of tourism enterprises. From Table 1, we can get the risk assessment indicators are mainly the profitability, debt servicing ability, operation ability, growth ability, capital strength and cash flow of the enterprise. Among them, profitability is the enterprise's ability to obtain profits in a certain period of time, mainly including operating profit margin, cost profit margin, etc. Debt servicing capacity is the ability and willingness of an enterprise to repay its bank debts, and is mainly an analysis of the enterprise's debt ratio. Operational capability reflects the business level of the enterprise, mainly through the capital turnover rate to determine the profitability of the enterprise. Growth capacity is the development prospect of the enterprise after the loan, which is mainly judged by the revenue growth rate and other indicators. Capital strength is the enterprise's strength in recovering capital, mainly assessed through indicators such as payment recovery rate. Cash flow reflects the cash flow of an enterprise, with positive cash flow representing an enterprise in profit mode and negative cash flow in loss mode.

As risk assessment in the financial sector is currently operated by computer, there is also a need to digitize and normalize the indicators in the TSC risk assessment system, allowing them to be converted into computer language. Set a three-level feature table with i primary features, a score of for primary features and a weight of $R_{11}, R_{12}, ...R_{1i}$ for primary features. The table has level 2 features, the score of level 2 features is and the

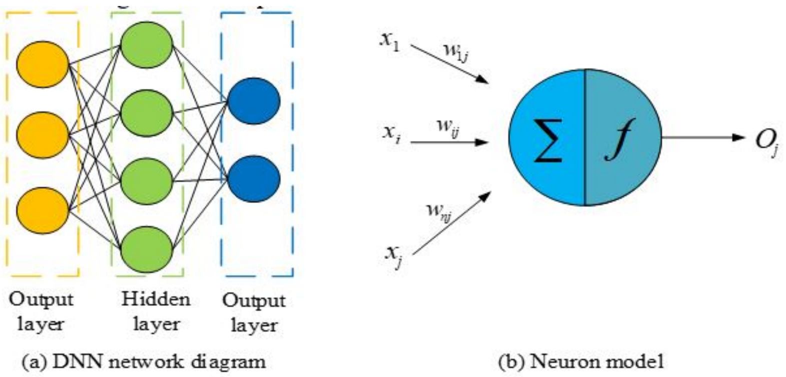


Fig. 3.3: Typical DNN diagram

weight of level 2 features is j $R_{21}, R_{22}, ...R_{2i}k$ level 3 features in the . There are table, the score of level 3 features is and the weight of level 3 features is. $S_{31}, S_{32}, ...S_{3i}S_{2x}$ The formula for calculating the score of the x second level feature is shown in equation (3.1).

$$S_{2x} = \sum_{a=1}^{i} R_{1a} * S_{1a} \tag{3.1}$$

$S_{2x}$ The of Eq. (3.1) is obtained by weighting the sum of the tertiary features under the secondary features. Similarly, the weighted sum of the secondary features under the primary features gives the fraction of the primary features $S_{1x}$, which is expressed in Eq. (3.2).

$$S_{1x} = \sum_{a=1}^{j} R_{2a} * S_{2a} \tag{3.2}$$

Equations (3.1) and (3.2) can convert the evaluation indicators into numerical form, but given the differences in units and value ranges of different indicators, normalization is also required before the DNN can perform operations on the data. To improve the speed of the operation, all data can be mapped to the interval range of [0-1] before the input values are pre-processed to obtain the expression for data normalization as in equation (3.3).

$$a` = \frac{a - a_{min}}{amin_{max}} \tag{3.3}$$

In equation (3.3), a is the original data value, a‘ is the data normalized value, $a_{max}$ is the data maximum value and $a_{min}$ is the data minimum value. In summary, after analyzing the financial risk structure and types of the TSC, a risk assessment system incorporating financial risk prediction is established. Based on this, this research proposes to construct a multi-level DNN-based TSC risk prediction model to identify and calculate the digitalized and normalized assessment indicators.

