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Research Article

An IGWOCNN Deep Method for Medical Education Quality Estimating

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The deep learning and mining ability of big data are used to analyze the shortcomings in the teaching scheme, and the teaching scheme is optimized to improve the teaching ability. The convolution neural network optimized by improved grey wolf optimization is used to train the data so as to improve the efficiency of searching the optimal value of the algorithm and prevent the algorithm from tending to the local optimal value. In order to solve the shortcoming of grey wolf optimization, an improved grey wolf optimization, that is, grey wolf optimization with variable convergence factor, is used to optimize the convolution neural network. The grey wolf optimization with variable convergence factor is to balance the global search ability and local search ability of the algorithm. The testing results show that the quality estimating accuracy of convolutional neural networks optimized by improved grey wolf optimization is 100%, the quality estimating accuracy of convolutional neural networks optimized by grey wolf optimization is 93.33%, and the quality estimating accuracy of classical convolutional neural networks is 86.67%. We can conclude that the medical education quality estimating ability of convolutional neural network optimized by improved grey wolf optimization is the best among convolutional neural networks optimized by improved grey wolf optimization and classical convolutional neural networks.

1. Introduction

The traditional medical education method has been difficult to meet the existing educational needs. In order to promote the optimization of big data and deep learning algorithms to the education industry, the deep learning and mining ability of big data are used to analyze the shortcomings in the teaching scheme, and the teaching scheme is optimized to improve the teaching ability. In order to optimize the education scheme, it is necessary to analyze the teaching data in order to improve the educational effect of the teaching scheme. Therefore, this paper proposes a medical education data analysis method based on convolutional neural networks optimized by improved grey wolf optimization, optimizes the education information data by using an artificial intelligence algorithm, and analyzes the education status through the characteristics of different levels of data. It is necessary to analyze the medical education data in order to realize the multilevel training program of medical education. This study uses the students' education and teaching materials, the relevant data generated by online learning and the students' examination results and evaluation data to analyze the learning degree data of students, and analyzes the requirements of relevant enterprises for the post.

Convolutional neural network is a popular deep learning method [1–3]. The difference between convolutional neural networks and traditional neural networks is that a convolutional neural network includes a feature extractor composed of a convolution layer and a pooling layer. The learning rate of convolutional neural networks is often based on human experience, which will lead to over-fitting or under-fitting of the model [4–6]. Therefore, a method with a simple structure, fast convergence speed, and easy implementation is needed to optimize the learning rate of a convolutional neural network.

The convolution neural network optimized by improved grey wolf optimization (IGWOCNN) is used to train the data, so as to improve the efficiency of searching for the optimal value of the algorithm and prevent the algorithm from tending to the local optimal value. Grey wolf optimization is a population intelligent optimization algorithm based on the social order of grey wolves, inspired by the activity of grey wolf hunting prey [7–11], which has the characteristics of strong convergence, few parameters, and easy implementation. In order to solve the shortcoming of grey wolf optimization, an improved grey wolf optimization, that is, grey wolf optimization with variable convergence factor, is used to optimize the convolution neural network. The grey wolf optimization with variable convergence factor is to balance the global search ability and local search ability of the algorithm. Thus, the improved grey wolf optimization is used to optimize the convolution neural network. The quality estimating accuracies of IGWOCNN, convolutional neural network optimized by grey wolf optimization (GWOCNN), and classical convolutional neural network (CNN) are shown in the testing results. From results of the test, we can conclude that the medical education quality estimation ability of IGWOCNN is the best among IGWOCNN, GWOCNN, and classical CNN.

2. The Optimization of Convolutional Neural Network Based on Improved Grey Wolf Optimization

A convolutional neural network is a popular deep learning model, which is a kind of feedforward neural network with a deep structure including convolution calculation. The difference between convolutional neural networks and traditional neural networks is that a convolutional neural network includes a feature extractor composed of a convolution layer and a pooling layer. In the convolution layer of a convolution neural network, a neuron is only connected with some adjacent neurons. The neurons of the same feature map share the same weight, named the convolution kernel [12, 13]. The convolution kernel is generally initialized in the form of a random decimal matrix, which will learn to obtain reasonable weights in the process of network training. The direct benefit of the convolution kernel is to reduce the connection between network layers and reduce the risk of over-fitting. A convolutional neural network usually includes four layers: a convolution layer, a pooling layer, a full connection layer, and a classification layer.

Each convolution layer of a convolutional neural network is composed of several convolution units, and the purpose of the first layer is to extract more features from the lower-level network. The pooling layer usually obtains features with large dimensions after the convolution layer. The fully connected layer combines all local features into global features to calculate the score of each last category. The classification layer outputs the probability of the corresponding category of medical education quality.

