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Research Article

Evaluation Method of Wushu Teaching Quality Based on Fuzzy Clustering

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The existing teaching quality evaluation methods cannot calculate the distance between the data points of teaching dataset and the center points of the large density grid, which leads to the poor classification of teaching data and the low accuracy of teaching quality evaluation. Therefore, a method of teaching quality evaluation of Wushu based on fuzzy clustering is proposed. In order to improve the comprehensiveness of teaching quality evaluation, the lost data of teaching resources were recovered. Based on this, the grid index of martial arts teaching data is established, and the relationship model between teaching quality and martial arts achievement is constructed. Based on the characteristics of Wushu teaching resources, the fuzzy clustering method is introduced to calculate the distance between each data point and the grid center with high data density. The experimental results show that the evaluation accuracy of the teaching quality is high, and the lost data can be accurately recovered. The evaluation efficiency, reliability, and stability of Wushu teaching quality are ideal.

1. Introduction

With the expansion of higher education in China, the evaluation and monitoring of teaching quality become the key link of teaching management and the center of teaching management. As a public course, Wushu is particularly important. Scientific evaluation of Wushu teaching quality is conducive to improving teaching quality and finding problems in teaching process. Therefore, the establishment of the most suitable Wushu evaluation model is an important research course in the current teaching reform of colleges and universities, and the quality of evaluation directly determines the teaching quality of the whole Wushu school. Determining the correct evaluation standard is the key to the evaluation of Wushu classroom teaching. In the process of evaluating Wushu classroom teaching evaluation, using modern evaluation theories and methods to analyze and judge the comprehensive value of Wushu teaching activities plays a very important role in implementing quality education and improving school teaching quality and scientific education management. Schools often do not pay attention to or even ignore the teaching of Wushu. Wushu teaching quality evaluation also depends on subjective judgment, and the results are uneven. However, the existing evaluation of Wushu teaching quality mostly relies on subjective judgment, and the results are uneven; resulting final evaluation results are also unsatisfactory, which can not provide reference for improving teaching quality.

In the evaluation of teaching quality, the application of fuzzy clustering algorithm is absolutely ideal. Fuzzy clustering algorithm is a common algorithm. According to the idea of fuzzy theory, the concept of membership degree is introduced to fuzzify the membership relationship between samples and clusters, allowing samples to belong to more than one clusters according to their degrees, thus improving the accuracy and performance of the algorithm. Fuzzy clustering algorithm measures the distance between sample points and cluster centers and takes the minimum distance between samples and clusters as the solution goal. The objective function is expressed as the sum of class distance weighted by membership degree, and the clustering problem after modeling is abstracted as the optimization problem of function with constraints, but the current application of the algorithm is relatively less [1, 2].

Yun and Bai [3] designed an evaluation method of computer experiment teaching effect based on big data analysis technology. Firstly, this paper analyzes the current research progress of computer experimental teaching effect evaluation, collects the relevant dataset of experimental teaching effect, and establishes the evaluation index of computer experimental teaching effect. Then, AHP is introduced to establish a hierarchical evaluation index system of computer experimental teaching effect, determine the weight of each index, and test the consistency, so as to realize the evaluation of computer experimental teaching effect. Finally, the specific computer experiment teaching is selected as the test object for simulation experiment. However, this method does not take into account the randomness in Wushu teaching, resulting in the unsatisfactory effect of teaching data classification. Chen et al. [4] introduced an intelligent teaching system based on deep learning. The system includes two parts: online personalized learning recommendation and offline classroom quality two-way evaluation. In the online system, performance prediction and online learning behavior analysis based on deep learning are designed, and learning emotion classification is realized combined with image processing technology. The training target detection model, face detection model, and face segmentation model in the offline teaching system are combined with the online teaching system to extract the characteristics of online learning behavior, complete offline performance prediction, and learn law analysis and personalized learning recommendation. At the same time, the evaluation and feedback of college teaching quality and students' learning behavior are realized through the offline classroom information data. The experimental results show that the system not only has a convenient and fast way to obtain information but also can reduce a lot of time, meet the new learning and teaching methods of combining online and offline, and can effectively improve teachers' teaching efficiency and students' learning efficiency. However, this method has not been applied to the specific subject teaching quality evaluation, and the accuracy of Wushu teaching quality evaluation needs to be further analyzed. Based on the comprehensive analysis of the above two literature methods, in order to accurately calculate the distance from the data point of the teaching dataset to the center point of the high-density grid, improve the classification effect of teaching data, and optimize the accuracy of quality evaluation, this paper proposes a Wushu teaching quality evaluation method based on fuzzy clustering.

