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Retraction

Retracted: Evaluation of Ideological and Political Education Using Deep Learning Neural Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. Sheng and Y. Gao, "Evaluation of Ideological and Political Education Using Deep Learning Neural Networks," *Mobile Information Systems*, vol. 2022, Article ID 3186250, 9 pages, 2022.

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Research Article

Evaluation of Ideological and Political Education Using Deep Learning Neural Networks

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The demand for talents extends beyond theoretical knowledge to include students' IPE (Ideological and Political Education). We can only continue to promote the rapid development of university teaching in China by putting in place a solid management system. It is the foundation of college students' IPE in this era of rapid information technology development to accurately adapt to and understand the actual problems and requirements of IPE proposed by the development of the times and innovate and develop accordingly. Deep learning (DL) is a sophisticated machine learning algorithm that outperforms previous technologies in speech and image recognition. In this paper, DLNN (deep learning neural network) technology is applied to IPE evaluation and a set of university-specific IPE evaluation index systems is developed. The BPNN (BP Neural Network) evaluation model is used to train and study a specific amount of teaching quality data in the MATLAB simulation tool. On the prediction of IPE evaluation, the BPNN algorithm has a prediction error of about 0.050.4 according to the findings. The validity and accuracy of using the BPNN algorithm to model IPE quality are demonstrated.

1. Introduction

Examining and evaluating college students for IPE (ideological and political education) is an important part of the process. The use of examination and evaluation is crucial for identifying educational issues and determining the worth of college students' IPE. Relevant teachers should also make clear the current state of IP and moral education in actual teaching, continuously strengthen the IP of college students, establish correct ideas and values for contemporary college students, and lay a solid foundation for cultivating all-round talents. The scientificity and objectivity of the examination and evaluation of IP theory courses for college students have a direct impact on the content and teaching methods used in IP theory courses. University IPE evaluation can effectively monitor and promote positive educational progress, which is conducive to increasing students' sense of responsibility, arousing students' enthusiasm and creativity, and achieving better results.

Teaching is at the heart of all schoolwork, IPE evaluation is critical to the overall management of a school's quality, and teaching quality is a key indicator of a school's success or failure. Teaching and learning are two aspects of the teaching process. It is far more difficult to assess the quality of teachers' IPE than it is to assess the quality of products. To obtain a comprehensive evaluation of teaching quality, Liu et al. [1] used fuzzy mathematics theory and method to deal with each index grade given by the evaluation subject [1]. Guo [2] stated in the course of his research that using qualitative or quantitative methods to evaluate teaching blindly is not comprehensive and that only some general data can be obtained [2]. Manzano [3] can collect relevant evaluation information in the shortest amount of time by taking advantage of the Internet's high speed, rapidity, and convenience and then process the data more quickly and obtain a more comprehensive evaluation result [3]. Vortherms [4] will examine and study the traditional evaluation model in order to identify its flaws, with the goal of

identifying more reasonable indicators and assigning scientific weights to them through various calculations, in order to create a more systematic and comprehensive evaluation system [4]. High-quality higher education is meeting the challenges of the new century as China enters a new stage of comprehensively promoting socialist modernization.

Deep learning neural networks (DLNNs) have been widely used in pattern recognition and classification, recognition and filtering, automatic control, prediction, and other fields in recent years as a new technology. The emergence of DLNN demonstrates exceptional superiority and introduces a new method for evaluating IPE. Applying DLNN to IPE evaluation can not only provide a new method for IPE evaluation but also broaden DLNN's application scope and advance artificial intelligence research. Teaching progress is largely determined by a series of evaluations of the teaching process, from which data can be analysed, problems can be identified, and experiences and lessons can be summarised. The theoretical and technical innovations of this paper mainly include the following:

(1) Combined with the multilabel characteristics of big data in nonstationary environment, a multilabel CNN model is proposed, which introduces label semantics into the model to improve the classification performance of the model.

(2) In this paper, DLNN theory is used to establish the evaluation model of university IPE, and the BPNN algorithm and algebraic algorithm are, respectively, selected to train the sample data to get the evaluation results, and then, the verification data are checked. The experimental results show that the neural network is completely feasible for IPE evaluation and meets the accuracy requirements.

The chapters and contents of the paper are arranged as follows: the first chapter introduces the research background and significance and then introduces the main work of this paper. The second chapter mainly introduces the related technologies of DLNN. The third chapter puts forward the concrete methods and implementation of this research. The fourth chapter verifies the superiority and feasibility of this research model. The fifth chapter is the summary of the full text.

2. Related Work

2.1. IPE Research. IPE evaluation is a process of setting up an index system according to the requirements of society and the actual situation of IPE evaluation objects and using advanced methods such as evaluation and statistics to make a value judgment on the actual effect of IPE. It provides an important basis for evaluating the work performance of educators and making scientific IPE decisions.

