

Research Article

Prediction of the Improvement Effect of Visualization Technology on Online Learning from the Perspective of the Neural Network

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In today's world, data visualization is employed in every aspect of life, and online course makers should take use of the wealth of behavioral data provided by students. Currently, data visualization is being used to suit the development needs of online education in the Internet age. It is also a strong assurance for the online course platform's improvement and implementation. Data visualization is already closely related to our lives. For online education, the application of data visualization can help course builders understand learners' learning time characteristics, learning behavior habits, and learning improvement effects, so as to provide learners with corresponding learning guidance, solve learners' learning difficulties, and improve learning efficiency and course teaching quality. In order to confirm the improvement effect of visualization technology on online learning, the following work is done in this study. This study describes the current state of visualization technology in the United States and internationally, as well as the foundation for the prediction approach that will be proposed later. There are many factors in the evaluation of the online learning effect, and it is dynamic, which is a nonlinear manifestation. The nonlinear computing, self-learning, and high fault endurance of artificial neural network technology are used in this article, and an online learning effect improvement prediction model based on the improved BP neural network is established, namely, the Levenberg–Marquardt back propagation (LMBP) prediction model. The experimental results suggest that the model has a good level of accuracy and may be used to forecast the effect of online learning improvement.

1. Introduction

It is an Internet age today, and online education has gradually spread to every corner of the world [1, 2]. Since 2012, large-scale online open courses have sprung up around the world. Education giants have successively opened highquality courses, leading many colleges and universities to launch unique courses on various educational platforms. With the rapid development of information technology with the universal application in people's lives, education has undergone tremendous changes in concepts or methods [3–5]. In this context, the General Office of the Ministry of Education clearly pointed out that it is necessary to comprehensively carry out the popularization of online learning space, identify more than 500 national high-quality online open courses in the second batch, and accelerate the construction of an online integrated learning environment. At the moment, online open courses are mostly used in two ways at colleges and universities: fully online learning and mixed learning. Among these, blended learning based on (Massive Open Online Courses) MOOCs has emerged as a new and significant technique of instruction in colleges and universities [6]. Learning materials may be shared, learning techniques can be self-directed, and learning activities can be integrated into one another. Learning evaluations can be integrated into the management of learning activities, and learning management can be informative. In today's world, the major force in promoting educational and instructional change is the college or university. In the teaching process, teaching evaluation through testing is the most common evaluation method. The test data contains a lot of educational information. These have an important feedback and guiding significance for students' learning and teachers' teaching. Through the data analysis after the test, it can give students and teachers effective guidance and help [7]. The current problem of test data analysis is that there are many literature on student test data, and there are a lot of research results, but there are certain deficiencies in solving the problems of students' personalized learning and teachers' targeted teaching work. Usually after the test, teachers and students get a report card, students see their own scores and rankings in each subject, teachers get the scores and rankings of the class, and students still cannot determine their own shortcomings. At the same time, teachers can only teach as a whole based on experience. The emergence of visualization technology helps to solve this problem. Data visualization technology has the function of presenting information patterns, and users can use data more intuitively and quickly, so as to make corresponding decisions more efficiently [8-10]. There are two layers of data visualization research items. One is to use icons or legends to represent numerical or statistical data, and the other is to come up with new or fascinating ways to represent abstract ideas. The main feature of data visualization is its powerful image generation ability, which can generate images that accurately correspond to the data; at the same time, the convenient operation of inputting data to obtain images can save people from tedious steps and facilitate users to accumulate data for a long time. It is the top priority of big data analysis [11]. The most widely used data visualization tool is Microsoft Excel, which is utilized by the majority of educators to create a wide range of educational charts. As can be seen, the use of visualization technologies in online education is a foregone conclusion. This research makes a prediction about the improvement effect of visualization technology on online learning using deep learning technology and a neural network model. It is hoped that this research will prove the important influence of visualization technology on online education, in order to make better use of visualization technology in the field of online education.

The research is organized as follows. The related works are presented in Section 2. Section 3 analyzes the methods of the proposed work. Section 4 discusses the analysis and experiments. Finally, in Section 5, the research work is concluded.