**3.2. Construction of a multi-level DNN-based risk prediction model for the TSC.** A DNN is a multi-layered structured neural network. Multi-level DNNs are designed to give machines the ability to learn and to analyses and recognize non-traditional data such as sounds, images etc [7]. The network's mode of operation is to first extract the non-linear relationship between the input data and the output result, then input the new data and derive the new output result from the resulting relational equation.

Figure 3.3 shows a typical DNN, where Figure 3.3(a) shows a DNN network structure with three layers: input, output and hidden layers, and neurons in one layer of the grid connect to neurons in the next layer. Figure 3.3(b) shows the neuron model, where the neuron is the basic structure of the DNN. When the input value of the neuron is greater than its threshold value, the neuron is activated and the output value is obtained through the activation function, which is then used as the input value of the next layer. In Figure 3.3(b),$x_1, x_2, ...x_n$ is the input value of the neuron, $w_{ij}$ is the weight, $\sum$ is the weighting operation, $O_j$ is the output, and f is the activation function. The presence of the activation function enhances the non-linear processing capability of the DNN and is generally located at the output position of the neuron. Three types of functions are commonly used, namely Sigmoid, Tanh and ReLU. The Sigmoid function is presented in equation (3.4).

$$f\left(x\right) = \frac{1}{1 + e^{-x}} \tag{3.4}$$

The Tanh function is presented in equation (3.5).

$$f\left(x\right) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3.5}$$

The real numbers in Eq. (3.5) take values in the range [-1,1] and are generally used to exaggerate the effect of features. The calculation for the ReLU function is Eq. (6).

$$f\left(x\right) = max(0, x) \tag{3.6}$$

Eq. (3.6) shows that the ReLU function is essentially a maximising function. Combining the analysis of equation (3.4), equation (3.5) and equation (3.6), it can be obtained that the interval range of both Sigmoid and Tanh functions are relatively small and will tend to saturate at the end values leading to a slower training speed, while the ReLU activation function has the ability of computational simplicity and resistance to gradient disappearance, so it is utilized as the activation function for this experiment. Based on this, the formula for calculating the output of this neuron can be obtained as in equation (3.7).

$$O_j = f\left(\sum_{i=0}^{\sum_{i=0}} n x_i w_i - \theta\right) \tag{3.7}$$

In Eq. (3.7),$\theta$ is the neural network parameter, whose expression is Eq. (3.8).

$$\theta = \left\{W^{(1)}\ , ..., W^{(n-1)}, b^{(1)}, b^{(n-1)}\right\} \tag{3.8}$$

In equation (3.8),$W^{(n)}$ is the weight vector and $b^{(n)}$ is the bias vector. During the computation of a neural network, the complex mapping of neurons in different layers is achieved by one-way propagation from the input space to the output space. The process by which the neural network normalises the feature vectors at the output layer and outputs the predicted values is known as the feed-forward process. Substituting the sample set $\Phi$ into the neural network for feedforward operation, the expression of the sample set $\Phi$ is shown in equation (3.9).

$$\Phi = \left\{\left(x_1, y_1\right), \left(x_2, y_2\right), .... \left(x_n, y_n\right)\right\} \tag{3.9}$$

In equation (3.9), $y_n$ is the actual value of the output and the predicted value of ${y_n}^*$ is passed on as shown in equation (3.10).

$$y_n^* = z^{(1)} \rightarrow O^{(1)} \rightarrow \bullet\bullet\bullet \rightarrow z^{(n)} \rightarrow O^{(n)} \tag{3.10}$$

In equation (3.10),z is the calculation result of the weighting operation. The parameter update of the neural node is calculated using the gradient descent algorithm, taking the first neuron in the neural network as an example, its parameter matrix is set as, $c^{(1)}$, and this update is shown in equation (3.11).

$$\left\{\begin{array}{l} C^{(1)} = C^{(1)} - \alpha \frac{\partial(C,c)}{\partial C^{(1)}} \\ c^{(1)} = c^{(1)} - \alpha \frac{\partial(C,c)}{\partial c^{(1)}} \end{array}\right. \tag{3.11}$$

