Quality Evaluation of Order-Based Talent Training in Internationalized Enterprises Based on Machine Learning

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Abstract—Internationalized enterprises conduct business and operation in more than one country. Their complex work processes raise a high demand for the work efficiency of employees. As a result, the enterprises in need of internationalization attach great importance to individual ability and quality when recruiting talents, and need to train talents based on orders. To improve the degree of specialization and employment quality of graduates, it is necessary to effectively evaluate the order-based talent training in internationalized enterprises, which helps to rationalize the training scheme and realize scientific education. However, there are very few studies that quantify the order-based talent training in internationalized enterprises. To fill the gap, this paper evaluates the quality of order-based talent training in internationalized enterprises based on machine learning. Section 2 summarizes the flow of order-based talent training in internationalized enterprises, and establishes an evaluation index system for the training quality, referring to the requirements of internationalized enterprises on the skills, cultural qualities, and professional ethics of talents. The feature data of the evaluation indies were preprocessed through principal component analysis (PCA), which reduces the computing load and increases the computing speed for the order-based talent training quality in internationalized enterprises. Section 3 optimizes the backpropagation (BP) neural network for prediction, and further reduces the dimensionality of the multi-dimensional data on the evaluation indices through locality preservation projection (LPP). The proposed model was proved effective through experiments.

Keywords—machine learning, artificial neural network, internationalized enterprises, order-based talent training, training quality evaluation

1 Introduction

The internationalization of enterprises is an objective phenomenon and general trend of global economy [1–5]. The enterprises in need of internationalization have different ownerships, working environments, business purposes, corporate atmospheres, and corporate cultures from state-owned enterprises. Internationalized enterprises conduct business and operation in more than one country. Their complex work processes raise a high demand for the work efficiency of employees. As a result, the enterprises in need of internationalization attach great importance to individual ability and quality when recruiting talents [6–9].

During talent recruitment, the enterprises in need of internationalization usually adopt the order-based training mode: With the approval of the departments of labor and social security, higher vocational colleges organize skills trainings for specific jobs, which meet the limited demand and scattered posts of a single enterprise in need of internationalization [10–15]. The order-based talent training can greatly reduce the frequency and losses of personnel turnover faced by the enterprises in need of internationalization, and help these enterprises save the human, material, financial, and time resources invested in personnel recruitment, retainment, and cultivation. Nevertheless, the current mode of order-based training has several defects: the teachers lack practical ability, the execution of many orders is not qualified, and the transformation and development of graduates are restrained to a certain extent [16–21]. To improve the degree of specialization and employment quality of graduates, it is necessary to effectively evaluate the order-based talent training in internationalized enterprises, which helps to rationalize the training scheme and realize scientific education. The effective evaluation facilitates higher vocational colleges and the enterprises in need of internationalization to unify their cultivation goals, and enables the enterprises to find more suitable talents.

Pan et al. [20] discussed the current situation of the internationalized development of Chinese enterprise standards, analyzed the recent problems and challenges faced by enterprise standards, and proposed the countermeasures and suggestions for the future. Their research mainly relies on qualitative analysis and case study. The primary and secondary information resources were collected to analyze and understand the progress of internationalization of Chinese enterprise standards. Facing the increasingly complex economic and financial environment, enterprises are pressurized to enter the internationalized networks and markets. The success of an enterprise rests on understanding the role of the determinants of internationalization. Herrero et al. [21] employed a cutting-edge feature selection method, and compared their findings with previous results to gain insights into strategies of foreign direct investment (FDI). More precisely, the evolutionary feature selector was chosen from the wrapper method, and two different classifiers were adopted as fitness functions: bagged trees and extreme learning machines. The average quality of Chinese talents, especially internationalized talents, lags behind the internationalized level. To introduce high-level internationalized talents, it is important to evaluate the training quality of high-level internationalized talents, which is the foundation of the other works. Jia et al. [22] studied the quality evaluation of internationalized talent training based on machine learning. Firstly, a framework was developed for the concept of internationalized talent training, and an evaluation index system was created for internationalized talent training with four basic elements, highlighting the importance of professional business English training and testing. In recent years, data mining has emerged as a broadly used application in various fields. Wu and Zhou [23] discussed the evaluation of learning management system (LMS), and proposed a new LMS evaluation method. Wang [24] suggested that, under the background of informatization, colleges urgently need to keep up with the pace of social development, be guided by industrial development and enterprise transformation and upgrading, and be supported by talent training and knowledge innovation. It is also necessary to strengthen the training of internationalized accountants from the aspects of synthesis, application, cooperation and innovation.