Golder and Stramski [5] pointed out that the purpose of school education is not only to cultivate students' intelligence but also to develop their intelligence and morality in an all-round way [5]. Rastorguev [6] believes that the goal of national curriculum is to promote spiritual, moral, social, and cultural development and also to promote personal, social, health, and civic education and skills development [6]. Klebanov [7] put forward the theoretical model of individual socialization. He believes that the most important way to socialize individuals is education, and the purpose of school moral education is to enable students to socialize morally and have the moral character needed by the society [7]. Lulat [8] studied from the angle of moral education mode and analysed and demonstrated the formation, development, modeling, and practice of college students' moral education mode [8]. Exarchos [9] believes that the tutor is not only the tutor of college students' professional study and academic research but also the tutor of college students' IPE. Therefore, we should build a tutor-led moral education model for college students and pay full attention to the important role of tutors in college students' moral education [9].

2.2. DLNN-Related Research. DL (deep learning) is actually a part of machine learning. Machine learning [10] has experienced two waves, from shallow machine learning to DL. Deep learning [11, 12] is a kind of representation learning, which can learn the high-level abstract representation of data and automatically extract features from data. In addition, the hidden layer in DL is equivalent to the linear combination of input features, and the weight between the hidden layer and the input layer is equivalent to the weight of input features in the linear combination.

Hong and Rioflorido [13] applied a word embedding model and multilayer one-dimensional convolution structure to solve four typical natural speech processing problems, such as word segmentation and part-of-speech tagging, and achieved good results [13]. Alamiyan-Harandi et al. [14] proposed to use a multilayer neural network to train high-dimensional features into low-dimensional features to solve the problem of dimension disaster and proposed to use the layer-by-layer training method to solve the problem that training in DL is difficult to achieve the best [14]. For the sentiment analysis of sentence text, Hanbay [15] applied DL technology to it, built a recursive neural network to build an analysis tree of sentence grammar, and added the grammatical information of the whole sentence as a feature to the training of the model [15]. Bie et al. [16] proposed a two-way gate unit recurrent neural network model of hierarchical attention mechanism for multiple-choice reading comprehension tasks, which introduced the hierarchical structure of documents so that context, questions, and candidates interacted at word and sentence level [16]. Zhang et al. [17] improved the coding layer and reasoning layer in the previous machine reading comprehension model: vocabulary and syntax features were integrated into the coding layer, and self-matching of documents was realized in the reasoning layer, and a memory-based answer extraction network was proposed, which performed well in segment extraction tasks [17].

Shi et al. [18] put forward a training method of pretraining and then fine-tuning, which involves unsupervised layer-by-layer pretraining, and then fine-tuning the whole network with backpropagation algorithm. Pretraining only

trains one hidden layer at a time to avoid the problem of gradient disappearance [18]. Gupta et al. [19] found that DL would be attacked by antagonistic samples, that is, correctly classified pictures plus small disturbances can make DL models misjudged into other categories [19]. After Xu et al. [20] adopted DLNN, the correlation information between features of sample data was fully expressed, continuous feature information was combined to form high-dimensional features, and DLNN model was trained through high-dimensional feature samples [20].

3. Methodology

3.1. Constructing IPE Evaluation System. Whether IPE is effective is closely related to the goal setting and content of IPE. If the goal and content of IPE are too high, too far away, or even too abstract, it will seriously deviate. From the actual situation of IP of IPE object, it is impossible to get good effect of IPE. At present, from the perspective of the assessment objectives of IP theory courses, it mainly focuses on assessing the degree of learning, understanding, and mastery of basic theories. Therefore, from the perspective of teachers, both in class and in life, teachers need to pay attention to the ideological health of college students. For college students with ideological problems, we should help them to correct them in time and carry out personnel management according to the assessment mechanism and assessment management system so as to lay a solid _foundation for cultivating positive and healthy college students [3].

The purpose of IPE evaluation is to promote teaching reform, improve teaching quality, reduce students' burden, develop students' intelligence, and cultivate students' ability to analyse and solve problems. When evaluating the teaching quality, we should keep an objective, fair, and rational attitude; not mix subjective speculation and personal feelings; and achieve the unity of ideological, scientific, and feasible. In the process of teaching evaluation, the teacher's morality is very critical and important, occupying a relatively large proportion, and his position is very important. On the contrary, for other evaluation projects, the professional development score is not big and important. That is, teachers think that the state of professional development is not high, and teaching attitude and teaching effect are more important, which shows that it is very important for teachers' teaching effect.