2. Related Works

Data visualization is very popular among researchers because data visualization can clearly display the information contained in a large amount of data, so as to better understand and solve a difficult task. Fu et al. [12] mentioned that they developed an interactive visual analysis system called iForum, which visualizes a large amount of data in MOOC forums, can effectively discover and understand temporal patterns in MOOC forums, and effectively discover and understand the dynamic process of learners, providing course builders with valuable insights to help them improve their courses and prepare them for the next launch. In addition, the visualization of learning behavior data on the online platform can also help the platform to predict the learning performance of learners, recommend courses suitable for learners, and improve the adaptability of online platform courses to learners. Yin et al. [13] pointed out that through data visualization, not only factors related to the dropout rate of learners, but also the correlation between the two courses taken by learners can be found. Students who begin their studies earlier tend to have lower dropout rates, and this course's learning efficiency has increased significantly, both of which contribute to the course's overall improvement in teaching quality. The foreign works such as "Visualizing Data," which have been on the hot-selling list, guide the practical operation of data visualization technology from the aspects of problem discovery, data collection, visualization classification and steps, visualization tool selection, and application skills [14-17]. There are also many domestic experts and scholars who have published works and academic papers on data visualization, proposed many university algorithms, and developed related technologies. In reality, visualization has been applied in various fields such as traditional medicine, social media, astronomy, and geography and has achieved certain results. At present, the research on data visualization is still in-depth [18]. Through reading a large number of domestic and foreign literature and books, it is found that people are more accustomed to classifying visualization into four categories: scientific computing visualization, data visualization, information visualization, and knowledge visualization. Scientific computing visualization is the visualization of data generated by research calculations or experiments. The visualized data include data generated by scientific computing and experiments [19]. With the rapid development of information technology, visualization extends from data generated by scientific computing to other types of data, and data visualization is born from this. Compared with scientific computing visualization, data visualization contains all digital data, so it can be said that scientific computing visualization belongs to data visualization, and scientific computing visualization can be regarded as a kind of data visualization. For example, in "Design and Implementation of the Data Visualization Exploration System," a general data visualization exploration system based on Web GL technology is designed and implemented, which can efficiently output complex visualization results [20]. Information visualization refers to the realization of the visualization of abstract information with the support of computer software in order to enhance people's cognition of nonphysical abstract information. Compared with data visualization, information visualization involves a new category because information not only includes data, knowledge, and graphics but also involves new ideas and philosophies. For example, a domestic article collects the information that can be visualized in WeChat, conducts indepth and detailed data information mining on the visualization of WeChat chat record information, and summarizes the value of the application of WeChat chat record information visualization. Knowledge visualization is a newly developed field following scientific computing visualization, data visualization, and information visualization. It uses visual effects to promote knowledge innovation and dissemination [21]. From this generalization, it can be concluded that knowledge

visualization refers to the use of all the complex knowledge that can be constructed and transmitted by graphical means. As mentioned in an article, by guiding students to make visual images of the inclined plane model, uniform speed linear motion, free fall motion, vertical upward throwing motion, and collision model, the implicit and abstract knowledge is made explicit and visualized. Combining figurative images with abstract language and words give full play to different functions of the left and right brains and further stimulate students' potential and enhance learning effects. Some scholars have used visualization tools such as concept maps, Venn diagrams, and flowcharts to explore the application of knowledge visualization in primary school Chinese composition teaching and judge whether it can improve students' composition level and improve students' emotions, attitudes, and values [22].

