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Retraction

Retracted: Fuzzy Neural Network for the Online Course Quality Assessment System

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] X. Bai and Y. Bai, "Fuzzy Neural Network for the Online Course Quality Assessment System," *Mathematical Problems in Engineering*, vol. 2022, Article ID 4865027, 10 pages, 2022.

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Research Article

Fuzzy Neural Network for the Online Course Quality Assessment System

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Under the influence of COVID-19, online office and online education has ushered in a golden period of development. The teaching quality of online education has been a controversial issue. Our study takes online course teaching quality assessment as the starting point, explores the influencing factors of online course quality assessment with online courses as the research object, and analyzes the latest research proposal for an online course quality index. To make the online course quality assessment more intelligent, we propose an online course quality assessment method based on a fuzzy neural network. The method uses fuzzy rules as the baseline and adds a TSK perception mechanism to expand the perception domain of the fuzzy neural network and improve the course quality index prediction accuracy. At the input side of the fuzzy neural network, we preclassify the online course data into four parts, and each part of the data represents a different assessment domain. Due to the large data cost, we expanded the collective amount of data using data augmentation methods. In addition, we parse the structure of the fuzzy neural network hierarchy and introduce the construction and role of the TSK perception mechanism in the fuzzy rules. An optimal learning strategy is proposed in the fuzzy neural network training. Finally, in the experimental session, we verify the effectiveness of data augmentation and explore the distribution of course quality assessment weights. In the comparison of the model prediction results with the actual assessment results, our method achieves an excellent matching rate, which proves the high efficiency of our method in the online course quality assessment system.

1. Introduction

Affected by COVID-19, economies around the world have been affected to varying degrees, and most industries have begun to change their office methods to online to minimize losses. For the education industry, online teaching has become the most ideal way due to the impact of the national-level antiepidemic policy. Although the teaching effect is not as good as offline teaching, online teaching also has advantages that cannot be matched by offline teaching [1–3]. The online teaching approach adds many features, is clearer in the presentation of teaching purposes, and is equally capable of face-to-face interactive teaching with the aid of visual sensors [4]. The construction of an online teaching environment can be personalized according to the teaching purpose, and compared with the traditional offline teaching mode, online teaching can obtain a better teaching presentation with the help of teaching environment construction. The advantage of online teaching is that it can be done with simple electronic devices for both students and teachers, which can greatly save the cost and time for teachers and students to move around [5–7].

Online teaching and learning, aided by computer vision and human-computer interaction technologies, has greatly improved the effectiveness of teaching and learning and also further motivated teachers and students to attend classes. Several researchers have also done several studies to enhance the effectiveness of online teaching and have worked to upgrade the online teaching model to that of face-to-face instruction [8]. The online teaching of the course is tailored

according to the differences like the course, and the student's interests and the teacher's teaching habits are simulated to learn through neural network algorithms, and different elements are inserted in the content, process, and structure of the online course teaching to enhance the experience and communication of the online course teaching. For the teaching materials involved in the course, some researchers build their online teaching database and crawl the Internet resources into the dataset synchronously so that students and teachers can get rich teaching resources in time during the online teaching process. Compared with traditional face-to-face teaching, the access rate and sharing rate of teaching materials have been greatly improved [9, 10]. Since the online teaching system has been put into use, the acceptance of online teaching mode by teachers and students varies. Many factors influence the evaluation of the teaching quality of online courses.

Many researchers have gradually shifted their research focus to the assessment of teaching quality, and some researchers have tried to rate classroom performance in teaching environments. Some researchers have tried to develop assisted adaptive apps to test the effectiveness of teaching. Other studies have attempted to add testing units to the teaching system to obtain evaluation results between teachers and students in both directions [11–13]. Some studies have also proposed to integrate parameters such as students' postclass grades, teachers' performance in class, and student's classroom performance into neural networks students to obtain trend lines of teaching effectiveness factors as an evaluation criterion. Researchers in the literature [14] on the development of online teaching systems point out that the quality assessment of online courses is a comprehensive evaluation system that requires researchers to reasonably control the course efficiency indicators from an objective perspective, and the evaluation system needs to fully take into account the student side and the teacher side of the course patterns and preferences and cannot be generalized with a uniform specification [15–18]. Different courses should also set up independent evaluation systems, establish independent human-machine models, and learn two-way evaluation indicators between teachers and students. Given that both teachers and students of each course have the right to choose in both directions, we should extend the course evaluation system to another human level to obtain better evaluation results while meeting the evaluation conditions of online courses [19].