The learning rate of convolutional neural networks is often based on human experience, which will lead to over-fitting or under-fitting of the model. Therefore, an optimization method with a simple structure, fast convergence speed, and easy implementation is needed to optimize the learning rate of a convolutional neural network.

This study analyzes the medical education data through the IGWOCNN algorithm and outputs the medical education quality information, so as to evaluate the quality of education, and complete the education scheme required by the students.

Grey wolf optimization is used to optimize the learning rate of convolutional neural networks because of its fast convergence speed and easy implementation. Grey wolf optimization based on the social order of grey wolves, inspired by the activity of grey wolf hunting prey [14, 15], has the characteristics of strong convergence, few parameters, and easy implementation. Grey wolves belong to the social canine family and strictly abide by a hierarchy of social dominance [16]. The first level of social hierarchy: the first wolf of social hierarchy is α wolf, which is mainly responsible for making decisions on predation, habitat, work and rest time, and other activities. Other wolves need to obey the orders of the α wolf. The second level of social hierarchy is β wolf, which obeys the α wolf and assists the α wolf in making decisions. The third level of social hierarchy is δ wolf, which obeys α and β wolves and dominates the remaining levels of wolves [17, 18]. In order to balance the global search ability and local search ability of the algorithm, the improved GWO, that is, grey wolf optimization with variable convergence factor, is used to optimize the convolution neural network, which includes the steps of the grey wolf's social hierarchy, encircling, hunting, and attacking prey, which are described as follows.

2.1. Grey Wolf's Social Hierarchy. Calculate the fitness of each individual in the population. Mark the three grey wolves with the best fitness as α, β, and δ.

2.2. Encircling. Encircling the prey, the grey wolf will gradually approach the prey and surround it when it ropes the prey. The mathematical model of this behavior is as follows:

$$\begin{aligned} D &= \left|C \cdot X_p(t) - X(t)\right|, \\ X(t+1) &= \left|X_p(t) - A \cdot D\right|, \\ A &= 2a \cdot r_1 - a, \\ C &= 2r_2, \end{aligned} \tag{1}$$

where t is the current number of iterations, A and C are synergy coefficient vectors, $X_p(t)$ is the position vector of the current prey, and $X(t)$ is the position vector of the current grey wolf. In the whole iterative process, a decreases linearly from 2 to 0, and r_1 and r_2 are random vectors in [0, 1]; a is the variable convergence factor:

$$a = 2\left(1 - \frac{t}{t_{\max}}\right), \tag{2}$$

where $t_{\max}$ is the maximum iteration.

2.3. Hunting. Grey wolves have the ability to identify the location of potential prey. The search process is mainly completed under the guidance of α, β, and δ grey wolves. However, the solution space characteristics of many problems are unknown, and the grey wolf cannot determine the exact location of prey (optimal solution). The mathematical model of the search behavior of a grey wolf can be expressed as follows:

$$\begin{cases} D_\alpha = \left|C_1 \cdot X_\alpha - X\right|, \\ D_\beta = \left|C_2 \cdot X_\beta - X\right|, \\ D_\delta = \left|C_3 \cdot X_\delta - X\right|, \end{cases} \tag{3}$$

$$\begin{cases} X_1 = \left|X_\alpha - A_1 \cdot D_\alpha\right|, \\ X_2 = \left|X_\beta - A_2 \cdot D_\beta\right|, \\ X_3 = \left|X_\delta - A_3 \cdot D_\delta\right|, \end{cases} \tag{4}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3}, \tag{5}$$

where X{α}, X{β}, and X{δ} are, respectively, the position vectors of α, β, and δ, and in the current population; D{α}, D {β}, and D{δ} are the distance between the current candidate grey wolf and the best three wolves, respectively.

2.4. Attacking Prey. In the process of constructing the attack prey model, the decrease of a value will cause the value of a to fluctuate. Searching for prey, grey wolves mainly rely on the information of α, β, and δ to find the prey.

The steps for optimizing the learning rate of convolutional neural networks are as follows:

Step 1: the range of the learning rate of convolutional neural network is initialized, and the GWO parameters are set. The size of the grey wolf population is 20, and the grey wolf population is randomly generated; the individual position of each grey wolf group is indicated, and the maximum number of iterations is set to 100.

Step 2: input the individual position to the convolutional neural network model to obtain the fitness value of the current grey wolf individual.

Step 3: according to the current fitness value, the grey wolf population is divided into α, β, and δ. Encircling prey, the grey wolf will gradually approach the prey and surround it when it ropes the prey.