At present, some scholars have applied the back propagation (BP) neural network technology to the school teaching evaluation system. In order to solve the problem that the neural network has a large number of calculations and a slow convergence speed, some scholars combine AHP and back propagation neural network (BPNN) technology, use AHP to calculate the initial weights of each evaluation index and then use the BPNN algorithm to correct the weights [23]. The research content is applied to the evaluation of the technological innovation ability of enterprises, and good results have been achieved. From the 1980s to present, people have gradually learned from new scientific methods in inquiry-based learning evaluation methods and cited them, such as the portfolio method, fuzzy comprehensive evaluation method, data mining, and other technologies, but the neural network technology has not been used in large-scale research in inquiry learning evaluation [24, 25]. Therefore, establishing an inquiry learning evaluation model based on BPNN technology has a very important research value. In view of the current research status at home and abroad, this study will also use the improved BPNN technology to develop an inquiry learning effect improvement prediction system based on the BPNN model and provide a new way for inquiry learning effect prediction.

3. Methods

3.1. Data Visualization. Different scholars have different definitions of data visualization. Although data visualization, information visualization, and knowledge visualization are similar, some scholars believe they are distinct. They believe that the object of visualization is still spatial data, and this is only an extension of computational visualization. Some scholars believe that data visualization is an evolving concept, and some scholars believe that scientific visualization, information visualization, and partial knowledge visualization are included in its scope. The segmentation of the scope of data visualization, on the other hand, is likewise inconclusive. Statistical graphics and thematic maps are two types of data visualization, according to some researchers. Other scholars divide data visualization into mind mapping, data display, and tool services, with a wider scope. Based on the above, this study agrees that data visualization can cover part of the content of scientific visualization, information visualization,

and knowledge visualization, and it is constantly developing and being accepted with the development of the times and the deepening of educational informatization.

3.2. BP Neural Network

3.2.1. Artificial Neural Networks. An artificial neural network (ANN) is a network with a high number of processing units that are linked across a vast area. In this way, the main properties of the human brain are reflected in abstraction, simplification, and simulation of the human brain. It is the goal of ANN research to understand human intelligence by analyzing how the structure of our brain works and simulating how our brain processes information. It is based on a variety of disciplines, including computer science and engineering, as well as neurology, mathematics, statistics, and other physical sciences. The research on ANN started in the 1940s, and now, there are hundreds of neural network models. There has been great progress in the field of the ANN. In an ANN, which is a network topology for simultaneous and distributed information processing, each neuron has a single output and may be coupled to several additional inputs, and each of these connections corresponds to a connection weight coefficient. The neuron model contains three essential elements as the basic units of the neural network: Each link has a weight, and this weight influences the link's strength. Positive weights imply rewards, whereas negative weights suggest inhibition, as seen by the weights shown above. Summation unit is for determining the weighted total of each input information. An excitation function functions as a nonlinear mapping and restricts the output amplitude of the neuron to a particular range. Besides that, there is a limit. Mathematically, the foregoing effects may be stated as

$$L_{k} = \sum_{b=1}^{R} w_{kb} x_{b},$$

$$M_{k} = L_{k} - \delta_{k},$$

$$y_{k} = \alpha(M_{k}),$$
(1)

where $X = (x_1, x_2, ..., x_n)^S$ is the input signal, $w_{k1}, w_{k2}, ..., w_{kR}$ is the weight of neuron K, L_k is the linear combination result, δ_k is the threshold, $\alpha(M_k)$ is the excitation function, and y_k is the output of neuron K.

From the perspective of connection methods, there are mainly two types of feed forward networks and feedback networks. The BPNN model is the most important learning algorithm of the multilayer feed forward neural network, which is mainly used in function approximation, pattern recognition, classification, and data compression. At present, in the practical application of the ANN, most of the neural network models are based on the BP algorithm or its variation.

3.2.2. Principle of the BP Neural Network. Neurons are arranged in three layers: input, hidden layer, and output layer, making the BPNN also known as a multilayer feed

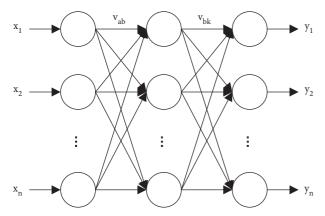


FIGURE 1: BP neural network structure diagram.

forward neural network. Figure 1 shows the BPNN's topology. There are no feedback connections between neurons in each layer of this neural network model; instead, neurons in each layer only link to neurons in the neighboring layers. When an input signal is sent to the network, it first travels to the hidden layer node, where it is transformed by the transformation function before being sent on to the output node, where it is supplied as the output result. Selected sigmoid-type functions are often seen in transformation functions. Layer by layer along the connection route, errors that do not meet criteria should be returned, and the weights and thresholds of each layer's connections should be adjusted to reduce error. After modifying the connection weights and thresholds, use the new connection weights and thresholds that are calculated on the input pattern to produce an output response that is compared with the expected output, and the calculation is repeated iteratively until the error is less than a given value.