2. Evaluation Method of Wushu Teaching Quality Based on Fuzzy Clustering

2.1. Recovery of Lost Teaching Data. Martial arts teaching resource transmission nodes have certain topological mobility, and the link is two-way transmission. Therefore, the link backbone link tree can be constructed according to the initial transmission node, and the branch with the smallest number of hops can be selected as the transmission link. According to the comprehensive analysis, for the missing

teaching data, the recovery method based on linear data self-sensing mechanism can be adopted. The specific recovery process is as follows.

For the lost dataset $J = (Y, A, V, f)$ in the transmission of Wushu teaching resources, the dataset can be divided into different subsets according to the loss attribute value $V_d = \{d_1, d_2, \ldots, d_l\}$, where S_l represents a lost subset in the lost dataset. Given two lost information objects x_i, $x_j \in S_l$, the probability that the same lost information decision object x_i is approximate to x_j in conditional attribute $\aleph$ is [5, 6]

$$R_k^+\left(x_i, x_j\right) = \begin{cases} \sum\left(\dfrac{|E_\aleph|}{|V_\aleph|}\right)^2 & \aleph(x_i) = \ast \wedge \aleph\left(x_j\right), \\[4mm] \dfrac{|\aleph(x_i)|}{|V_\aleph|} & \aleph(x_i) \neq \ast \wedge \aleph\left(x_j\right), \end{cases} \tag{1}$$

where $|E_\aleph|$ represents the number of lost information objects corresponding to the two lost information objects with the same value on the loss condition attribute $\aleph$ in the transmission of Wushu teaching resources, $|V_\aleph|$ represents the number of lost information objects with non-empty value on the lost information condition attribute $\aleph$, $|\aleph(x_i)|$ represents the number of lost information objects with $|\aleph(x_i)|$ value on the condition attribute $\aleph$, and $\aleph(x_j)$ represents the value of the lost information object x_j on the condition attribute $\aleph$; then, the approximation of the lost information objects x_i and x_j in the transmission of Wushu teaching resources can be expressed by

$$R^+\left(x_i, x_j\right) = \prod_{\aleph \in C} R_k^+\left(\aleph x_i, x_j\right), \tag{2}$$

where C represents the set of discrete attributes with all missing information. The weight ρ_i of each selected lost information attribute k_i is calculated by the correlation degree of the remaining lost information attributed to it, which reflects the ability of some attributes other than k_i to replace k_i; then, the weight coefficient can be defined by

$$a_i = \frac{|\rho_i|^{-1}}{\sum_{j=1}^m |\rho_j|^{-1}}, \tag{3}$$

where ρ_j reflects the ability of non-k_j's lost information attribute to replace k_j. It requires a certain time complexity to calculate ρ_j, so that ω_{ij} represents the correlation coefficient between lost information attribute k_i and attribute k_j, which can accurately determine the correlation between each attribute of lost information [7, 8].

$$\omega_{ij} = \frac{\sum_{t=1}^m \left(g_{ti} - \overline{g}_i\right)\left(g_{tj} - \overline{g}_j\right)}{\sqrt{\sum_{t=1}^m \left(g_{ti} - \overline{g}_i\right)^2 \sum_{t=1}^m \left(g_{tj} - \overline{g}_j\right)^2}}, \tag{4}$$

where $\overline{g}_i$ represents the average value of the attribute value of the i-th lost information in the transmission of Wushu teaching resources, $\overline{g}_j$ represents the average value of the attribute value of the j-th lost information in the transmission of Wushu teaching resources, g_{ti} and g_{tj} represent

the extreme values of the i-th and j-th lost information attributes, respectively, and t represents the number of set discrete areas of lost information. Take a_i as the weight of g_{ti}, and greater a_i indicates that the relationship between k_i and itself is relatively large. By setting the threshold ε, it is determined to change the data to lost information when $a_i < \varepsilon$ is met.

2.2. Establishment of Wushu Teaching Data Grid Index.
The key to the establishment of grid index is spatial grid division. Taking the upper left corner of martial arts teaching data spatial database as the coordinate origin [9, 10], the martial arts teaching data spatial database is equally divided into $M \times N$ copies, and the obtained data objects are divided into blocks as $\mathrm{Bl}[k, j]$. Among them, the division diagram of $0 \leq k < N$, $0 \leq j < M$ and data grid is shown in Figure 1.