Only in this manner can we observe and analyse the evaluation objects from a variety of perspectives, accurately reflecting the purpose and requirements of IPE evaluation; otherwise, it will stray from the path, resulting in IPE evaluation errors. Repetition of indicators will only add to the evaluation workload, have an impact on the evaluation process, and have no practical value. People's thinking will not be confused unless the specific indicators are independent of one another, and evaluators will have a clear understanding of the indicators, allowing for effective evaluation work. The index system is important in reflecting the scientificity, fairness, and rationality of IPE evaluation. Because different universities have different divisions of labour, positioning, and characteristics, a scientific and reasonable evaluation index system for each university should be established. This necessitates setting the evaluation flag to be fault tolerant so that a more accurate conclusion can be drawn in the event of incomplete evaluation information or other interference.

The evaluation of university IPE work elements and the evaluation of university IPE work process have laid the premise for scientific and objective evaluation of university IPE work. The evaluation of university IPE work effect (i.e., educational effect, first-class index) should be composed of four second-class indexes: campus style, IP quality of teachers and students, safety and stability, and social reputation as shown in Figure 1.

Teaching style is the comprehensive embodiment of school teachers' educational philosophy, working attitude, and academic spirit. Good teaching style can not only improve the overall quality of teachers, provide high-quality guarantee for outstanding teachers, but also promote the construction of study style and create conditions for the all-round development of schools. Only by combining the satisfaction evaluation of employers and service-oriented social units can we get a complete, true, and objective evaluation result.

Compared with the traditional machine learning algorithm, DL is inspired by the model, and the visual cortex cells of the cat brain have the advantage of self-learning layer by layer. In the process of model training, the training data used are usually one-to-one full-map data from labeled samples. Few models use multilabel data or use implicit label semantics between labels of different semantic levels in the model to improve model performance. Multitask learning differs from the definition of different tasks and the hierarchical relationship of different tasks, so the modeling method is based on the traditional modeling method in multitask learning. As shown in Figure 2, it is a multilabel CNN (Convective Neural Network) model.

Using the prior knowledge that the semantic range of the parent tag is larger than that of the child tag in the actual natural tag, the output result of the child tag is constrained and treated as a probability. In the modeling of the first-level label classification process and the second-level label task classification process, combined with the multitask learning method, two different tasks share some parameters and have the same low-dimensional characteristics.

Set the maximum confidence threshold ε, sequentially accumulate the maximum probability value of the first-level label classification result to the set threshold $\sum_{j=1}^{k} h_{\theta_2}(Y_j) \leq \varepsilon$, and output the corresponding second-level label category under the selected first-level label in combination with $\mathrm{num}_{\mathrm{loc}_k}$. $\mathrm{num}_{\mathrm{loc}_k}$ is calculated as shown in the following formula:

$$\mathrm{num}_{\mathrm{loc}_k} = \mathrm{floor}\left(\frac{h_{\theta_2}(Y_k)}{\sum_{j=1}^{k} h_{\theta_2}(Y_j)}\right) * 6. \quad (1)$$

In practice, a matrix X is often input, so if q, k, v is transferred to the matrix and marked as Q, K, V, the output can be marked as

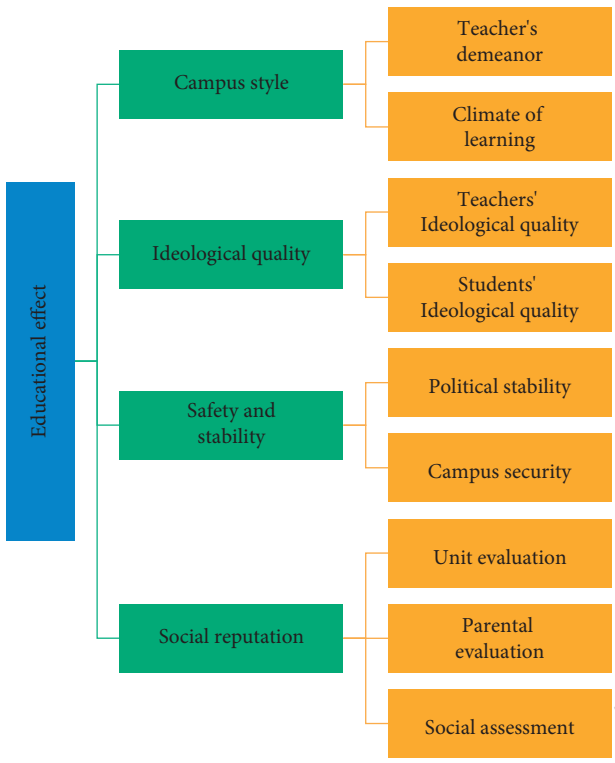

Figure 1: Evaluation index of university IPE work effect.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{\text{QKT}}{\sqrt{d_k}}\right)V. \quad (2)$$

A single attention mechanism is combined by multiple heads to obtain a multihead attention mechanism, which aims to expand the ability of the model to pay attention to different positions (analytical reference ability). In addition, the attention layer in the multihead mechanism represents multiple subspaces and has multiple groups of W^Q, W^K, W^V weight matrices.