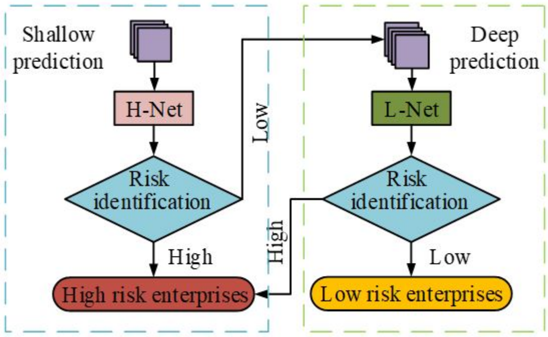


Fig. 3.4: Structure diagram of multi-level DNN system

In equation (3.11), $\alpha$ is the learning rate of the negative feedback operation process of the neural network. The above process allows the parameters in the neural network to be updated iteratively, and finally it gets the optimal values of the parameters. After completing the optimization of the neural network parameter values, this research used multi-level DNNs to construct a supply chain risk prediction model for tourism enterprises. The model is divided into two network layers, H-Net and L-Net, to predict supply chain risk hierarchically. The input values of H-Net are the secondary characteristics of the enterprises TSC, and the input values of L-Net are the tertiary characteristics of the enterprises TSC, and the output values of both network layers are the risk assessment values of enterprises TSC. Firstly, the model will generate an initial score table based on the tertiary characteristics table by the system before prediction, and then weight and sum the table data to get the secondary characteristics score table, then the system will input the secondary characteristics score table into H-Net and calculate the supply chain risk score of this enterprise. If the risk score is lower than 60, the enterprise is a high-risk enterprise, and if the risk score is higher than 60, the enterprise is a low-risk enterprise. Finally, the three-level characteristic score table of the low-risk enterprise obtained from H-Net is input into L-Net for further evaluation, and if the score is lower than 60, the enterprise is a high-risk enterprise, otherwise vice versa. In the model development stage, through in-depth analysis of historical data, the study observed that when the enterprise risk score is below 60, the default rate of these enterprises is significantly higher than that of enterprises with a score above 60. In addition, compared with industry standards and similar studies, it is found that this threshold can effectively distinguish high - and low-risk enterprises. It can be seen that using 60 points as the dividing point to distinguish between high and low risks can maximize the prediction accuracy and sensitivity of the model and ensure the accuracy and practicality of the assessment.

In the risk assessment process, especially when using L-Net deep network for detailed risk analysis, this study constructs a score table based on three levels of characteristics, which is used to quantify and evaluate the performance of enterprises on different risk dimensions. Tertiary features refer to the detailed data points extracted from the daily operations and financial reports of an enterprise as detailed expansion features of primary and secondary features. Tertiary features are used to assess the specific risk status of an enterprise. The score table is created by quantifying and standardizing the above three levels of characteristics, each of which is assigned a score and weight. Scores are typically based on industry standards or historical performance data, determined by comparing a company's actual performance to the industry average. The weights are assigned according to the importance of the feature in the overall risk assessment. The main impact of the score table is to provide a quantitative, easy-to-understand way to assess the level of risk in a business. By scoring the three levels of characteristics together, risk managers can quickly identify those risk areas that may require further attention, while also having a clear view of the overall risk profile of the organization. In addition, the score table can also be used to monitor changes in the level of enterprise risk and provide support for enterprise risk management and decision-making.

Figure 3.4 shows the structure of the multi-layered DNN system. H-Net is designed as a shallow predictive network that is primarily responsible for processing and evaluating secondary features, i.e. features received directly from the data input layer. The primary purpose of this network layer is to quickly screen and initially assess possible risks, providing a preliminary risk assessment result in order to quickly identify high-risk entities or situations. Due to its relatively simple structure, H-Net can initially process large amounts of data while maintaining speed, and screen out potentially high-risk cases for further analysis. Compared to H-Net, L-Net is a deeper network specifically designed to handle more complex data analysis tasks. It receives output from H-Net and mainly deals with tertiary features for more in-depth risk analysis. The purpose of L-Net is to provide a more refined risk assessment by deeply analyzing detailed operational data of an enterprise, assessing subtle risk changes, and predicting long-term risk trends. The analysis results of this layer are more accurate and suitable for further verification and analysis of low or uncertain risks after screening.