To sum up, there are very few studies that quantify the order-based talent training in internationalized enterprises. The existing studies concentrate on the development features, problems, and solutions of the training mode. Very few scholars have quantified the order-based talent training of internationalized enterprises. To fill the gap, this paper evaluates the quality of order-based talent training in internationalized enterprises based on deep learning. Section 2 summarizes the flow of order-based talent training in internationalized enterprises, and establishes an evaluation index system for the training quality, referring to the requirements of internationalized enterprises on the skills, cultural qualities, and professional ethics of talents. The feature data of the evaluation indies were preprocessed through principal component analysis (PCA), which reduces the computing load and increases the computing speed for the order-based talent training quality in internationalized enterprises. Section 3 optimizes the back-propagation (BP) neural network for prediction, and further reduces the dimensionality of the multi-dimensional data on the evaluation indices through locality preservation projection (LPP). The proposed model was proved effective through experiments.

2 Index system and PCA

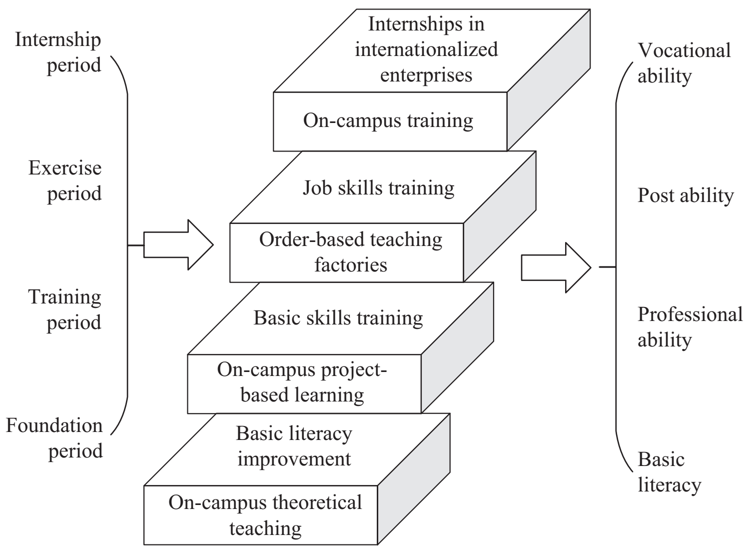

Fig. 1. Flow of order-based talent training in internationalized enterprises

Figure 1 shows the flow of order-based talent training of internationalized enterprises. Unlike traditional vocational education, the order-based talent training of internationalized enterprises emphasizes specialization and professionalization, and calls for an unconventional curriculum system. The professional curricula for talent training must be determined through consultation between the higher vocational college and the enterprise in need of internationalization. The higher vocational college should prepare the talent training program from the surface to the depth, according to the actual needs of the enterprise (development concepts, product attributes, and innovation directions), and the learning state of the students in the order class. Referring to the needs of the enterprise in need of internationalization for talents' skills cultural qualities, and professional ethics, this paper chooses to evaluate the quality of order-based talent training in internationalized enterprises against the following indices:

Layer 1 (Goal layer)

A={A_1}={quality standard for order-based talent training in internationalized enterprises};

Layer 2 (Criteria layer)

A_1={A_{11}, A_{12}, A_{13}, A_{14}, A_{15}, A_{16}, A_{17}}={ talent training standard, training courses, teacher level, practical training practice, teaching management and organization, policy and industry background, corporate participation };

Layer 3 (Index layer)

A_{11}={A_{111}, A_{112}, A_{113}, A_{114}}={ talent training specifications, student selection mechanism, vocational qualification standard, talent training program};