According to the grid index theorem and related research results, when the distribution characteristic index p of data elements in Wushu teaching data space is small, the effect of primary grid index mechanism is better than that of traditional grid index mechanism. Let the number of data elements in each data bucket after primary grid division be K, and the calculation formula is

$$K = \frac{m \times n}{M \times N}. \tag{5}$$

When only a single spatial object is considered, the probability that the spatial data element of Wushu teaching data is covered by the spatial object can be calculated by the following formula:

$$q = 1 - p. \tag{6}$$

Assuming that the retrieval time of the data elements in each data bucket obtained from the division of Wushu teaching data is X, the calculation formula of the mathematical expected value $E(X) B$ of the random variable is as follows [11, 12]:

$$E(X) = \frac{1}{K}q^k + \left(1 + \frac{1}{K}\right)\left(1 - q^k\right)$$
$$= 1 - q^k + \frac{1}{K}. \tag{7}$$

When the value of p is small, the value of q is approximately 1. At this time, the expected value of retrieval times is only determined by the value of K. The effect of grid indexing mechanism can be guaranteed by adjusting the value of K.

According to the prior knowledge, if $p < 0.2929$, only one grid division is required, and the obtained grid index mechanism can achieve good results. Otherwise, two-level grid division, three-level grid division, and multi-level grid division are required to build a new grid index mechanism.

In the newly established grid index mechanism, the number of grid division levels is not the more the better, but the division levels need to be selected and determined according to the actual needs, so as to ensure the index effect
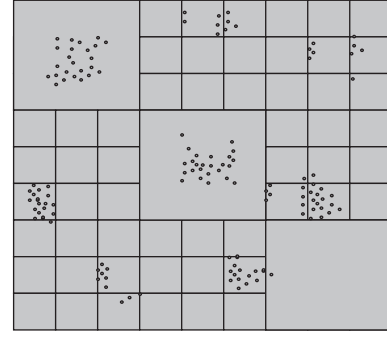

FIGURE 1: Data grid division diagram.

and avoid excessive space consumption. They can be selected and determined according to the actual needs to ensure the index effect and avoid excessive space consumption.

2.3. Modeling the Relationship between Teaching Quality and Wushu Achievement.
In the process of constructing the relationship model between teaching quality and martial arts performance, first obtain the historical samples of students' martial arts performance estimation in each stage, give the observation matrix of students' martial arts performance, and then calculate the a priori state estimation value of students' martial arts performance, based on which the students' martial arts performance estimation model is established [13, 14].

Take the students' autonomous learning motivation and students' autonomous learning strategies at each stage as the observation vector of students' Wushu performance and calculate the observation transfer matrix of students' Wushu performance at each stage by using the following formula:

$$H_t = [h_{1t}, h_{2t}, \ldots, h_{nt}], \tag{8}$$

where h represents the effect of students' autonomous learning in each stage and n represents the content of students' autonomous learning in each stage. The adjacent stages X_{t+1} and X_t are basically the same. Therefore, the state transition matrix of various influencing factors of students' Wushu achievement is the unit matrix, that is, $\Phi_t = I$ and $\mathfrak{R}$ represent the vector of students' sense of decision making in autonomous learning, and the state equation of various influencing factors of students' Wushu achievement is expressed by

$$X_{t+1} = \frac{\varphi_{t+1/t}X_t}{\mathfrak{R}}. \tag{9}$$

It is assumed that the optimal filter estimation $\widehat{X}_t$ of the state X_t of the influencing factors of students' autonomous learning has been obtained in stage $t + 1$, but before the observation value has been obtained, ω_t represents the inestimable state vector sequence of students' sense of responsibility for autonomous learning [15]. A priori estimation of the state vector X_{t+1} of each influencing factor of students' autonomous learning is made according to the existing amount of information, which is expressed by

$$\widehat{X}_{t+1/t} = \varphi_{t+1/t} \widehat{X}_t. \tag{10}$$

The Kalman filter gain is introduced to adjust the difference to obtain the optimal estimation [16, 17]. The a priori state estimation of the error covariance matrix is expressed by

$$P_{t+1} = (I - K_{t+1} H_{t+1}) \cdot \widehat{X}_{t+1}. \tag{11}$$

The relationship model between teaching quality and Wushu achievement is established by using the following formula:

$$L_{t+1/t} = H_{t+1} \cdot \widehat{X}_{t+1}. \tag{12}$$

2.4. Feature Extraction of Students' Wushu Teaching. In the process of establishing the estimation model of students' Wushu teaching characteristics, first integrate the grey correlation entropy analysis theory to analyze the correlation degree of various influencing factors of students' Wushu teaching characteristics, calculate the correlation coefficient between students' Wushu teaching characteristics, and select the key influencing factors [18–20]. The specific process is as follows.

Assuming that the sequence of the correlation factor set of students' Wushu teaching characteristics is $\{x_k(j)\}$ $(k = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$, m and n, respectively, representing the length of the sequence and subsequence of the correlation factor set of students' Wushu teaching characteristics, determine its reference sequence x_0 and comparison sequence x_k. According to the above indicators, the sequence difference of each correlation factor of Wushu teaching characteristics is calculated, as shown in the following formula:

$$D_k(j) = |x_0(j) - x_k(j)|, \tag{13}$$

where $x_k(j)$ represents the estimated value of Wushu teaching characteristics of students in stage j and $x_0(j)$ represents the value of factor k D in the initial stage.