There is no quick solution to the cost minimization problem, and iterative optimization algorithm is usually used. After deriving the cost function, the gradient formula of the cost function is as follows:

$$\nabla_{\theta_j} J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[x^{(i)}\left(1\left\{y^{(i)} = j\right\} - p\left(y^{(i)} = j|x^{(i)};\theta\right)\right)\right], \quad (3)$$

where $\nabla_{\theta_j} J(\theta)$ itself is a vector and its l element $\partial J(\theta)/\partial\theta_{jl}$ is the partial derivative of $J(\theta)$ to the l component of θ_j.

In order to optimize it, we need to calculate the derivative, and here, we give its derivative formula as follows:

$$\nabla_{\theta_j} J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[x^{(i)}\left(1\left\{y^{(i)} = j\right\} - p\left(y^{(i)} = j|x^{(i)};\theta\right)\right)\right] + \lambda\theta_j. \quad (4)$$

Finally, the softmax regression classification model can be realized by minimizing the cost formula $J(\theta)$.

3.2. IPE Evaluation Model Based on DLNN. It is the concentrated embodiment of political economy and the assurance of safeguarding a specific class group's economic interests. Each class or group must strive for or maintain its own political government in order to protect and realize its own economic interests. We must conduct appropriate political education in order to win and consolidate our own political government. Please respect the fact that people pursue material interests and pay attention to the views and opinions of educational objects on material interests in the IPE method, as all human activities are ultimately based on and driven by material interests. It is possible for college students to achieve their IPE goals once they have developed a good IP quality and society has established a reasonable IP standard. Everything that people are forced to accept through administrative means frequently causes the educational object to rebel.

At present, there are four common types of IPE evaluation subjects in Chinese universities: student evaluation based on student evaluation, teacher evaluation based on teacher evaluation, team evaluation based on school supervision, and expert evaluation method based on experts. Therefore, on the basis of comprehensive evaluation, we should focus on key issues, and the key evaluation objects mainly refer to the indicators with relatively large weights in the indicator system. For example, the evaluation of the IPE work process must be conducted with a key evaluation, which leads to understanding the problems existing in the process and school education. Practice is conducive to the improvement and promotion of IPE work in schools.

BPNN (BP neural network) repeats learning until the error between the output value and the expected value is reduced to a specified range, and the system stops learning. At this time, the new sample is input into the trained network, and the corresponding output value can be obtained. The network can also correctly map from the input space to the output space by inputting nonsampled data that have not been seen during training. This ability becomes the generalization ability of multilayer feedforward network, and it is an important aspect to measure the performance of multilayer feedforward network.

Therefore, the basic idea of IPE evaluation using BPNN is to form the input vector of BPNN by using four evaluation indexes representing the quality of the test paper and the original score and to form the output vector of BPNN by using the evaluation value. The reasonable design of network and training, the network model obtained after the system error meets the specified requirements, is the comprehensive evaluation model required for the examination results. In order to construct IPE evaluation model based on BPNN, in this subject, MATLAB simulation tool is used to realize the evaluation model, and gradient descent method is used to solve the approximation problem of neural network. Taking $X = [x_1, x_2, \cdots, x_n]$ as the input vector of the training network and $H = [y_1, y_2, \cdots, y_j]$ as the radial quantity of the training network, the formula of the Gaussian function is

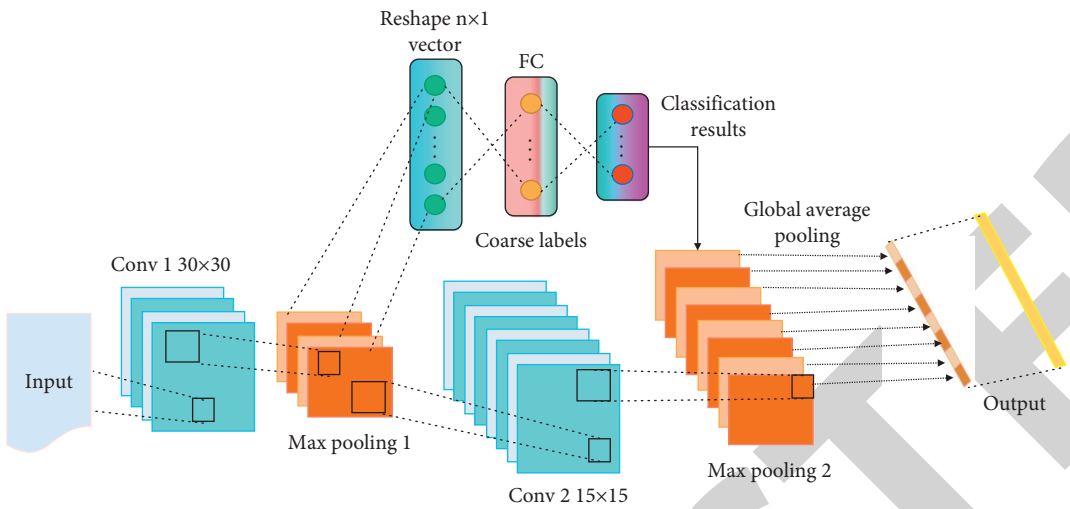

Figure 2: Multi-label CNN model.

$$y_j = \exp\left(-\frac{\left\|X - C_j\right\|^2}{2b_j^2}\right) j = 1, 2, \cdots, m, \tag{5}$$

where C_j is the center vector of the j th node of the neural training network, b_j is the base width parameter of node j, and $b_j > 0$. X is the weight vector of the network.