Synthesizing previous studies in the literature, we decided to adopt a deep learning approach to explore the influencing factors of online course quality assessment by taking online course teaching quality assessment as the starting point. We propose a fuzzy neural network-based online course quality assessment method. The method uses fuzzy rules as the baseline and adds TSK perceptual agencies to expand the perceptual domain of fuzzy neural networks. In addition, we will explore the factors influencing the educational quality of online courses and develop a weight percentage assessment of them. Finally, we verify the effectiveness of our method through experiments.

The other studies in this paper are distributed as follows. Section 2 presents the latest research progress related to the field of online course evaluation. Section 3 details the principle and implementation process of the online course quality assessment method based on an improved fuzzy deep neural network. Section 4 presents the experimental results of the online course quality assessment effectiveness test and the analysis of the data enhancement test. Finally, Section 5 reviews our study and reveals its shortcomings of the study.

2. Related Work

Considering that course quality assessment is a highly comprehensive project, if we want to automate course quality assessment, we need to cover the course process comprehensively with course assessment factors, for example, course curriculum, course purpose, course scheduling, course participant survey, course instructor effectiveness assessment, and course practice effectiveness testing. In a study exploring advanced course quality assessment, researchers in the literature [20] noted that the quality assessment results of a course can only be described if course participant satisfaction, self-efficacy, and course comprehension are considered in combination with the factors and weighted results are given. The authors applied a hybrid quality assessment approach in their study to efficiently complete the collection and analysis of course quality assessment data. The study in the literature [21] is oriented towards a comprehensive assessment of different disciplines, and the researchers proposed a linear regression learning-oriented model of transferable course assessment, which takes the guided learning framework [22] and the availability principle as a baseline, or presents student perceptions, teacher perceptions, classroom effects, and postclass tests related to the course from different dimensions of coordination complexity, and reduces the course assessment through a perceptual machine The process of course assessment is recreated by a perceptual machine. Finally, the authors demonstrated the effectiveness of the method through experimental validation. The study in the literature [23] is an exploration of the validity of online education, and the authors first stated the need for online education in the context of COVID-19. To investigate the validity of online education, the authors proposed a visual strategy instructional assessment method, which analyzed the feasibility of online education from the perspective of online education participants and designed single- and mixed-group experiments to verify the reliability of course assessment. The experimental results demonstrate that the method provides a valid measure of the pedagogical direction and purpose of online courses. The researcher in the literature [24] added an online course quality assessment system to the online course archiving system. The study was based on rich course data and aimed to improve students' online course experience, and the authors proposed a metacognitive reflection-based course quality assessment method. The method gives students and instructors great freedom in course feedback efforts, fully satisfies the needs and suggestions of individual online course participants, and forms a closed-loop dual

institutional system for online education feedback and assessment.

Online course quality assessment is a comprehensive system, and a large number of researchers have presented research results on it. The assessment system of online courses is more specifically divided, and the research of each system represents the weight ability of online assessment factors. Neural network models can greatly improve the efficiency and accuracy of online course assessment, and there is a large amount of research that has been conducted to prove this. In different online course assessment applications, the applicability of neural network models needs to be considered, and the development of specialized deep neural network structures based on specific assessment needs can effectively improve the robustness and generalization of online course assessment systems. In a study in the literature [25], the researcher used the facial expressions of online course participants as the focal point to transform classroom teacher-student interaction expressions into course quality assessment weights. By experimenting with different combinations of neural networks and Bayesian optimization structures, the facial expressions were defined as "understanding," "not understanding," and "doubtful" to determine that the online system can automatically analyze the performance of students and teachers. The system automatically analyzes the complex facial expressions of students and teachers and converts the expression learning and fusion analysis into course evaluation metrics to improve the generalization performance of the course evaluation system. The researchers in the literature [26] provide a new research idea for online course quality assessment, where the authors will use deep neural networks to capture the effects of efficiency in online course testing. The study uses data from three online courses as the basis of the research and tries to collect the effect of online course tests from the student side and then matches the test results with the course quality feedback results. Finally, the online course test evaluation weights are learned through deep neural networks, and the experimental results prove that the method can effectively improve the testing efficiency of the online course posttesting system and provide a local reference standard for course evaluation.

Several researchers agree that the most reflective factor of course quality and efficiency in online courses is the interaction between the instructor and students, and to quantify this interaction in a visual form as a factor for course quality assessment, many researchers have shown rich results in this study. The study in the literature [27] focused on the study of student and teacher engagement in online courses, learning about the interaction between teachers and students in online courses through a large dataset to predict course efficiency and quality assessment of online courses. The authors used Bayesian networks as the basic structure in processing the teacher-student interaction data, and then the student behavior learning process can determine whether the students enter the learning state in the online course, and then mapping correlation with the postclass test results can obtain the course learning efficiency of students. In this way, the authors transformed the quality assessment of online courses into visual behavioral analysis and achieved excellent accuracy in the experiment. The researcher of the literature [28] considered the issue of student learning efficiency in online courses as the most critical factor in the quality assessment of online courses. To quantify the learning efficiency of students in online courses, the authors proposed a two-layer framework based on convolutional neural networks and memory unit networks that can unify the parameters of multiple dimensions such as students' course scores, posttest scores, teacher averages, student feedback, and classroom performance into one assessment dimension. To reduce the model's false negatives, the authors also performed a sensitive optimization of the loss function to balance the anisotropy problem of various parameters in the model. The experimental results show that the model can provide direct assessment weights for online course evaluation with an accuracy of 87%.