Use formula (14) to calculate the grey entropy correlation degree of each factor sequence x_k of students' Wushu teaching characteristics [21, 22]:

$$\text{En}(R_k) = H \frac{[(R_k) \cdot \partial_k]}{H_{\text{max}}}. \tag{14}$$

Among them, confidence ∂_k has the greatest influence on the awareness of autonomous learning. H_{max} represents the maximum entropy of the difference information column composed of n attribute factors. According to the correlation coefficient R_k and the grey entropy correlation degree $\text{En}(R_k)$, the grey entropy equilibrium correlation degree of each correlation factor of students' martial arts teaching characteristics can be obtained:

$$\text{Ea}(k) = \text{En}(R_k) r_{\text{ok}}, \tag{15}$$

where r_{ok} represents the will of students to study independently.

According to formulas (14) to (15), the correlation degree of each correlation factor of students' martial arts teaching characteristics is calculated, and the correlation factor with high correlation degree is selected.

2.5. Fuzzy Clustering Method of Wushu Teaching Data. Fuzzy clustering belongs to unsupervised learning in pattern recognition. It does not need training samples. It can achieve the purpose of automatic classification directly through machine learning. The key technology in pattern recognition is feature extraction. Fuzzy clustering can not only extract features from the original data but also optimize the selection and dimensionality reduction of features: after extracting features, the nearest neighbor prototype classifier in the fuzzy clustering algorithm can reduce the dimension of data through spatial division and formulating fuzzy rules. In addition, fuzzy clustering has also achieved good results in the specific fields of Chinese character preclassification in pattern recognition, classification and matching in speech recognition, and so on. In object recognition and line detection, fuzzy clustering can be used in the original data and transform domain. In some specific application fields of pattern recognition, fuzzy clustering has also achieved good results, such as character preclassification in Chinese character recognition, classification and matching in speech recognition, and so on.

Therefore, based on the martial arts teaching data grid division, this paper applies the fuzzy clustering method to the martial arts teaching data classification and uses the following formula to calculate the grid center:

$$A_{k'} = \frac{\sum_{X_i \in G_{k'}} X_i}{d(G_{k'})}, \tag{16}$$

where $A_{k'}$ represents the abstract center point of grid $G_{k'}$ and X_i and $d(G_{k'})$ represent Wushu teaching data vector and data distribution density in grid E, respectively. Taking the farthest distance between data points in the grid and $A_{k'}$ as the data distribution radius $R_{k'}$, the formula is as follows:

$$R_{k'} = \max_j \left\{ \|X_i - A_{k'}\|^2 \right\}. \tag{17}$$

According to the data distribution density and the preset density threshold τ_c in the grid, the martial arts teaching data grids meeting the constraint conditions are merged to form a new data grid and recorded. The new martial arts teaching data grid center and data distribution radius are as follows:

$$A_k' = \frac{A_i d(G_i) + A_j d(G_j)}{d(G_i) + d(G_j)}, \\ R_k' = \max\{R_i, R_j\} + \frac{\|A_i - A_j\|^2}{2}, \tag{18}$$

where A_i, A_j and R_i, R_j represent the center and data distribution radius of C and D, respectively.

For the grid with high density of data distribution in martial arts teaching, the adjacency table shall be constructed for it, and the data points in the grid with low density of data distribution shall be investigated accordingly, and the distance between each data point and the center point of the grid with high density of data shall be judged. If the distance threshold satisfies the requirements set, the data point shall be included in the data block with high density of data, and the center

point and radius of the data cluster in the grid shall be adjusted again [23, 24]. Through the above process, the rigid boundary of Wushu teaching data grid can be softened, and part of the data in the natural cluster separated by the grid boundary can be returned to the original cluster, thus improving the accuracy of fuzzy clustering of Wushu teaching data [25]. During the boundary softening process, for each data point X_i included, the new grid center and data distribution radius expressions are obtained as follows:

$$A_{k'}^* = \frac{d(G_{k'}') + X_i}{d(G_{k'}') + 1}.$$ (19)

In order to further improve the accuracy of data clustering results, the membership degree of the data points in each data cluster is calculated. According to the membership degree calculation results and the preset membership threshold, the membership value of the data points in the data cluster after fuzzy clustering is determined, and the data points in the data cluster are wrongly classified into the data cluster to which the data cluster belongs. Every time new martial arts teaching data are received, the distribution of the above data can be used to determine the cluster attribution of the new data [26, 27].