In practical application, the BPNN can set up multiple hidden layers according to the needs of the problem. In the BPNN, issues such as nonlinear classification and any nonlinear function may be approximated with arbitrary accuracy by altering the weights of the connections and the network's size. To accurately represent the input-output mapping, the BPNN must be trained, which requires modifying its weights and thresholds after it has been formed. The trained BPNN can also provide appropriate outputs for inputs not included in the sample set. This property is called generalization ability. From the perspective of function fitting, this shows that the BPNN has an interpolation function. The BP algorithm essentially takes the sum of squares of network errors as the objective function. During the initial step of forward propagation, data from the input layer are sent to the hidden layer, which performs processing, before being sent back to the input layer. This process's weight coefficient is unaltered. The second step of back propagation should be used if the result does not match the predicted output: the output error calculates the error of each unit of the hidden layer forward layer by layer and uses this error to correct the weights of the previous layer to minimize the deviation signal. The network weight adjustment adopts the

delta learning rule, that is, the gradient along the error surface descends the fastest according to the gradient method, so as to minimize the network error.

(1) Forward propagation calculation f(x) is the transfer function, generally a sigmoid function:

$$f(x) = \frac{1}{1 + e^{-x}}.$$
 (2)

The hidden layer calculates the output value of each neural unit O_b according to the transfer function:

$$O_b = f\left(\sum_{a=1}^A v_{ab} x_a - \delta_a\right). \tag{3}$$

The output layer calculates the output value of each neural unit y_k according to the transfer function:

$$y_k = f\left(\sum_{b=1}^K w_{bk} O_b - \delta_a\right). \tag{4}$$

Calculate the error E_R of the network. In the BP learning algorithm, the network output y_k^R generated by a single sample is consistent with the expected response output P_k^R , and the j^{th} sample error is

$$E_R = \frac{1}{2} \sum_{k=1}^{K} \left(P_k^R - y_k^R \right)^2.$$
 (5)

(2) Error back propagation calculation, starting from the output layer, when the deviation samples are returned back, weight coefficients of each hidden layer are changed to reduce the deviation signal. To find the minimum deviation, the most common method is the optimal gradient descent method. Calculate the correction error of each neuron in the output layer and the hidden layer. The correction error of the neurons in the output layer is

$$e_{k} = (P_{k} - y_{k})y_{k}(1 - y_{k}).$$
(6)

According to the correction error e_k of each neuron in the output layer and w_{bk} , O_b , the correction error of each neuron in the hidden layer can be calculated as

$$e_b = \left[\sum_{b=1}^{B} e_k w_{bk}\right] O_b (1 - O_b).$$
⁽⁷⁾

In order to minimize the error, the fastest gradient descent method is used to optimize the weights, and the direction of change of the weights and thresholds is the direction of the fastest decline according to the operation processing function, that is, the negative direction of the gradient. The weights are corrected from the output layer, and then. the weights of the previous layer are corrected, that is, w_{bk} is adjusted first and then v_{ab} is adjusted.

$$\Delta w_{bk} = -\lambda \frac{\partial E}{\partial w_{bk}}$$

$$= \lambda e_k y_k$$

$$= \lambda (P_k - y_k) y_k (1 - y_k) y_k,$$

$$\Delta v_{ab} = -\lambda \frac{\partial E}{\partial v_{ab}}$$

$$= \lambda e_b x_a$$

$$= \lambda \left[\sum_{k=1}^{K} (P_k - y_k) y_k (1 - y_k) w_{bk} \right] O_b (1 - O_b) x_a,$$
(8)

Where λ is the learning efficiency and $\partial E/\partial w_{bk}$ is the error gradient.