Step 4: the search process is mainly completed under the guidance of α, β, and δ grey wolves, and the position of each individual in the wolf group is updated according to Eqs. (3)–(5). α, β, and δ are selected from the current wolves by using the fitness value.

Step 5: searching for prey grey wolves mainly relies on the information of α, β, and δ to find prey.

Step 6: if the maximum number of iterations is reached, the iteration is terminated; otherwise, the algorithm returns to Step 2.

Step 7: the optimized learning rate of convolutional neural network is employed, and the optimized convolutional neural network is employed.

3. Experimental Study of Medical Education Quality Estimating Method Based on IGWOCNN

In this experiment, we collected 15 medical education quality data as our testing samples to study the feasibility of the medical education data analysis method based on IGWOCNN. Figure 1 gives the flowchart of the medical education data analysis based on IGWOCNN. The flow of the medical education data analysis is composed of data source, data acquisition, depth analysis, and medical education quality. The data source are the influencing features of medical education quality, which include the students' education and teaching materials, relevant data generated by online learning, and students' examination results and evaluation data, as well as the requirements of relevant enterprises for the post, which is given in Table 1. Data acquisition includes data extraction and conversion, digitally extract these data, and storing them in the database. The IGWOCNN algorithm is used as a deep analysis method. Input the students' education and teaching materials, relevant data generated by online learning, and students' examination results and evaluation data, as well as the requirements of relevant enterprises for the post, and calculate the teaching quality value by using the IGWOCNN algorithm, so as to evaluate the teaching quality and optimize the teaching scheme. The values of medical education quality are 1–9, and the bigger the value is, the better the medical education quality is.

In order to show the medical education quality estimating ability of IGWOCNN, the comparison of the estimating values of medical education quality among IGWOCNN, GWOCNN, and classical convolutional neural networks are given in this paper. As shown in Figure 2, the quality values of all the testing samples are correct in the medical education quality estimation values of 15 testing samples based on IGWOCNN. As shown in Figure 3, the quality value of only one testing sample is incorrect in the medical education quality estimation values of 15 testing samples based on GWOCNN. As shown in Figure 4, the quality values of two testing samples are incorrect in the medical education quality estimation values of 15 testing samples based on classical CNN. As shown in Table 2, the medical education quality estimating accuracy of IGWOCNN is 100%, the medical education quality estimating accuracy of GWOCNN is 93.33%, and the medical education quality estimating accuracy of classical CNN is 86.67%. Therefore, we can conclude that the medical education quality estimating ability of IGWOCNN is best among IGWOCNN, GWOCNN, and classical CNN.

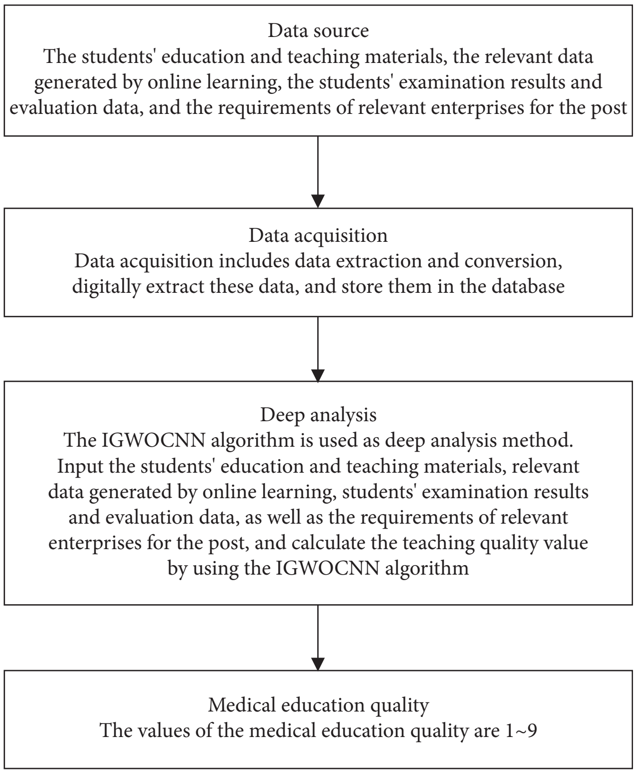

Figure 1: The flowchart of the medical education data analysis based on IGWOCNN.

Table 1: The influencing features of medical education quality.