A_{12}={A_{121}, A_{122}, A_{123}}={ teaching standard, graduate standard, assessment standard };

A_{13}={A_{131}, A_{132}, A_{133}, A_{134}}={ skill standard, overall teacher level, knowledge standard, job competency standard };

A_{14}={A_{141}, A_{142}, A_{143}}={practical teaching standard, counterpart practice arrangements, practice standard};

A_{15}={A_{151}, A_{152}, A_{153}, A_{154}}={ student process management, resource per student, teaching management, teaching condition organization };

A_{16}={A_{161}, A_{162}}={ policy support, industry change speed};

A_{16}={A_{161}, A_{162}, A_{163}, A_{164}, A_{165}, A_{166}, A_{167}}={ enthusiasm of internationalized enterprises, demand of internationalized enterprises, teacher participation of internationalized enterprises, openness of training courses of internationalized enterprises, arrangement of teacher internship of internationalized enterprises, mutual employment of enterprise employees and college teachers, enterprise supervision system }.

This paper firstly preprocesses the feature data of the evaluation indices through PCA to lower the computing load and increase the computing speed of the quality of order-based talent training in internationalized enterprises. Figure 2 presents the flow of PCA. Firstly, the original data of the evaluation indices for the quality of order-based talent training in internationalized enterprises were compiled into an $n\times m$-dimensional matrix C:

$$C=\begin{bmatrix} o_{11} & K & o_{1m} \\ N & X & N \\ o_{n1} & K & o_{nm} \end{bmatrix}=(o_1,o_2,o_3,K,o_m) \tag{1}$$

Let o_j^* and ε be the mean and standard error of the indices in column j, respectively. Then, C needs to go through z-score normalization:

$$o'_{ij} = \frac{o_{ij} - o_j^*}{\varepsilon}, (i = 1, 2, 3, K, m, j = 1, 2, 3, K, n) \tag{2}$$

$$o_j^* = \frac{1}{m}\sum_{i=1}^{m} o_{ij} \tag{3}$$

$$\varepsilon = \frac{1}{m+1}\sum_{i=1}^{m} (o_{ij} - o_j^*)^2 \tag{4}$$

Based on the o'_{ij} of each index, it is possible to derive the normalized matrix C'. The corresponding covariance matrix R can be given by:

$$R = \frac{1}{m-1}\sum_{i=1}^{m} o_i o_i^T = \frac{1}{m} OO^T \tag{5}$$

The eigenvalue and eigenvector of R can be obtained through feature decomposition:

$$\left|\mu I - S\right| = 0 \tag{6}$$

The eigenvectors v_1, v_2, v_3, K, and v_l corresponding to the top-l eigenvalues can be composed into a dimensionally reduced matrix $V = v_1, v_2, v_3, K, v_l$. Then, the $m \times n$-dimensional matrix O goes through dimensionality reduction $PH = OV$, where V and PH are of $m \times l$ and $n \times l$ dimensions, respectively:

$$PH = OV = \begin{bmatrix} o_{11} & K & o_{1m} \\ N & X & N \\ o_{n1} & L & o_{nm} \end{bmatrix} \begin{bmatrix} v_{11} & K & v_{1l} \\ N & X & N \\ v_{m1} & K & v_{ml} \end{bmatrix} \tag{7}$$

The selection of the top-l eigenvalues from V is closely associated with the information retained in the index data after dimensionality reduction through PCA. Let η_{XG} be the cumulative information contribution rate. Then, the selection condition for the number l of eigenvalues in V is that η_{XG} reaches the preset value. Let μ be the eigenvalue of covariance matrix R. Then, η_{XG} can be calculated by:

$$\eta_{XG} = \frac{\sum_{i=1}^{l} \mu_i}{\sum_{i=1}^{m} \mu_i} \tag{8}$$

where, the denominator and numerator are the sum of all eigenvalues in V and the sum of the top l eigenvalues, respectively.