3.3. Improved BP Neural Network Algorithm. Due to the limitations of the BP neural network, many effective improved algorithms have been proposed at home and abroad, and the improved BP algorithms are mainly divided into two categories. The first are those BP algorithms that use heuristic information techniques, including adding a momentum term to the learning algorithm, variable learning rates, and elastic BP algorithms. Its essence is to increase the learning rate when the error gradient changes slowly and reduce the learning rate when the change is severe. The second is the BP algorithm with numerical optimization technology because training the forward neural network to reduce the mean square error itself is a numerical optimization problem, and this type of technology is very mature, including the conjugate gradient method, Levenberg-Marquardt algorithm, and so on. LMBP is an algorithm that uses Levenberg-Marquardt to optimize the BPNN. The weight adjustment rate of the algorithm is selected as

$$\Delta w = -\left(H^T H + \sigma S\right)^{-1} H^T e, \tag{9}$$

where *H* is the Jacobian matrix of the error differential to the weight, *e* is the error vector, σ is the adaptively adjusted learning rate, and *S* is the identity matrix.

The LMBP algorithm has stable performance, the fastest learning, and training speed among all algorithms and the least number of iteration steps, which is very suitable for online learning of the network. In practical applications, the LMBP algorithm in MATLAB has the fastest convergence time, the least number of training times, and a better training effect. Therefore, for medium-sized networks, the LMBP algorithm is the most suitable. At the same time, this study will use the LMBP algorithm in the prediction of the effect of inquiry learning.

3.4. Evaluation System of the Online Learning Improvement Effect. Four principles must be paid attention to when conducting online course inquiry learning evaluation: developmental principle, subjectivity principle, motivational

TABLE 1: Inquiry-based online learning evaluation indicators.

Index	No.	Label
The ability to ask problems	1	<i>A</i> 1
The ability to compare and evaluate problems	2	A2
The ability to assume and conjecture about problems	3	A3
The ability to obtain information from multiple sources	4	A4
The ability to analyze and process data	5	A5
The ability to link disparate evidence	6	A6
The ability to write written plans	7	A7
The ability to discover problem-solving details	8	A8
The ability to try to improve the program	9	A9
Easy-to-understand expression skills	10	A10

principle, and process principle. Based on the existing inquiry-based learning evaluation indicators, combined with the characteristics of inquiry-based learning in most online courses, an index group of inquiry-based learning evaluation indicators suitable for online courses is obtained through analysis and improvement, as given in Table 1.

Since a 3-layer BP network can approximate any mapping relationship with arbitrary precision, this study adopts a 3-layer BPNN structure. The specific steps of establishing an inquiry-based learning evaluation neural network model are as follows.

(1) Determination of input layer nodes:

The student learning improvement effect index is divided into 10 secondary indicators, and the 10 secondary evaluation indicators are used as the input of the input layer of the neural network. Therefore, the number of nodes in the input layer of the BPNN is correspondingly determined to be 10.

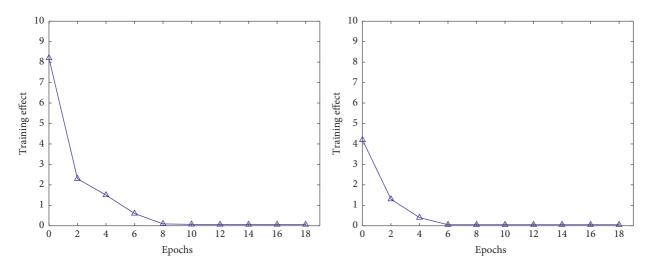
- (2) Determination of the number of output layer nodes: The feature extractor of the network is only configured to one output terminal because there is only one student learning progress outcome.
- (3) Determination of the number of hidden layer nodes: The problem of determining the ideal number of discrete layer nodes remains unsolved. Theoretically, if the current hidden layer nodes chosen are too little, the overall neural network's convergence rate will be delayed and converge will be tough. On the other hand, if the number of hidden layer nodes chosen are too high, the neural network would fail. The topological structure is complicated, network training takes a long time, and the error is not always the best. Currently, the following formula is generally used:

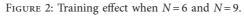
$$h = \sqrt{l + m + n},\tag{10}$$

Where *h* represents the number of hidden layer nodes, *l* represents the number of input layer nodes, *m* represents the number of output layer nodes, and *n* represents an integer between 1 and 10. The number of hidden layer nodes, according to the formula, is 5–14. The appropriate number of hidden layer nodes is determined by testing each one by one at a time.