Through experimental comparison, this paper sets the transfer functions of hidden layer and output layer nodes of the BPNN network to tan-sigmoid and log-sigmoid, respectively. The function forms are as follows:

$$\begin{aligned} f(x) &= \frac{2}{1 + e^{-2x}} - 1, \\ f(x) &= \frac{1}{1 + e^{-x}}. \end{aligned} \tag{6}$$

In the process of designing a neural network, the network is trained with several different learning rates, and the selected learning rate is judged by observing the attenuation rate of the sum of squares of errors after each training. If the sum of square errors decreases rapidly, the learning rate is enough. After obtaining the question-article attention weight α and the article-question attention weight β, the accompanying article vector P and the accompanying question vector Q are calculated as follows:

$$P = \sum_i \alpha P_i, Q = \sum_i \beta Q_j. \tag{7}$$

The design of affinity function and the calculation of affinity are very important. The matching process between unknown antigen and antibody in antibody memory is carried out between different convolution kernel sets, that is, the similarity between arrays corresponding to different convolution kernels is calculated. The convolution kernel set in the first convolution layer is selected as the antibody to participate in affinity calculation, marked as w_j, and the features of the input image are extracted by noise reduction self-encoder and marked as unknown antigen w_0, as shown in the following formula:

$$\begin{aligned} &w_j\left(w_j^1, w_j^2, \cdots, w_j^N\right), J = 1, 2, \cdots, H, \\ &w_0\left(w_0^1, w_0^2, \cdots, w_0^{N_0}\right), \end{aligned} \tag{8}$$

where $w_0^{k_0}, w_0^{k_j}$ is the k_0 convolution kernel of unknown antigen and the k_j convolution kernel of j antibody in the antibody memory bank, respectively. The affinity function between them is defined as $f\left(w_0^{k_0}, w_j^{k_j}\right)$, and H is the number of antibodies in the antibody memory bank, that is, the number of first-level tag categories in the training data set.

Different positions on the error plane may require different learning rates. In order to reduce the training times and the training time to find the learning rate, this paper adopts the variable adaptive learning rate so that the network training can automatically set different learning rates at different stages. This document applies it to the adaptive learning of BPNN. The IPE evaluation model based on BPNN is shown in Figure 3.

Each new classification category must be retrained as the best parameter when using single-label CNN. As a result, because CNN can train on multiple data sets at the same time, the training time of CNN based on immune theory is greatly reduced. This chapter, on the other hand, focuses on the impact of structural parameters on the recognition performance of the nervous system, such as the number of convolution filters in each CNN network layer, especially when that number is difficult to obtain in many cases. It is an excellent option for testing samples and examining CNN's training and recognition abilities. To achieve organic unity, quantitative analysis, comparison, and synthesis should be conducted on the basis of qualitative evaluation, and qualitative evaluation should be conducted at a higher level.

4. Experiment and Results

The multitag CNN model is divided into the first-level tag classification process and the second-level tag classification process, and the two processes share the Conv1 layer and the Max Pooling layer of the model. Therefore, when training the whole network, first remove the first-level label

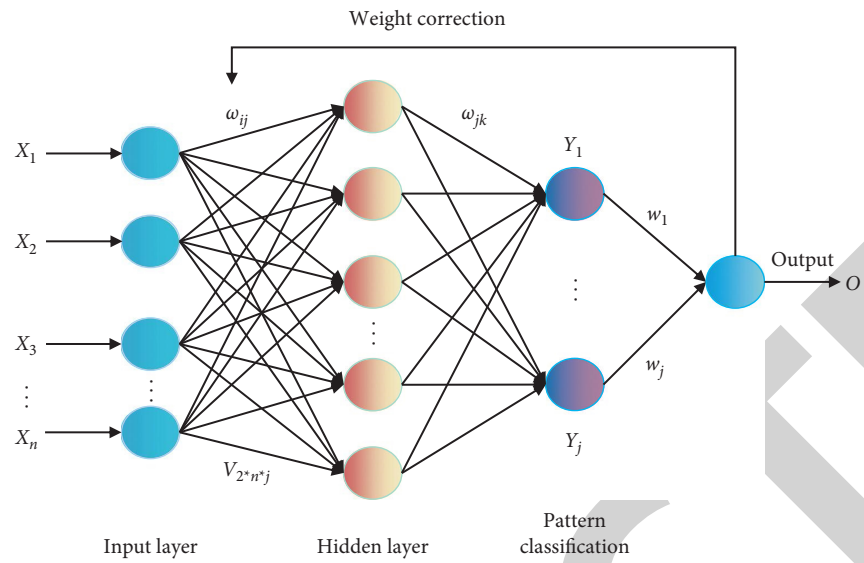

Figure 3: IPE evaluation model based on BPNN.