From the above, the DNN input values used in this experiment are the secondary and tertiary structures of the enterprise supply chain, and the number of neurons in the input layer of the H-Net layer and L-Net layer is 6 and 20. respectively. And the number of neurons in the output layer of both networks is 1. The number of hidden layers needs to be calculated and solved by the formula method, and the expression is as in equation (3.12).

$$p = \sqrt{n + q} + a \tag{3.12}$$

In equation (3.12), $p$ is the quantity of neurons in the hidden layer, n is the quantity of neurons in the input layer, and a is the mediation parameter, which takes values in the range of [1-10]. To sum up, this research first carries out the assessment index confirmation of the TSC risk of enterprises, then data and normalization of the index, then constructs a multi-level DNN model to calculate the characteristics of the processed index, and finally judges the TSC risk degree of the enterprise according to the calculation results.

The development process of multi-level DNN model based on TSC risk prediction is as follows. The first is data preparation and preprocessing. Various types of data are collected, including market data, supply chain transaction records, and policy changes. The data is cleaned to remove missing values and outliers, and then normalized to fit the input requirements of the neural network. The second is the model architecture design. A neural network with two levels, H-Net and L-Net, is designed. H-Net handles the primary risk assessment, while L-Net further analyzes businesses that are initially identified as high-risk. Each network layer consists of input layer, several hidden layers and output layers, and the specific number of layers and neurons is obtained based on experimental optimization. The next step is feature selection and network training. In the feature selection phase, methods based on information gain and correlation analysis were used to determine which features were most important for risk prediction. The selected features are fed directly into the neural network. The back-propagation algorithm was used for the training of the network, and Adam was chosen by the optimizer because it can effectively adjust the learning rate to suit the needs of our model after many iterations. Finally, the model is evaluated and verified. To evaluate the performance of the model, metrics such as accuracy, recall, and F1 scores were used. In addition, the prediction results of the model were compared with other machine learning algorithms to prove its superiority.

## 4. 4 Analysis of the results of multi-level DNN-based TSC risk prediction management.

**4.1. Experimental analysis of multilevel DNNs for ablation.** The experiment was run on a workstation, and the experimental data used real transaction data of a core enterprise in the tourism industry within the last five years, of which 80% was used as the training set and the remaining 20% as the test set. The evaluation metrics were first datatized and normalized according to equations (1), (2) and (3) to normalize the values of all data to the range of [0-1], then the network structure was built through the API in TensorFlow, then the neural network function was used to initialize the network parameters and build TFRecord to transfer the data into the neural network, and finally the optimization of loss function, activation function and other neural network parameters, call the session.run function for training, and output the results.

Figure 4.1 shows a schematic diagram of the bench configuration and the experimental flow. Where Figure 4.1(a) shows the bench configuration parameters and Figure 4.1(b) is the experimental flow chart. The purpose of using Multi-level DNN in this study is to use neural networks of different levels to process and analyze complex data relationships, so that the model can learn nonlinear features in the data more deeply, so as to improve the accuracy of risk prediction. The ablation experiments were set up to verify the specific contribution