2.6. Teaching Quality Evaluation Model. Based on the above contents, a reasonable and scientific evaluation index system can improve the accuracy of teaching quality evaluation. However, teaching quality evaluation is influenced by many factors, such as teaching methods, teaching attitude, teaching content, teaching management, and teaching effect. Then, the evaluation index system of teaching quality is established by referring to relevant literature and research and adopting AHP [28–30].

The evaluation index system of Wushu teaching quality is established through AHP, but these indexes have multiple collinearity and serious information redundancy. Principal component analysis (PCA) is a data processing method that can use a few indicators to describe the original teaching quality indicators and reduce the dimension of input vectors. The steps of the PCA's evaluation index system for the quality of martial arts teaching are as follows [31–33]:

(1) In order to eliminate the adverse effects of data differences among indicators on SVM learning process, they are normalized, namely:

$$y_{ij} = \frac{x_{ij} - \overline{x_j}}{s_j} \in Y,$$ (20)

(i) where $\overline{x_j}$ represents the index value and s_j represents the j-th value of the i-th index.

(2) Calculate the characteristic covariance matrix:

$$\Gamma = \frac{[Y - \overline{Yl})[Y - \overline{Yl}]^T}{N}.$$ (21)

(3) Solve the characteristic covariance matrix value and the corresponding U value according to the characteristic equation.

(4) Sort according to the eigenvalue and accumulate the contribution rates of the principal component variance. When the cumulative contribution rate is more than 85%, the number of principal components can be obtained (m) [34].

(5) These principal components can be input into the SVM for learning, reducing the input dimension of the SVM and improving the learning efficiency of the SVM [35, 36].

The steps for evaluation of Wushu teaching quality are as follows:

(1) According to the actual requirements of expert system, frontline teachers, and teaching quality evaluation, the hierarchical index system structure of teaching quality evaluation shall be established by adopting AHP.

(2) Teaching quality data are collected according to the evaluation index system selected by the AHP.

(3) PCA is adopted to select the evaluation indicators, and the teaching quality data shall be correspondingly processed according to the evaluation indicators.

(4) The evaluation index selected by the PCA shall be used as the input vector of the SVM, and the grade of teaching quality shall be used as the output of the SVM, and the corresponding training set and test set shall be established.

(5) Teaching quality indicators shall be normalized to eliminate the adverse effects of differences in indicators and dimensions.

(6) Input the training set into the SVM for learning, use particle swarm optimization algorithm to find the optimal SVM parameters, and establish the teaching quality evaluation model.

(7) The established evaluation model shall be adopted to test the test set, and if the accuracy is determined to meet the preset requirements, the optimal evaluation model of teaching quality shall be obtained.

(8) The best evaluation model of teaching quality shall be adopted to evaluate the teachers' teaching level, and the corresponding evaluation level shall be output.

3. Simulation Experiment

3.1. Data Sources. In order to verify the performance of the Wushu teaching quality evaluation model, simulation experiments are carried out on MATLAB 2020 software. 10000 data were collected from the martial arts teaching quality data of a school. A total of 10,000 data have been collected, and each kind of data includes 4 evaluation indicators, with the grade divided into excellent ("1" represents), good ("2" represents), qualified ("3" represents), and unqualified ("4" represents). The data of teaching quality are shown in Table 1.

TABLE 1: Wushu teaching quality evaluation data.

Number	5	2	3	4
5	88.32	88.58	78.87	74.05
2	68.85	75.47	58.20	64.83
3	74.05	505.82	88.65	78.40
4	76.78	80.85	88.50	86.28
5	72.87	88.86	86.63	75.03
6	85.08	82.37	78.47	83.58
7	60.45	85.33	74.32	83.27
8	78.86	83.38	77.73	83.36
8	35.45	44.82	55.82	42.74
. . .	. . .	. . .	. . .	. . .
50000	70.65	84.78	80.68	80.58
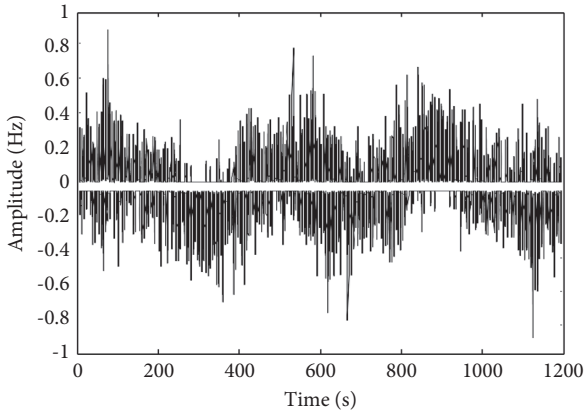
FIGURE 2: Time-domain distribution of sampled data.