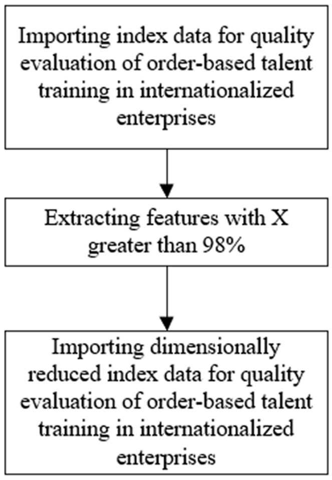

Fig. 2. Flow of PCA

3 Design of evaluation model

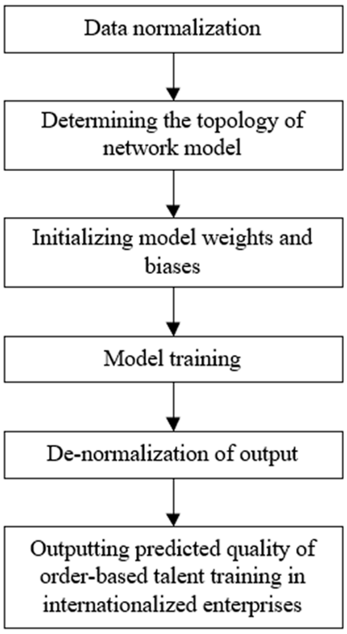

Fig. 3. Prediction flow of BP neural network

For the quality evaluation of order-based talent training in internationalized enterprises, the index data are nonlinear time series. This paper selects 14 features as the training data, and uses the BP neural network to predict the quality of order-based talent training in internationalized enterprises. Figure 3 summarizes the prediction flow of BP neural network.

The weights and biases of the BP neural network were optimized by the idea of evolutionary algorithm, which improves the accuracy of local optimization and global search. The specific steps of the model are detailed as follows:

After the PCA, a list of principal component contribution rates is generated. Then, the dimensionally reduced and normalized index data are imported to the evaluation model. The data are normalized as follows:

$$o_i = \frac{o_i - o_{min}}{o_{max} - o_{min}} \tag{9}$$

The initial weights and biases of the model are encoded. Let R be the code length; R_1, R_2 and R_3 be the number of input layer nodes, hidden layer nodes, and output layer nodes, respectively. Then, the encoding can be expressed as:

$$R = R_1 \times R_2 + R_2 \times R_3 + R_2 \times R_3 \tag{10}$$

Convergence and dissimilation operations are performed iteratively on the individuals in the original population, and mature sub-populations. The iteration is terminated after reaching the maximum number of iterations and the preset error. The initial weights and biases of the model are the decoding form of the optimal individual. After the settings are completed, the model can be trained, and the model output is de-normalized to predict the quality of of order-based talent training in internationalized enterprises.

The evaluation model can learn more information, as more features of the index data are imported to the model. However, the growing dimensionality of data features will suppress the convergence speed of the model. To solve the problem, the dimensionality of the index data is further reduced through LPP. For better prediction, this paper also designs the prediction method for different training stages. Figure 4 displays the prediction flow of the optimized BP neural network.

In essence, the LPP algorithm generates the projection matrix B for the index data. The dimensionally reduced matrix can be obtained by $P = B^T O$. The optimal projection matrix b can be solved by setting the objective function $arg\,min 1/2\sum_{i=1}^{M}(p_i - p_j)^2 Q_{ij}$ under the objective function:

$$\begin{aligned}
&\frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}(b^T o_i - b^T o_j)^2 Q_{ij} \\
&= \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}(b^T o_i o_i^T b + b^T o_j o_j^T b - 2b^T o_i o_j^T b)^2 Q_{ij} \\
&= b^T\left(\sum_{i=1}^{M} o_{ii} C_{ii} o_i^T\right)b - b^T\left(\sum_{i=1}^{M}\sum_{j=1}^{M} o_i Q_{ij} o_j^T\right)b
\end{aligned} \tag{11}$$

Since o_i and o_j are adjacent to each other, Q_{ij} is a symmetric matrix. Suppose C is a diagonal matrix satisfying $C_{ii} = \sum_{i=1}^{M} Q_{ij}$. The Laplacian matrix can be expressed as $K = C - Q$. Then, formula (11) can be transformed into a matrix:

$$\begin{aligned} & b^T OCO^T b - b^T OKO^T b \\ & = b^T O(C-Q)O^T \\ & = b^T OKO^T b \end{aligned} \tag{12}$$