No.	The influencing features of medical education quality
1	The students' education and teaching materials
2	The relevant data generated by online learning
3	The students' examination results and evaluation data
4	The requirements of relevant enterprises for the post

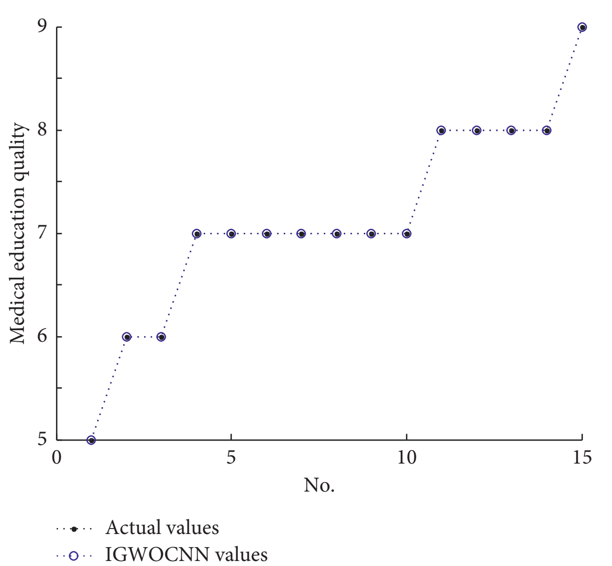

Figure 2: The medical education quality estimating values of 15 testing samples based on IGWOCNN.

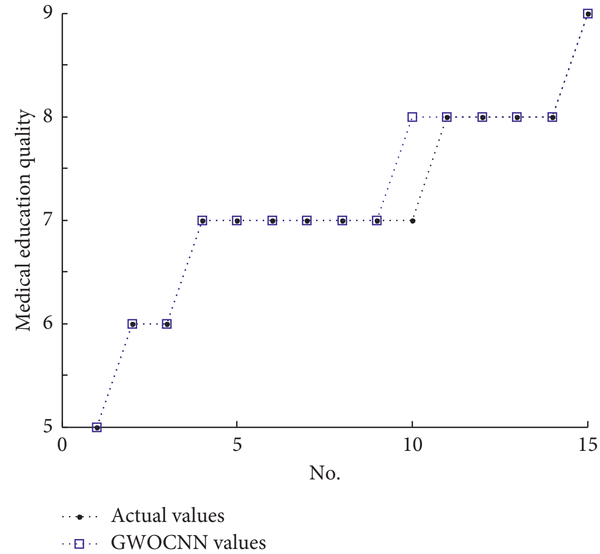

Figure 3: The medical education quality estimating values of 15 testing samples based on GWOCNN.

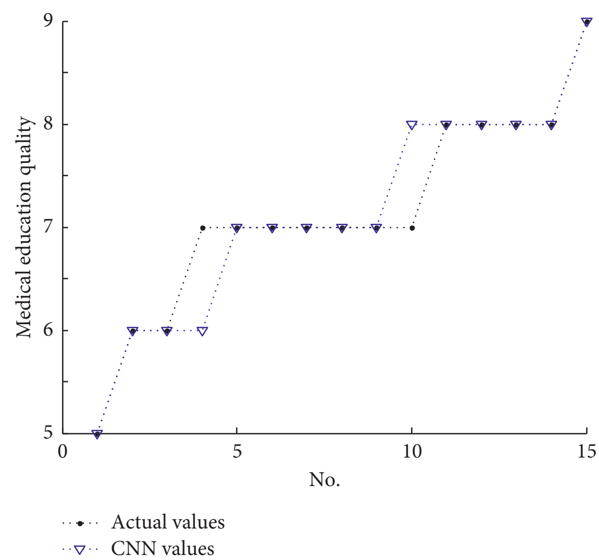

Figure 4: The medical education quality estimating values of 15 testing samples based on classical CNN.

Table 2: The medical education quality estimating accuracies of IGWOCNN, GWOCNN, and classical CNN.

Neural networks	Quality estimating accuracy (%)
IGWOCNN	100
GWOCNN	93.33
Classical CNN	86.67

4. Conclusion

This study presents the convolution neural network optimized by improved grey wolf optimization for medical education quality estimating so as to complete the education scheme required by the students. In this paper, the improved grey wolf optimization algorithm, that is, grey wolf optimization with variable convergence factor, is used to optimize the convolution neural network so as to improve the efficiency of searching for the optimal value of the algorithm and prevent the algorithm from tending to the local optimal value. The medical education quality estimation accuracy of IGWOCNN is higher than that of GWOCNN and classical CNN. In conclusion, we can conclude that the medical education quality estimation algorithm based on IGWOCNN can run more accurately.

Data Availability

The dataset used to support the findings of the study can be accessed upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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