Set the length of Wushu teaching resources data sampling as 1024 and the frequency of data sampling as 120 KHz. The time-domain distribution of Wushu teaching resource data to be evaluated is shown in Figure 2.

3.2. Comparative Analysis of Experimental Results. In this experiment, the teaching quality evaluation method based on big data driven proposed in reference [3] and the teaching quality evaluation method based on deep learning proposed in reference [4] were selected as the control methods, and the experimental test results were compared with the method proposed in this paper. Accuracy rate is one of the basic conditions that must be satisfied in teaching quality evaluation. Assuming that M represents the total number of lost information values of teaching resources and N represents the total number of correctly recovered lost information values, the recovery accuracy of lost information can be calculated by

$$C = \frac{N}{M}. \tag{22}$$

Formula (23) is used to calculate the relevance of continuous attribute values of Wushu teaching resource data:

$$L'' = \frac{\left(\sum_{i \subset U} i\_\text{tag} \times \text{node\_num} \right)}{\sum_{i \subset N} \text{re\_num}}, \tag{23}$$

where U represents the set of continuous attributes of all lost data.

Figure 3 shows the experimental results of the accuracy (%) of the method proposed in this paper for recovering the lost information in the transmission of martial arts teaching resources when $L'' = 0.2$ and $L'' = 0.5$ on the sample dataset.

It can be seen from Figure 3 that whether the correlation of continuous attribute values of Wushu teaching resource data is 0.2 or 0.5, the accuracy of this method to recover the lost information in Wushu teaching resource transmission is higher than that of the comparison method, and the accuracy can reach 90%. The main reason is that this method uses the recovery method based on linear data self-sensing mechanism, The Wushu teaching resource data in transmission are recovered and retrieved, and the recovery accuracy is improved.

In order to better judge and compare the clustering effects of different methods, the evaluation indexes of average hop number and maximum hop number are added to realize the evaluation. The minimum jump number is expressed as a parameter to measure the quality of Wushu teaching. The specific evaluation results are shown in Figure 4.

It can be seen from Figure 4 that when the number of multi-hop nodes is determined, the average number of hops and the maximum number of hops are the smallest with the increase of the number of martial arts teaching data. The main reason is that this method constructs the link backbone link tree according to the initial transmission node and selects the branch with the smallest number of hops as the martial arts teaching quality data transmission link, which reduces the impact of the growth of martial arts teaching data.

In the same experimental environment, the comparison of the evaluation efficiency (%) of Wushu teaching quality by the three models is described in Figure 5.

According to Figure 5, the efficiency of Wushu teaching quality evaluation using the model in this paper is higher than the teaching quality evaluation method based on big data proposed in reference [3] and the teaching quality evaluation method based on deep learning proposed in reference [4]. The reason is that this model uses the grey correlation entropy analysis theory to analyze the correlation degree between various influencing factors of students' Wushu teaching characteristics, reduces the classification time of teaching characteristics, and further improves the estimation efficiency of Wushu teaching characteristics.

In the same experimental environment, the comparison of the reliability (%) of the teaching quality evaluation of the three models of martial arts is described in Figure 6.

According to the analysis of Figure 6, the reliability of Wushu teaching quality evaluation using this model is higher than that of reference [3] and reference [4]. The main reason is that this method recovers the lost data of teaching resources and improves the comprehensiveness of teaching quality evaluation. Based on this, the grid index of Wushu teaching data is established, the relationship model between teaching quality and Wushu performance is constructed, and the teaching quality of Wushu is preliminarily evaluated by students' performance. On this basis, the evaluation model of Wushu teaching quality is established, which
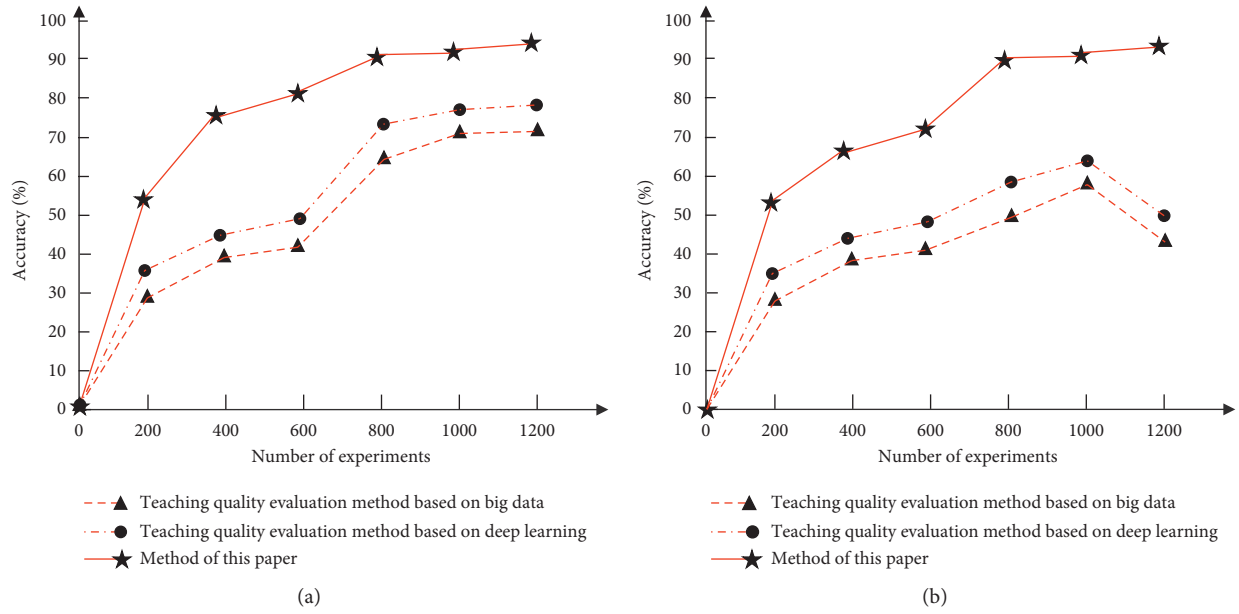
(a)