Then, constraint $b^T\ OKO^T b = 1$ can be introduced to build the following objective function:

$$\begin{aligned} & \arg\min b^T OKO^T = b \\ & s.t. \quad b^T OKO^T b = 1 \end{aligned} \tag{13}$$

The partial derivative of the projection matrix b is solved by the Lagrange multiplier method:

$$\begin{aligned} & K(b,\mu) = b^T OKO^T b - \mu(o^T OKO^T b - 1) \\ & \frac{\partial K}{\partial b} = OKO^T b - \mu(OKO^T b) = 0 \\ & OKO^T b = \mu(OKO^T b) \\ & \left[(OCO^T)^{-} OKO^T\right] b = \mu b \end{aligned} \tag{14}$$

According to the definition of eigenvalues and eigen equations, we have eigenvectors [(OCOT)-OKOT]. Taking the eigenvectors $b1$, $b2$, $b3$, K, and $b3$ corresponding to the smallest first l nonzero eigenvalues, the corresponding projection matrix B can be constructed, which satisfies $P = B^T O$. The LPP is implemented in three steps: preparing an adjacency weighted graph for the index data samples, calculating a weight matrix, and constructing a feature map.

In the adjacency weighted graph, the distance between index data samples is characterized by the Euclidean distance. The weight matrix Q is constructed based on the uniform weight of Euclidean distance. If samples i and j are connected, then:

$$Q_{ij} = \begin{cases} t^{-\frac{\|o_i - o_j\|}{2e^2}}, M_l(o_i)\ or\ o_i \in M_l(o_j) \\ 0, otherwise \end{cases} \tag{15}$$

Suppose the evaluation index e is greater than zero and $e \in R$. A set of model samples o_i or o_j can be represented as $M_l(o_i)$ or $M_l(o_j)$.

Before preparing the feature map, it is necessary to compute the minimum eigenvalue of the generalized eigenvalue problem. The computed result is adopted to optimize the transform matrix:

$$OKO^T Y = \mu OCO^T Y \tag{16}$$

where, C is the diagonal matrix (the elements can be obtained by summing up the columns of Q; $C_{ii} = \sum_{i=1}^{M} Q_{ij}$); $K = C - Q$; Y is composed of the optimal projection vector s corresponding to the eigenvalue. Taking the eigenvectors b_1, b_2, b_3, K, and b_3 corresponding to the smallest first l nonzero eigenvalues, the corresponding projection matrix B can be constructed. The dimensionally reduced data can be obtained by $P = B^T O$.