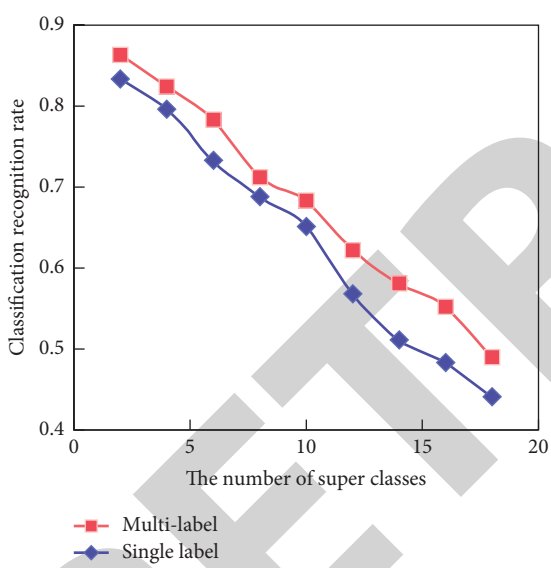

Figure 4: Comparison of top-1 classification recognition rate.

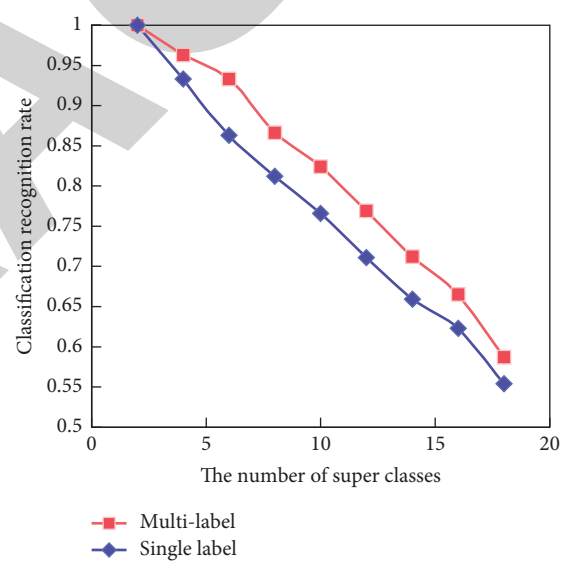

Figure 5: Comparison of top-3 classification recognition rate.

classification process and separately train the network corresponding to the second-level label classification process. In the experimental stage, the image classification and recognition rate of multilabel CNN model and single-label CNN model, namely, single-label CNN model, will be compared. Figures 4 and 5 show the comparison results of Top-1 and Top-3 ranking recognition rates, respectively.

Compared with the traditional CNN model that only uses a single label, the multilabel CNN model proposed in this paper can achieve better image classification results on multilabel data sets, in which the recognition rate of top-1 is increased by 2.4% on average and that of top-3 is increased by 2.8% on average. With the increase in the number of classification categories, the difference in top-1 recognition rate gradually increases, which is because multitag CNN introduces tag semantics in classification. Specifically, in the process of secondary label classification, when the probability distribution of primary labels is moderate, the classification accuracy of primary labels is high, which has a good guiding and limiting effect on the classification results. Therefore, if the complexity of the first-level label classification process increases with the number of classification categories, that is, if the network depth of the first-level label

Table 1: Comparison of experimental results of four network models.

Classifier	$C1$	$C2$	$C3$	Misclassification rate (%)
LeNet-5	8	18	130	9.3
Conv Net-1	8	18	130	11.4
Conv Net-2	5	14	70	12.6
Conv Net-3	10	25	185	18.5

Table 2: Training sample.

Serial number	Reliability	Validity	Difficulty	Distinguishing degree	Original scores	Evaluation value
1	0.65	0.77	0.2	0.3	6	0.1
2	0.65	0.77	0.2	0.3	14	0.1
3	0.83	0.77	0.2	0.3	32	0.3
4	0.83	0.96	0.4	0.3	26	0.5
5	0.91	0.96	0.4	0.5	4	0.2
6	0.91	0.96	0.4	0.5	10	0.6