(b)

Figure 3: Accuracy test results. (a) $L'' = 0.2$. (b) $L'' = 0.5$.
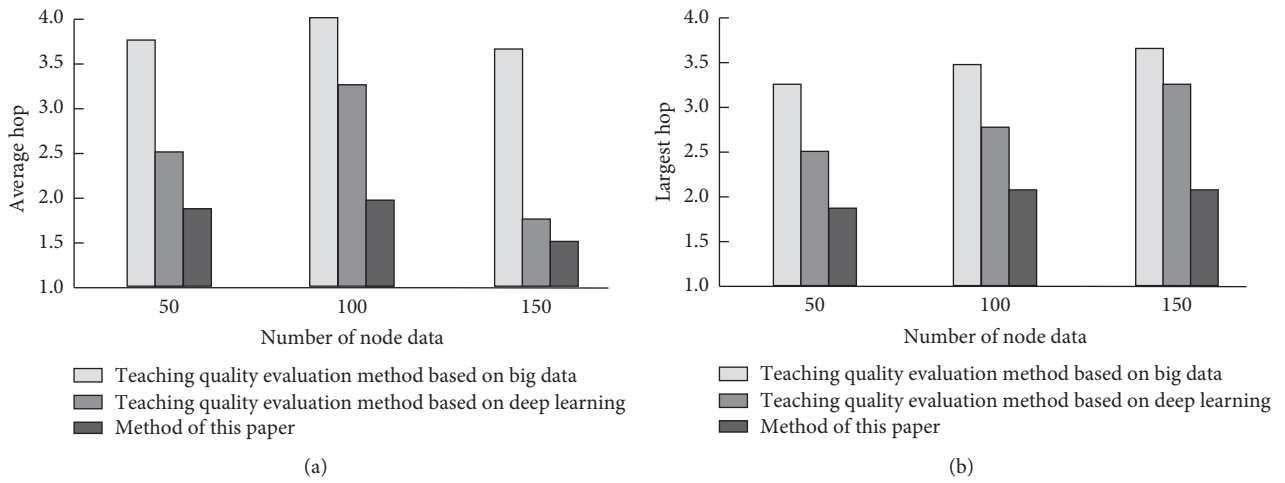

(a)

(b)

Figure 4: Comparative test results of average hop count and maximum hop count. (a) Average hop count comparison. (b) Maximum hop count comparison.
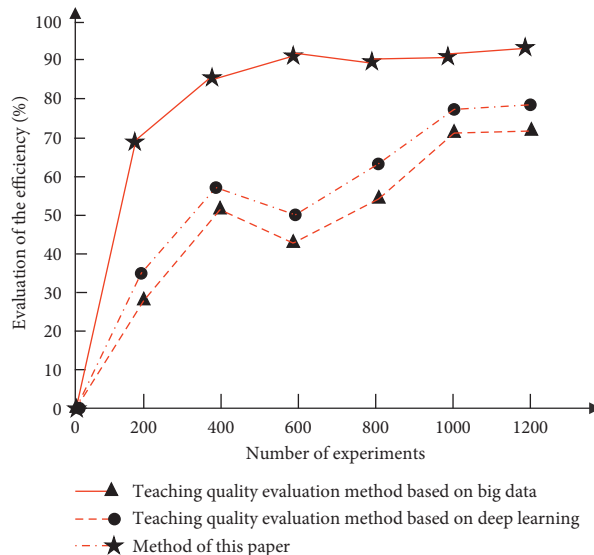