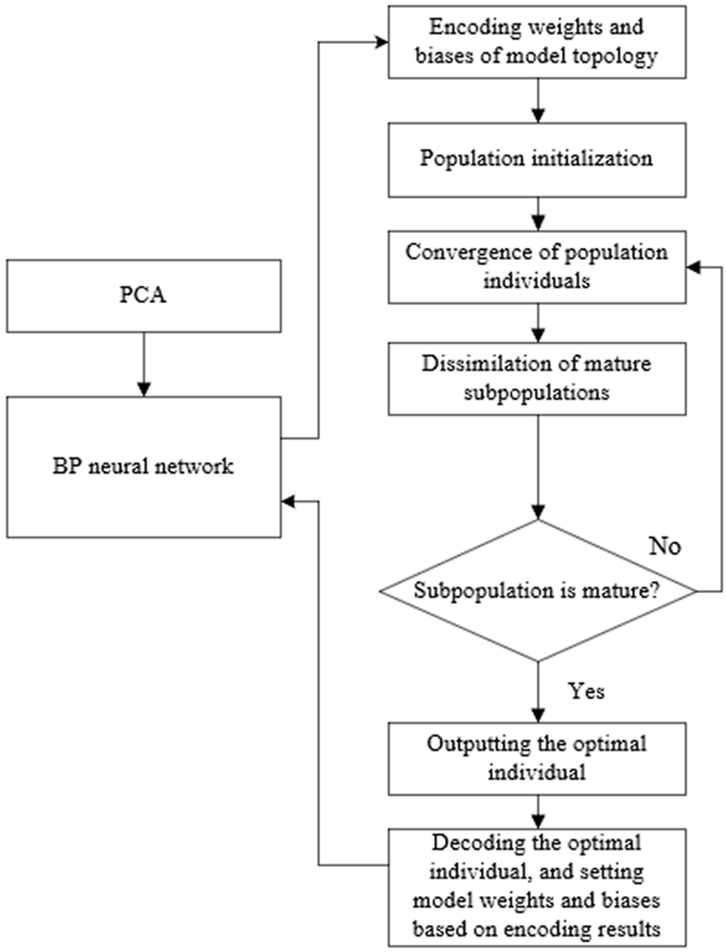

Fig. 4. Prediction flow of optimal BP neural network

4 Experiments and results analysis

To evaluate the quality of order-based talent training in internationalized enterprises, our evaluation model adopts the index data of over 90 training cycles with the following features: talent training standard, training courses, teacher level, practical training practice, teaching management and organization, policy and industry background, and corporate participation. The dataset was divided into a training set and a test set by 4:1. The PCA was performed to analyze the factors affecting the quality of order-based talent training in internationalized enterprises, and reduce the dimensionality of the data. Figure 5 presents the PCA results of the criteria layer, and Figure 6 gives the histogram of principal component contribution rates of the criteria layer. To preserve the information of the index data and provide it for model to learn, the top 13 elements in terms of principal component contribution rate were focused on, and l value was determined as 13.

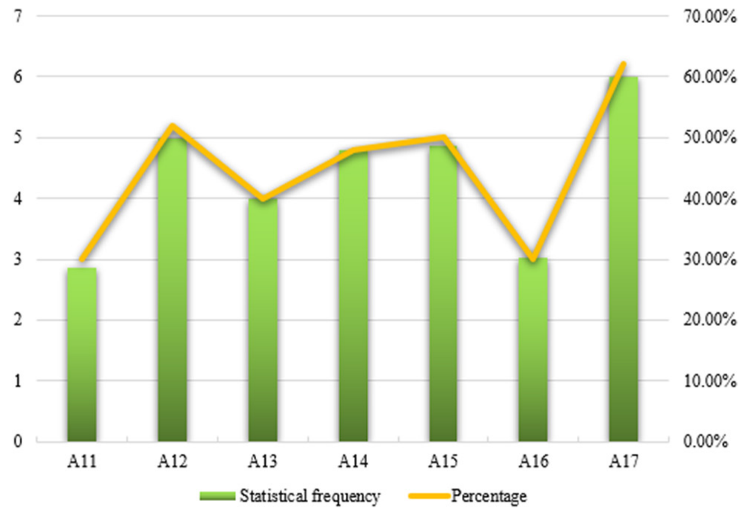

Fig. 5. PCA of the criteria layer

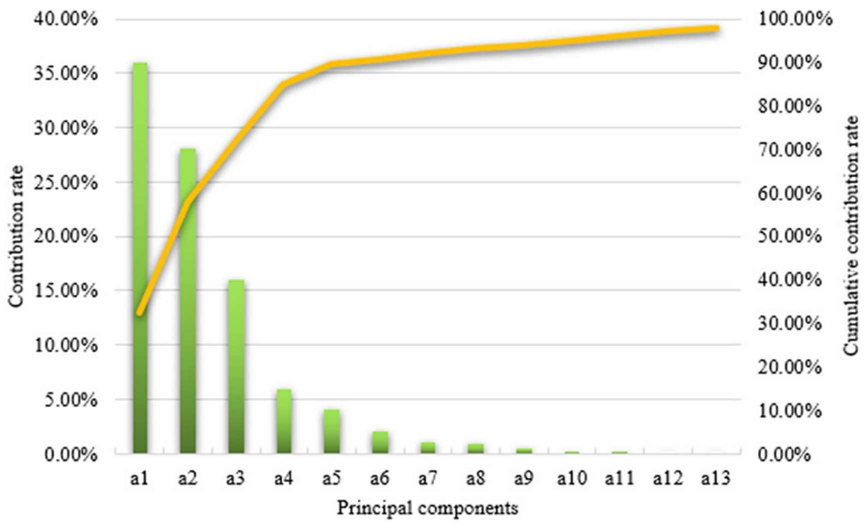

Fig. 6. Histogram of principal component contribution rates of the criteria layer