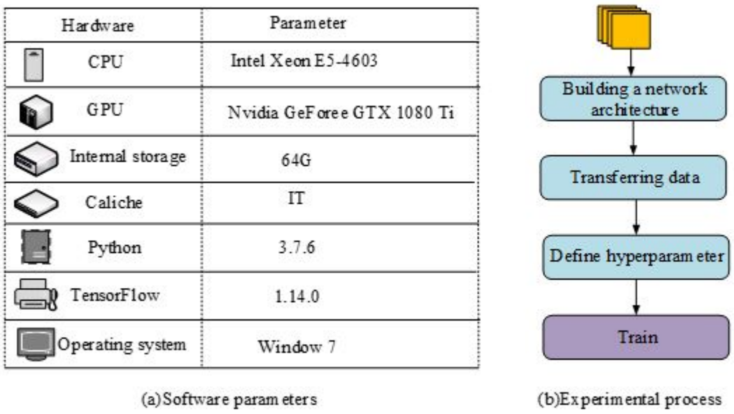


Fig. 4.1: Workbench configuration and experimental process

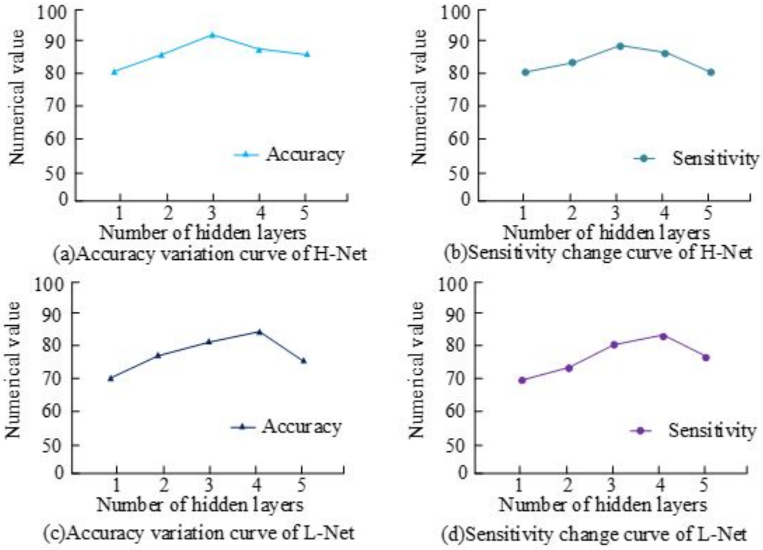


Fig. 4.2: Hidden layer ablation experiment

of each hidden layer to the performance of the model and to ensure that the optimization of the model was effective. In the ablation experiment, different layers from the input layer to the hidden layer are removed one by one, and the importance of these layers in the overall network is assessed by comparing the performance of the model after removing specific layers. In this way, the study was able to clearly identify the network layers that contributed the most to the prediction results, thus providing a basis for further optimization of the model structure. Since the features of the DNN affect the output results, it is necessary to first determine the influence of the quantity of neural network layers on the H-Net and L-Net.

Figure 4.2 shows the multi-level DNN hidden layer ablation experiment. Among them, Figure 4.2(a) and Figure 4.2(b) show the curve of model accuracy and sensitivity with the number of H-Net hidden layers, respectively. When the quantity of hidden layers is at 3, the accuracy of the model prediction results reaches a maximum of 91.24% and the sensitivity is as high as 87.89%. The analysis of Fig. 4.2(a) and Fig. 4.2(b) shows that when hidden layers is greater than 3, the accuracy and sensitivity of the prediction results decrease

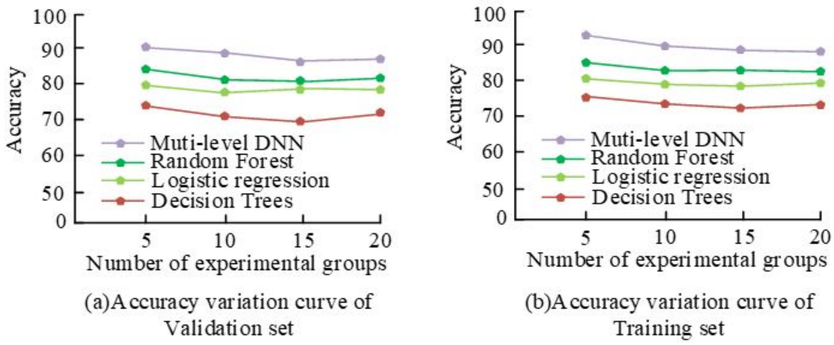


Fig. 4.3: Comparison of Model Accuracy under Four Algorithms

gradually as the H-Net hidden layers increases. Figure 4.2(c) and Figure 4.2(d) denote the curve of model accuracy and sensitivity with the quantity of L-Net hidden layers, respectively. When the hidden layers are 4, the model accuracy and sensitivity get the highest value of 84.79% and 82.12%, respectively. To sum up, within a certain range, raising the number of hidden layers can improve the data fitting ability of the model. The multi-level DNN performs best when the H-Net hidden layer is 3 and the L-Net hidden layer is 4.