3. Method

3.1. Online Course Quality Assessment System Process. In this section, we detail the fusion of fuzzy rules with perceptual neural network structures and compare the distribution of network layers in the same dimension. Before considering the fusion of fuzzy rules, we compared a large number of perceptual neural networks and found in the experimental validation that the structural design of the feedforward neural network is more compatible with our research needs. Therefore, based on the structure of feedforward neural networks, we designed dedicated fuzzy rules and proposed an online course quality assessment method based on perceptual fuzzy feedforward neural networks. We also designed the online course quality assessment system, and the overall composition of the system is shown in Figure 1.

As can be seen from Figure 1, we divided the online course index assessment into four parts. The first part is the online classroom assessment, which contains the classroom interaction rate, question and answer rate, classroom participation, and other factors composition. The second part is the course arrangement assessment, which contains the rationality, scientificity, and overall control of the teaching schedule of the online course arrangement by the school's academic affairs office. The third part is the course test evaluation, which includes factors such as the completion of postclass assignments, the passing rate of postclass tests, and the overall assessment of the course completion. The fourth part is the course feedback, which includes students' opinions on the course, students' ratings of the teacher's teaching tasks, the school's ratings of the course, and the teacher's teaching tasks. The above four parts represent different influencing factors of online courses, and these four influencing factors are input as online course quality assessment parameters into TSK fuzzy neural network to fuse and learn the course quality weights and finally output the course quality assessment results.

3.2. Fuzzy Neural Network Structure. Considering that online course quality assessment involves different dimensions of assessment metrics, we reconstructed each

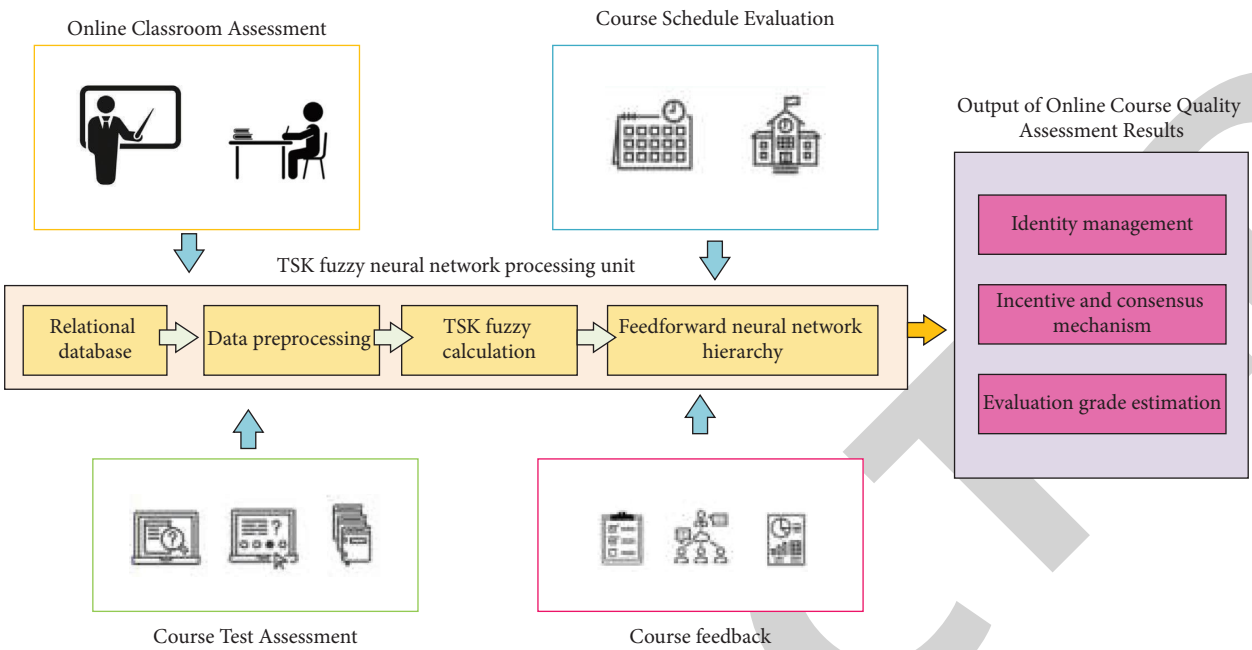

Figure 1: Online course quality assessment system process.

independent layer in the process of designing the deep neural network structure and gave each independent layer similarity to the data fit according to TSK fuzzy rules. In the network layers we designed, the main network structure consists of seven layers. It is shown in Figure 2.