TABLE 2: Learning rate error comparison.								
Learning rate	0.01	0.03	0.05	0.07	0.09	0.10		
Training times	8	4	6	9	14	18		
Error	0.02	0.13	0.19	0.27	0.36	0.55		

TABLE 3: Part of the experimental dataset.									
Label	No.								
	1	2	3	4	5	6			
A1	0.925	0.847	0.794	0.937	0.890	0.718			
A2	0.933	0.895	0.782	0.951	0.842	0.792			
A3	0.879	0.912	0.735	0.912	0.891	0.785			
A4	0.795	0.776	0.791	0.878	0.856	0.869			
A5	0.912	0.785	0.783	0.891	0.917	0.875			
A6	0.954	0.921	0.824	0.895	0.919	0.912			
A7	0.887	0.814	0.846	0.923	0.863	0.861			
A8	0.859	0.874	0.755	0.918	0.865	0.872			
A9	0.933	0.921	0.791	0.885	0.869	0.793			
A10	0.962	0.923	0.772	0.879	0.817	0.827			





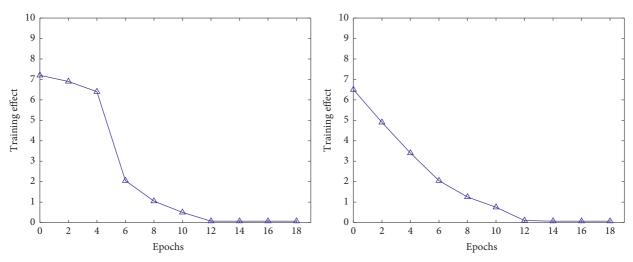


FIGURE 3: Training effect when N = 12 and N = 15.

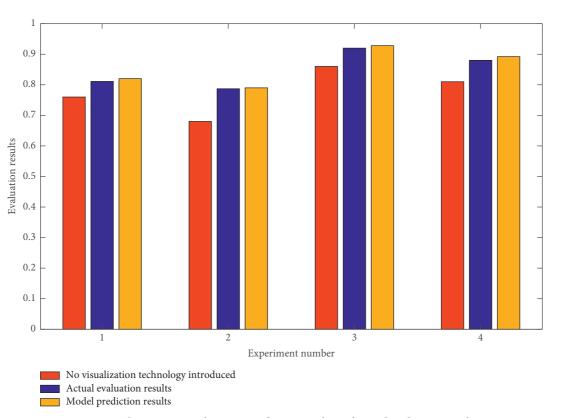


FIGURE 4: The comparison between prediction results and actual evaluation results.

In the BPNN, the learning rate remains unchanged. If the learning rate is too large, the network weights will be adjusted to a larger extent each time they are updated, which may cause the neural network to jump back and forth around the minimum error value during the update iteration process. When it is true, the network diverges and cannot converge. On the contrary, if the learning rate is too small, the adjustment speed of the network weights will be small each time, and the convergence speed will be slow. Taken together, although the learning rate is small, the convergence rate will be slow, but it will eventually converge to the vicinity of the minimum error value. Therefore, this study tends to select a smaller learning rate to ensure the stability of the system. As given in the experimental test in Table 2, the final learning rate is 0.03.

4. Experiment and Analysis

This survey mostly takes the form of a questionnaire in order to gain a preliminary. In this section, we define dataset, hidden layer neuron experiment, and prediction experiment of the LMBP model.