**4.2. Performance analysis and application of multi-level DNN models in TSC risk prediction.** To further demonstrate the effectiveness of Multi-level DNNS, the study compared Multi-level DNNS to several other common machine learning algorithms, including logistic regression, decision trees, and random forests. These particular algorithms were chosen because they each exhibit unique performance characteristics when dealing with classification problems. Logistic regression is often used for baseline comparison because of its concise model and strong explanatory results. Decision trees are easy to understand because they can generate decision rules. As an ensemble learning method, random forest can improve the stability and accuracy of prediction. By comparing with these algorithms, this study can comprehensively evaluate the practicability and effectiveness of multi-level deep neural network in the risk prediction of tourism enterprise supply chain. The models under all three algorithms and the multilevel DNN model are applied to the supply chain risk prediction of tourism companies and the results of the training and test sets are compared to analyses their accuracy and sensitivity.

Figure 4.3 shows a comparison of the accuracy of the models under the four algorithms. Where Figure 4.3(a) and Figure 4.3(b) shows the accuracy results obtained for the test set and the training set, respectively. From Figure 4.3, the results of the training set under all four models are slightly higher than the results of the corresponding test set, which indicates that the classification of the dataset is effective. In addition, the accuracy of the proposed multilevel DNN algorithm is higher than that of the other algorithms, with the highest accuracy result of 93.35% in the training set. The model under the multi-level DNN algorithm has a certain accuracy in predicting the risk of the TSC.

Figure 4.4 shows a comparison of the sensitivity of the models under the four algorithms. Among them, Figure 4.4(a) and Figure 4.4(b) are the sensitivity results obtained from the test set and the training set, respectively. From Figure 4.4, it can obtain that the sensitivity results of the training set under all four models are slightly higher than the corresponding test set results, and the sensitivity of the model under the multi-level DNN algorithm is higher than the other algorithms, with the highest sensitivity of 84.13% in the training set. The sensitivity represents the response time of the model when performing data processing, which indicates that the model built with multi-level DNN can enter the data computing mode faster and reduce the time cost. In summary, it can be concluded that the model under multi-level DNN algorithm has higher application value.

Figure 4.5 shows the iteration curves under the four algorithms, where Figure 4.5(a) shows the iteration curve obtained from the test set and Figure 4.5(b) shows the iteration curve obtained from the training set. From Figure 4.5, the iterative stabilization rate of the test set is slightly lower than that of the training set. The multilevel DNN algorithm in the training set starts to converge after 25 iterations, while the random forest