Our evaluation model employs a three-layer network structure (14-11-1). To obtain the ideal activation function and training function, this paper derives the optimal model parameters through repeated tests, by the control variates method. Training functions 1–8 are *trainlm, traincgf, trainbr*, *traincgb*, *traincgp*, *trainbfg*, *trainscg*, and *trainrp*; activation functions 1–3 are *tansig, Logsig,* and *purelin*.

As shown in Table 1, the MSE of 33.5147, ACC of 0.9092, R^2 of 0.8529 and RMSE of 5.1282 were achieved with training function 6 and activation function 1. Thus, tansig and trainbfg were adopted as the activation function and training function, respectively. Tables 2–4 present the evaluation effects with different minimum errors, learning rates, and maximum numbers of iterations, respectively.

Table 1. Evaluation performance with different training functions and activation functions

Serial Number of Training Functions	Serial Number of Activation Functions	*MSE*	*ACC*	R^2	*RMSE*
1	1	83.269	0.841	0.7692	8.4169
1	2	81.195	0.8596	0.6815	9.3124
1	3	92.6152	0.8347	0.639	9.8247
2	1	63.2518	0.8162	0.7481	8.6253
3	1	67.4185	0.8425	0.7295	8.5175
4	1	45.6208	0.8691	0.8162	7.4192
5	1	40.2396	0.8736	0.8341	6.3205
6	1	33.5147	0.9092	0.8529	5.1282
7	1	36.5281	0.9627	0.8642	5.369
8	1	34.2659	0.9764	0.8836	5.3417

Note: MSE, ACC, R^2 and RMSE are short for mean squared error, accuracy, chi-square, and root mean squared error, respectively.

Table 2. Evaluation effects with different minimum errors

Minimum Error	*MSE*	*ACC*	R^2	*RMSE*
0.01	68.5142	0.8192	0.7158	8.4159
0.001	66.3928	0.8574	0.7695	8.5274
0.0001	63.5184	0.8062	0.7350	8.5102

Table 3. Evaluation effects with different learning rates

Learning Rate	*MSE*	*ACC*	R^2	*RMSE*
0.2	71.5297	0.8162	0.7125	8.5216
0.03	62.5192	0.8574	0.7691	8.3524
0.06	74.5186	0.8029	0.7485	8.5019
0.08	78.5249	0.8617	0.7119	8.3517

Table 4. Evaluation effects with different maximum numbers of iterations

Maximum Number of Iterations	*MSE*	*ACC*	R^2	*RMSE*
120	85.1692	0.8694	0.7629	9.5218
150	61.0258	0.8162	0.7352	8.5174
180	67.3514	0.8629	0.7416	8.9628
210	60.5187	0.8475	0.7192	8.3214
240	63.5281	0.8023	0.7845	8.5069

The results in Tables 2–4 show that the model achieved the optimal effect with the learning rate of 0.03, minimum error of 0.001, and maximum number of iterations of 210. The other parameters are as default in MATLAB. During the model training, the iterative process terminates when the number of iterations surpasses 200 or the MSE falls below 0.0001.