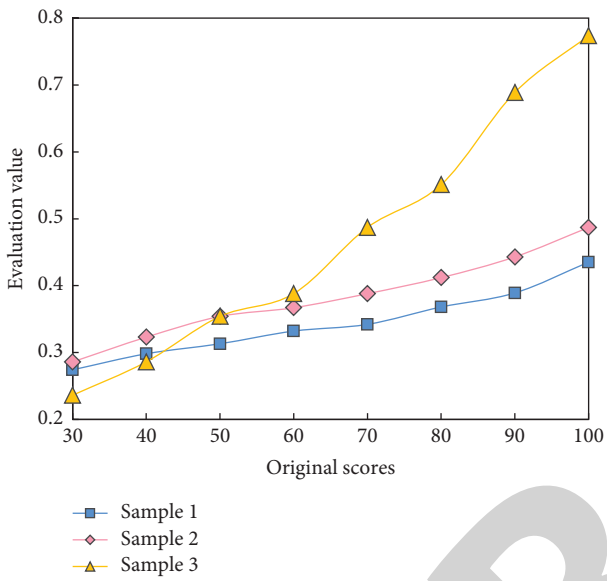

Figure 6: Test sample simulation results.

classification model increases, the top-1 recognition rate will be greatly improved.

When the number of ranking categories exceeds ten, the gap in ranking recognition rate between the top three increases slightly. This is because the top-3 rankings take into account the first-level tag probability distribution of the first-level tag ranking results. The primary label classification output of multilabel CNN is probabilistically transmitted to the secondary label classification process. The reason for this is that the low-dimensional sample features used in the first-level label classification process are not enough to keep the classification results at a high level of accuracy. Too many convolution filters and insufficient training sample data make it difficult for the network model to learn stable image features from the perspective of convolution filters and image features. When the training sample data is limited, the experimental results show that increasing the number of convolution filters in the network model increases the number of weight parameters to be learned, making the network more difficult to achieve. The recognition effect will be reduced in the steady state during training. Table 1 compares the experimental results of four network models.

It can be seen that there are few training samples, that is to say, the number of training samples is insufficient. The recognition performance of Conv Net-1 network model is similar to that of LeNet-5 network model. In Conv Net-2 network model, by appropriately reducing the number of convolution filters in each layer, the network can still maintain a certain recognition rate, and the training speed of the network is faster. Conv Net-3 model shows the characteristics of nonconvergence and high false recognition rate in the experiment, which is largely limited by the relatively few samples that can be used for training. Based on the above principles, this paper designs and obtains a set of training samples shown in Table 2 according to the following methods, selects a set of typical index values, adds some actual data calculated by students in a school, and gives corresponding evaluation values so as to obtain the required training samples.

In order to verify the evaluation effect of the model, this paper takes the IP course test results of a school as an example and forms three groups of test samples, which are input into the established evaluation model, and the evaluation values shown in Figure 6 can be obtained through simulation calculation.

It can be seen that the evaluation value of each group of samples increases with the increase of the original score, which is consistent with people's understanding of the qualitative relationship between the original score and the evaluation value, which shows that the model established in this paper is reasonable. When the original scores are the same, the evaluation values of the three groups of samples will inevitably show an upward trend, that is, the evaluation value of sample 2 must be larger than sample 1 and smaller than sample 1. The neural network MATLAB program which is verified to be reasonable after training can be further transformed into the evaluation component of VC++ program, and the packaged component can be directly used for the IPE evaluation of this document. After the experimental simulation test, the results are shown in Figure 7.

According to the final result, it can be found that in the teaching evaluation model, when it comes to the neural network teacher evaluation judgment realized by related IP, the neural network teacher evaluation system should be used to judge the formation. Similarly, different professions and disciplines must choose the neural network that adapts to it for sample training so as to evaluate the teaching quality of each profession or discipline more accurately. In order to better illustrate the superiority of the algebraic algorithm, this paper selects sigmoidal function as the excitation function of hidden neurons and compares ref [18] algorithm with the BPNN algorithm. The results are shown in Figure 8:

The error between the output value of the teaching effect measured by the BPNN algorithm and the real value is relatively small when compared to the prediction results of