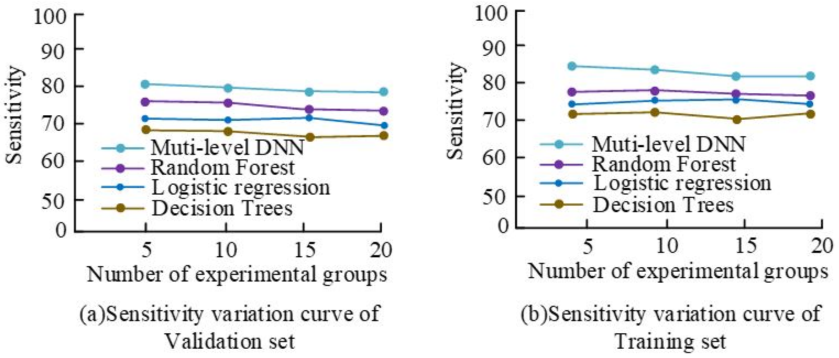


Fig. 4.4: Comparison of Model Sensitivity under Four Algorithms

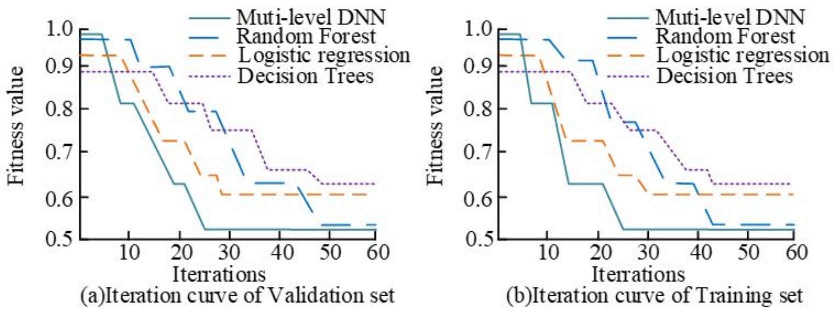


Fig. 4.5: Iteration curves under four algorithms

starts to converge at 48 iterations, the logistic regression starts to converge at 28 iterations and the decision tree starts to converge at 49 iterations, so the multilevel DNN algorithm has a better optimization finding ability and eventually reaches an optimal fitness value of 0.52.

Figure 4.6 shows the iteration curves under the four algorithms, where Figure 4.6(a) shows the loss curve obtained from the test set and Figure 4.6(b) shows the loss curve obtained from the training set. From Figure 4.6, the loss values of the four algorithms gradually decrease and stabilize with more iterations, and the overall loss values of the training set are lower than those of the test set. The loss value of the multi-level DNN algorithm in the training set is 0.8 when it reaches stability during the iterations, that of the random forest is 1.1, that of the logistic regression is 1.8, and that of the decision tree is 1.9. Therefore, the multi-level DNN algorithm has a lower loss rate during the operation and has better application value.

Figure 4.7 shows the risk assessment trend of the tourism enterprise over a five-year period. The predicted value is the risk assessment score obtained through the multi-level DNN algorithm model, the traditional predicted value is the risk assessment score obtained using the traditional weighted summation algorithm, and the true value is the real risk value of the enterprise. From Figure 11, it can get that the results obtained by the multi-level DNN model are closer to the true value, and the prediction error is less than 2.5%, which indicates that the DNN can better evaluate and predict the TSC risk of enterprises. In summary, the model constructed using multi-level DNN proposed in this research can objectively and accurately manage the risk prediction of the TSC of enterprises.

**5. Discussion.** The multi-level deep neural network model proposed in this study has demonstrated significant predictive ability in tourism supply chain risk management, but its implementation strategies and potential challenges in real world scenarios need to be further explored to transform this model into an effective