Table 5. Evaluation performance at different stages of training

Model	*MSE*	*ACC*	R^2	*RMSE*
Model 1-1	235.1641	0.849	0.7926	10.6291
Model 1-2	148.7469	0.8162	0.8341	15.2483
Model 1-3	261.5937	0.8274	0.7629	14.256
Model 1-4	105.2711	0.8162	0.7035	11.3027
Model 1-mean	136.7546	0.8349	0.8629	13.2059
Model 2-1	162.3852	0.9361	0.8552	11.6920
Model 2-2	61.5205	0.9528	0.9147	8.1026
Model 2-3	169.3429	0.8025	0.8029	16.208
Model 2-4	169.3257	0.8917	0.718	13.526
Model 2-mean	122.4838	0.8631	0.8162	11.519
Model 3-1	22.6192	0.9516	0.9374	5.2813
Model 3-2	7.3158	0.9709	0.925	2.5187
Model 3-3	31.2041	0.962	0.9027	5.2015
Model 3-4	52.3428	0.9475	0.9674	7.4951
Model 3-mean	25.1602	0.9328	0.9162	5.2039

Table 5 compares the evaluation performance of our model at different stages of training, including internship period, exercise period, training period, and foundation period, which are numbered 1–4, in turn. In Table 5, the traditional BP neural network, the PCA-based model, and our model are denoted by Model 1, Model 2, and Model 3, respectively.

It can be seen from Table 5 that our model achieved the best prediction accuracy (ACC = 0.9709) of the quality of order-based talent training in internationalized enterprises in the exercise period, and realized a mean ACC, mean MSE, and mean RMSE of 0.9328, 25.1602, and 5.2039, respectively. Thus, our model improves the prediction effect and reduces the oscillation of prediction error for the quality of order-based talent training in internationalized enterprises.

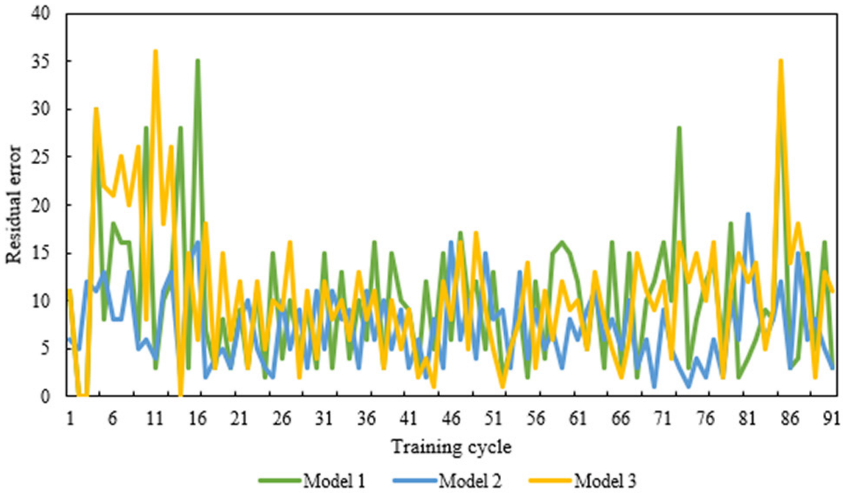

Fig. 7. Comparison of prediction residual errors of different models

The prediction residual error visually reflects the prediction performance of each model. Figure 7 compares the prediction residual errors of different models. It can be seen that the maximum residual of the three models was 36. In the first 30 training cycles, the prediction residual errors of the traditional BP neural network, and the PCA-based model both fluctuated obviously, while the prediction residual error of our model was below 16. This means our model does better in prediction than the two contrastive models.

5 Conclusions

This paper explores the quality evaluation of order-based talent training in internationalized enterprises based on deep learning. Section 2 sums up the flow of order-based talent training in internationalized enterprises, establishes an evaluation index system for the training quality, referring to the requirements of enterprises in need of internationalization on the skills, cultural qualities, and professional ethics of talents, and preprocesses the feature data of the evaluation indies by PCA, which reduces the computing load and increases the computing speed for the order-based talent training quality in internationalized enterprises. Section 3 optimizes the BP neural network for prediction, and further reduces the dimensionality of the multi-dimensional data on the evaluation indices through LPP. Through experiments, the authors obtained the PCA results on the criteria layer, and plotted the histogram of principal component contribution rates of that layer. In addition, the evaluation effects of our model were tested with different training functions and activation functions, and the learning rate, minimum error, and maximum number of iterations of the model were optimized to assure the best effect. In addition, our model was proved effective by comparing the evaluation performance of different models in different training stages, and comparing the prediction residual errors of different models.

6 Acknowledgment

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