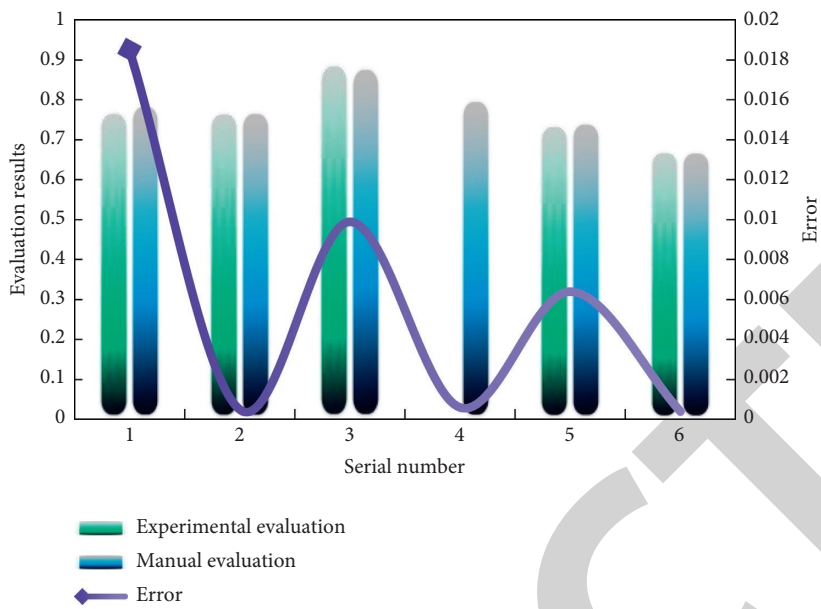

Figure 7: Comparison between experimental results and manual evaluation results.

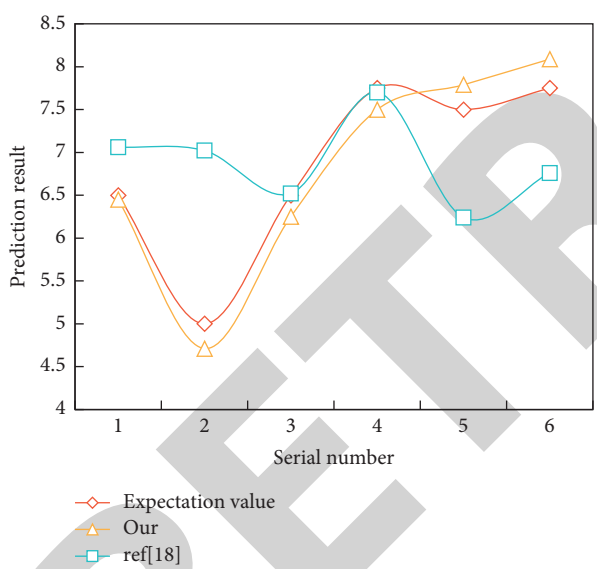

Figure 8: Comparison between expected value and predicted value of training results of two algorithms.

eight samples by ref [18] algorithm. In the prediction of IPE evaluation, it can be seen that the prediction ability based on DLNN has stronger approximation ability and more accurate prediction effect, and the prediction error of the BPNN algorithm is around 0.050.4. As a result, the effectiveness of the model can be demonstrated by evaluating the teaching quality and impact of universities in a scientific and precise manner.

The DLNN model effectively overcomes the shortcomings of traditional evaluation methods, thanks to its highly nonlinear feature mapping function and adaptive self-learning ability. The more precise the evaluation value, the more precisely the effect quality can be described. To improve the network model's evaluation effect, the selection of training samples should be improved further. College students, as the main driving force behind China's future social development, not only bear heavy responsibilities but also take the lead. To create an evaluation mechanism, we must first cultivate students' political beliefs so that today's college students can have specific beliefs and understand the significance of correct political beliefs to their own development. Schools should not ignore the spread of Marxist ideas but should prioritise classroom instruction so that college students can improve their IP while learning theoretical knowledge.

In the IPE work, if the expected effect is achieved, if the proposed goal is realistic and feasible, and if there is room for developing higher goals after the current goal is achieved, we can understand and evaluate each other through IPE. IPE evaluation adopts scientific evaluation methods and analyses and compares the quality and quantity of IPE work in a certain period or unit so as to help evaluators know the differences between evaluation objects. Through evaluation, excellent personnel and units with excellent IP quality can also be selected as role models. On the basis of ensuring the main position of professional teachers' evaluation, IP-related teachers, school student management departments, professional social organizations, etc. should be the participants of evaluation, especially the students who are the objects of evaluation. At the same time, although the evaluation of results is emphasized, more attention is paid to students' will, feelings, methods, attitudes, and progress in the learning process. Students' ability of self-reflection, self-adjustment, and self-improvement in their learning behavior is evaluated and a process evaluation system is built. Attention is paid to the integration of IP theory in artistic expression and IP theory is applied to students. With the integration of professional ability development, we will guide the assessment degree, build an applied assessment

system, and realize diversified assessment and full coverage of assessment.

5. Conclusions

With the advancement of university teaching reform, the question of how to improve teaching quality and cultivate more talents has become a central issue, and the establishment of an IPE evaluation system centred on improving teaching quality further emphasises its importance. In terms of training speed and fitting result, the network based on DLNN constructed in this paper is clearly superior to the prediction result of a simple neural network. We measured and controlled the number of hidden nodes and repeated experiments to get the optimal solution to the problem, ensuring high accuracy and perfection. Simultaneously, the analysis of the experimental results shows that as the number of classification categories increases, the model in this work will achieve better classification results if the model complexity of the first-level label classification process is properly adjusted. The results are displayed and analysed using concrete examples, demonstrating the effectiveness of using the BPNN algorithm to model teaching quality.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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