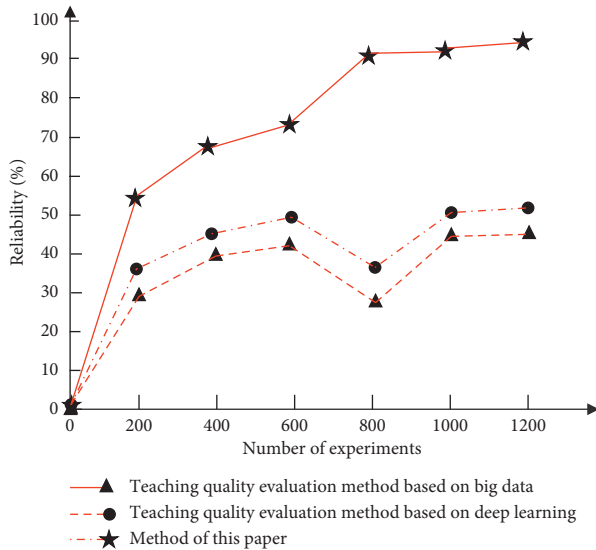Figure 5: Comparison of estimated efficiency of different models.

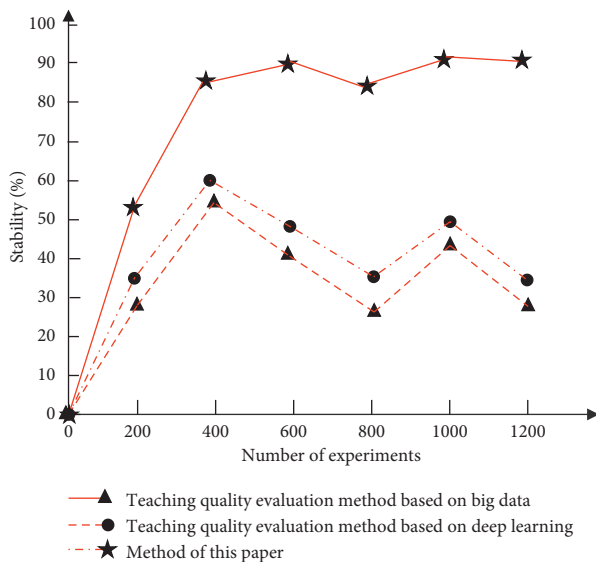Figure 6: Comparison of estimated reliability of different models.

Figure 7: Comparison of estimation stability of different models.

makes the model in this paper have high reliability in the estimation of students' Wushu teaching characteristics.

The methods of this paper, reference [3], and reference [4] are used to carry out Wushu teaching quality evaluation experiments. The comparison of the stability (%) of Wushu teaching quality evaluation of the three models is described in Figure 7. The comparison of the stability (%) of the three models of Wushu teaching quality evaluation is described in Figure 7.

By analyzing Figure 7, it can be seen that using this model to evaluate the teaching quality of Wushu is more stable than the methods of reference [3] and reference [4]. This is mainly because this method establishes the index of Wushu teaching data grid, constructs the relationship model between teaching quality and Wushu achievement, and preliminarily evaluates the teaching quality of Wushu

through students' achievement. On this basis, the characteristics of Wushu teaching resources are extracted, the fuzzy clustering method is introduced to calculate the distance from each data point to the grid center with high data density, and the evaluation index system is established to realize the high stability evaluation of Wushu teaching quality. This is mainly because this method establishes the Wushu teaching data grid index and constructs the relationship model between teaching quality and Wushu achievement. The teaching quality of Wushu is preliminarily evaluated by students' achievements. This paper extracts the characteristics of Wushu teaching resources, introduces the fuzzy clustering method, calculates the distance from each data point to the grid center with high data density, establishes the evaluation index system, and sets up the Wushu teaching quality evaluation model on this basis.

4. Conclusion

In order to solve the problem that the data classification effect of traditional teaching quality evaluation methods is not ideal and the accuracy of quality evaluation is low, a new Wushu teaching quality evaluation method based on fuzzy clustering is designed. The following conclusions are drawn:

(1) In this paper, the accuracy of teaching quality evaluation is effectively optimized by restoring the lost data of teaching resources and establishing Wushu teaching data grid index. Then, the fuzzy clustering method is used to establish the evaluation index system to realize the evaluation of Wushu teaching quality.

(2) The experimental results show that the evaluation accuracy of the bookstore teaching quality of the proposed method can reach more than 90%, the lost data can be recovered accurately, and the evaluation efficiency of Wushu teaching quality is always higher than 90%, and its reliability and stability indexes are high.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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