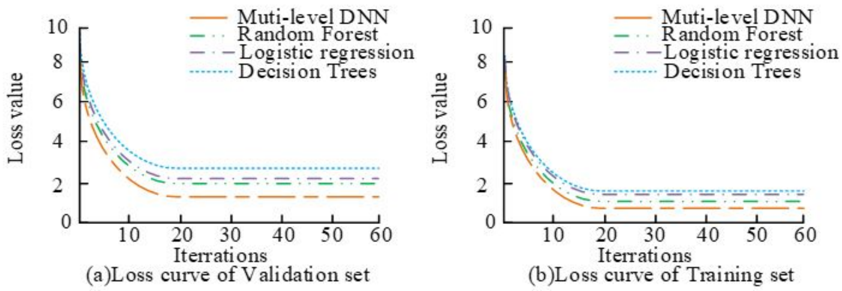


Fig. 4.6: Loss curves under four algorithms

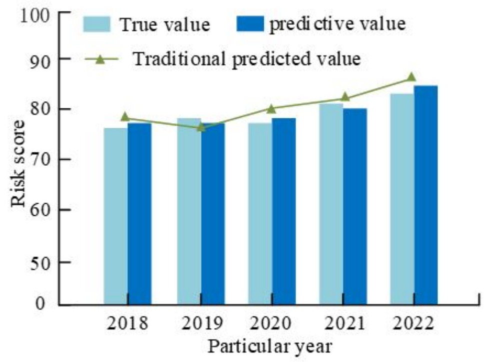


Fig. 4.7: Score chart of enterprise evaluation within five years

tool in practical applications. The following is the specific analysis of the model in practical application. The first is the problem of system integration. In order to deploy this risk management model in the travel industry, it first needs to be integrated into the existing supply chain management system. This step may require working closely with the IT department to develop appropriate interfaces to ensure real-time data updates and a smooth flow of information. The second is user training and support. Implementing new risk management tools requires not only technology integration, but also training of enterprise managers and operators, a process that includes a detailed explanation of how the model works, how it operates, and its application in risk identification and response. The next step is the real-time processing and analysis of the data. The efficient operation of the model depends on high quality and real-time data. In practical applications, it is necessary to ensure that the system can process information from different data sources, such as market dynamics, customer feedback, and internal operational data, and can quickly turn this data into risk predictions and alerts. Finally, risk response mechanism and continuous monitoring and optimization. Another key application of the model is the establishment of automated risk response mechanisms. Based on the model's predictions, the system should automatically trigger appropriate preventive or mitigation actions, such as adjusting supply chain configuration, optimizing inventory management, or reallocating resources to mitigate potential negative impacts. Continuous monitoring and periodic performance evaluations are necessary after the model is deployed. This not only ensures that the model accurately reflects the actual state of the supply chain, but also allows the model to be adjusted and optimized based on the latest business and market conditions. In summary, through the above measures, the risk management model can not only improve the enterprise's ability to predict potential risks, but also enhance the enterprise's adaptability and response speed in the face of market changes. This will greatly enhance the overall resilience and competitiveness of the tourism supply chain, bringing real business value to enterprises.

**6. Conclusion.** As the country's economic strength increases, the domestic tourism industry is booming. Many tourism businesses need a large amount of capital to be incorporated in order to keep up with the pace of development. However, because financial institutions currently lack a way to assess the risk of tourism enterprises, many of them experience difficulties in financing. In this study, after improving the risk assessment system of the TSC, a multi-level DNN was used to construct a risk prognosis model to predict the risk of tourism enterprises with the assessment index. The above results indicate that the number of hidden layers of H-Net and L-Net of DNN affects the data fitting ability of the model, and the model has the best sensitivity and accuracy performance when the hidden layers of H-Net are 3 and the hidden layers of L-Net are 4. Based on this, the performance of the model constructed using multi-level DNN was compared with that of models under other algorithms, and it can be obtained that the model constructed using multi-level DNN has the highest accuracy of 93.35% and sensitivity of 84.13%, and starts to converge at 25 iterations, and the final stability loss value is only 0.8, which is better than the models under other algorithms. Applying this model to the risk prediction of the business and comparing it with the real risk value of the business over a five-year period, it was finally obtained that the predicted value obtained by the model was within 2.5% of the real value. In summary, the model constructed by this experiment using multi-level DNN outperforms models under other commonly used algorithms, with higher accuracy and sensitivity, and has some practicality in the field of TSC risk prediction. However, as this experiment only verified the risk level of one relevant enterprise, the generality of the model has not been well proven, and a large amount of enterprise data can be collected for its subsequent Validation.

**7. Future Work.** Although this study has achieved encouraging results in the risk prediction of tourism supply chain, there are still the following deficiencies. Future research will focus on the following aspects to promote the further improvement of the model and the deepening of practical application.

First, increased data diversity and coverage. In order to enhance the generalization of the model, future work will explore a wider range of data sources, including different regions, different sizes of tourism companies, and longer time horizons. This will help the model capture a wider variety of risk factors and market dynamics.

Second, the impact of data quality on model performance is analyzed. Considering that data quality and integrity can have a significant impact on prediction results, future research will strengthen data cleaning and preprocessing efforts and explore new methods to reduce the impact of missing data and mislabeling.

The third model refinement and algorithm optimization. Based on the preliminary results of this study, further refinement of the model structure and optimization algorithm will be an important research direction. In particular, exploring new techniques in deep learning, such as transfer learning and reinforcement learning, may provide new solutions for dealing with complex risk assessment problems.

Fourth, practical application and deployment. In view of the theoretical success of this research model, it is an important step in the future to apply the model to the actual tourism supply chain management system. Feedback from the actual deployment will be used to further validate and refine the model to ensure its validity and applicability in the real world.

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*Edited by:* Zhengyi Chai
*Special issue on:* Data-Driven Optimization Algorithms for Sustainable and Smart City
*Received:* Nov 23, 2023
*Accepted:* Jun 3, 2024