4.1. Dataset. In order to verify the prediction of the improvement effect of online learning by visualization technology, this study designs a dataset for experiments and divides the dataset into a test set and an experimental set according to the ratio of 4:1. A portion of the dataset is given in Table 3.

4.2. Hidden Layer Neuron Experiment. In order to select the optimal number of neurons in the hidden layer, the appropriate number of neurons in the range must be selected for one experiment. In this study, the number of neurons in the hidden layer is selected to be 6, 9, 12, and 15 for experiments, respectively. The final experimental results are shown in Figures 2 and 3.

According to the above experimental results, it can be judged that when the number of neurons in the hidden layer is 9, the training effect of the model is the best, so the number of neurons in the hidden layer is finally selected to be 9.

4.3. Prediction Experiment of the LMBP Model. The comparison of the experimental results of the LMBP model proposed in this study consists of three parts: the evaluation results without visualization technology, the model prediction results after using visualization technology, and the actual evaluation results. The actual evaluation result is the evaluation data given by the experts of the educational administration system after using the visualization technology. The specific experimental results are shown in Figure 4. From the experimental data, it may be concluded that the visualization technology based on the LMBP neural network is totally acceptable as a prediction model for the online learning enhancement effect and that it is a scientific, rational, and feasible model.

5. Conclusion

With the advent of the information age, a new type of visual expression is born, namely, big data visualization, which transcends the visual boundaries of the physical world in reality, and can clearly present the information contained in virtual data and show the relationship between data. Researchers can harvest the value of the data by making connections and distinctions. Simply put, it is the process of classifying and analyzing a large amount of data using tools, programming, and other methods and then visually displaying the data and data classes, so that people can explore the internal relationship, pattern, or structure between the data in order to discover and solve problems. It is very consistent with the visual perception characteristics of human beings, and it is a research technology of visual representation. It is the product of mutual development and mutual promotion of scientific visualization, user interface, and computer graphics and is the most important step in the life of big data. Data visualization is used in almost every part of life nowadays, and online course creators should take advantage of the plethora of behavioral data offered by students. Currently, data visualization is being used to suit the development needs of online education in the Internet age. It is also a powerful guarantee for the improvement and application of the online course platform. Relying on the neural network, this study predicts the improvement effect of visualization technology on online learning and finally completes the following work:

- This study introduces the development status of visualization technology at home and abroad and lays the groundwork for the prediction method proposed later
- (2) There are numerous aspects to consider when evaluating the impact of online learning, and it is dynamic, resulting in a nonlinear expression. In this research, an online learning impact enhancement forecast model based on the enhanced BPNN, namely, the LMBP prediction, is built using ANN technology's nonlinear processing, self-learning, and high fault tolerance. The experimental results show that the model has a high accuracy and can be used for actual online learning improvement effect prediction.

Data Availability

The datasets used during the current study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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References

- P. Moreno-Ger, D. Burgos, I. Martínez-Ortiz, J. L. Sierra, and B. Fernández-Manjón, "Educational game design for online education," *Computers in Human Behavior*, vol. 24, no. 6, pp. 2530–2540, 2008.
- [2] T. Volery and D. Lord, "Critical success factors in online education," *International Journal of Educational Management*, vol. 14, no. 5, pp. 216–223, 2000.
- [3] P. Shea and T. Bidjerano, "Community of inquiry as a theoretical framework to foster "epistemic engagement" and "cognitive presence" in online education," *Computers & Education*, vol. 52, no. 3, pp. 543–553, 2009.
- [4] A. F. Mayadas, J. Bourne, and P. Bacsich, "Online education today," *Science*, vol. 323, no. 5910, pp. 85–89, 2009.
- [5] J. Seaman and E. Allen, "Faculty and online education, 2012," Babson Survey Research Group, vol. 10, no. 4, p. 55, 2012.
- [6] A. Zapalska and D. Brozik, "Learning styles and online education," *Campus-Wide Information Systems*, vol. 23, no. 5, pp. 325–335, 2013.
- [7] S. Kariya, "Online education expands and evolves," *IEEE Spectrum*, vol. 40, no. 5, pp. 49–51, 2003.
- [8] J. Levis and L. Pickering, "Teaching intonation in discourse using speech visualization technology," *System*, vol. 32, no. 4, pp. 505–524, 2004.
- [9] K.-L. Ma, "Machine learning to boost the next generation of visualization technology," *IEEE Computer Graphics and Applications*, vol. 27, no. 5, pp. 6–9, 2007.
- [10] S. Li and C. Tang, "Evaluation of training effect of new professional farmers based on BP neural network," in *Proceedings of the International Conference on Artificial Intelligence and Security*, pp. 348–357, Springer, Dublin, Ireland, July 2021.
- [11] G. H. Shen, D. X. She, and P. Sun, "Research and application of power system visualization technology," *Power System Technology*, vol. 33, no. 17, pp. 31–36, 2009.
- [12] S. Fu, J. Zhao, W. Cui, and H. Qu, "Visual analysis of MOOC forums with iForum," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 201–221, 2017.
- [13] H. Yin, J. Costa, and G. Barreto, "A framework for application of tree-structured data mining to process log analysis," *Intelligent Data Engineering and Automated Learning*, vol. 10, no. 52, pp. 423–434, 2012.
- [14] B. Usadel, F. Poree, A. Nagel, M. Lohse, A. Czedik-Eysenberg, and M. Stitt, "A guide to using MapMan to visualize and compare Omics data in plants: A case study in the crop species, Maize," *Plant, Cell and Environment*, vol. 32, no. 9, pp. 1211–1229, 2009.
- [15] R. Wang, A. Fabregat, D. Ríos et al., "PRIDE Inspector: A tool to visualize and validate MS proteomics data," *Nature Biotechnology*, vol. 30, no. 2, pp. 135–137, 2012.

- [16] B. S. Penn, "Using self-organizing maps to visualize highdimensional data," *Computers & Geosciences*, vol. 31, no. 5, pp. 531–544, 2005.
- [17] A. H. Debarger, W. R. Penuel, S. Moorthy, Y. Beauvineau, C. A. Kennedy, and C. K. Boscardin, "Investigating purposeful science curriculum adaptation as a strategy to improve teaching and learning," *Science Education*, vol. 10, pp. 1–40, 2017.
- [18] R. Leplae, T. Hubbard, and A. Tramontano, "GLASS: A tool to visualize protein structure prediction data in three dimensions and evaluate their consistency," *Proteins-structure Function & Bioinformatics*, vol. 30, no. 4, pp. 339–351, 2015.
- [19] R. J. Marshall, "Scaled rectangle diagrams can be used to visualize clinical and epidemiological data," *Journal of Clinical Epidemiology*, vol. 58, no. 10, pp. 974–981, 2005.
- [20] Y. M. Hu and A. Liang, "The application of different types of data visualization methods in educational research," *Educational Measurement and Evaluation*, vol. 8, pp. 10–23, 2016.
- [21] D. Y. Li and J. Y. Cao, "The visualization research of WeChat application status in Chinese education field," *China Educational Technology*, vol. 3, pp. 39–43, 2016.
- [22] Q. Y. Xie, "Research on the application of knowledge visualization in Chinese composition teaching in primary schools," *Dushu Wenzhai*, vol. 000, no. 25, pp. 315-316, 2016.
- [23] H. M. Lee, C. M. Chen, and T. C. Huang, "Learning efficiency improvement of back-propagation algorithm by error saturation prevention method," *Neurocomputing*, vol. 41, no. 1-4, pp. 125–143, 2001.
- [24] J. Li, Z. Zhou, J. Wu et al., "Decentralized on-demand energy supply for blockchain in Internet of things: A microgrids approach," *IEEE Transactions on Computational Social Systems*, vol. 6, no. 6, pp. 1395–1406, 2019.
- [25] W. Duan, J. Gu, M. Wen, G. Zhang, Y. Ji, and S. Mumtaz, "Emerging technologies for 5G-IoV networks: Applications, trends and opportunities," *IEEE Network*, vol. 34, no. 5, pp. 283–289, 2020.