After the data is input to the deep neural network, the neuron processing nodes in the input layer convert the input variables into a set of identifiable sequences with labels, which are assumed to be X. The mathematical equations are expressed as follows:

$$X = [x_1, x_2, \ldots, x_n]^T. \tag{1}$$

The transformation layer is located after the input layer, and in the design of the transformation layer, we fully consider the interactions between the factors of evaluation variables of different dimensions. The neurons in the network produce a reversal linear transformation of the variables to map the interaction links between the variables to a higher-level feature transformation layer [29]. For the initial mapping of interactions between variables, the following mathematical equation is satisfied.

$$Z_i = \Gamma_i^T (X - M_i), \tag{2}$$

where M_i denotes the center of the i-th fuzzy calculation rule definition and can be given as

$$M_i = [m_{i,1}, m_{i,2}, \ldots, m_{i,n}], \tag{3}$$

where Γ_i^T denotes the i-th transpose matrix generated by the fuzzy calculation to represent the variable mapping trajectory in the noninteraction space as follows:

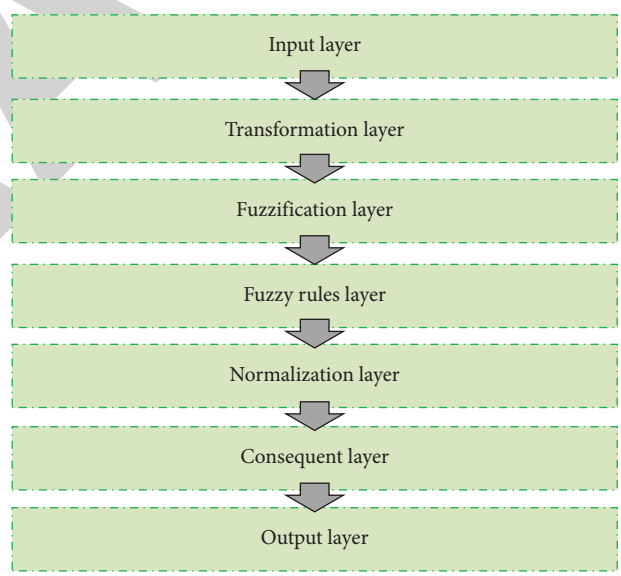

Figure 2: Network hierarchy distribution.

$$\Gamma_i = \begin{bmatrix} \gamma_{1,1,i} & \gamma_{1,2,i} & \cdots & \gamma_{1,j,i} & \cdots & \gamma_{1,n,i} \\ \gamma_{2,1,i} & \gamma_{2,2,i} & \cdots & \gamma_{2,j,i} & \cdots & \gamma_{2,n,i} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \gamma_{l,1,i} & \gamma_{l,2,i} & \cdots & \gamma_{l,j,i} & \cdots & \gamma_{l,n,i} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \gamma_{n,1,i} & \gamma_{n,2,i} & \cdots & \gamma_{n,j,i} & \cdots & \gamma_{n,n,i} \end{bmatrix}, \tag{4}$$

where $\gamma_{1,j,i}$ denotes the trajectory mapping matrix of the l-th row and j-th column of the Γ_i matrix.

The fuzzification layer can make full use of each neuron to calculate the affiliation in the noninteractive mapping results of the variable data. According to the definition of fuzzy rule for introducing power bi, the random mapping relationship of different variables needs to match the affiliation of the j-th mapping value, and its calculation equation is given as

$$\mu_{ij} = A\left(z_{ji}, \beta_i\right) = e^{-1/2\left(\left(z_{ji}\right)^2\right)^{\beta_i}}, \tag{5}$$

where z_{ji} denotes the j-th characteristic dimensional variable of the matrix computed at the i-th fuzzy rule.

The fuzzy rules layer unites local neuron nodes to achieve mapping links for different interaction space variables. For variables of different dimensions, we additionally add T-Norm operators to enhance the computational accuracy of the fuzzy rules. The mathematical equation expressions are given as

$$\mu_i = \prod_{j=1}^{n} \mu_{ij}, \tag{6}$$

The normalization layer regularizes the fuzzy matrix affiliation features extracted from the previous layer and coordinates the feature strengths of different variables by normalization. For instance, regarding variable response input, different types of fuzzy rules need to be selected to trigger the affiliation strength. The mathematical equation is given as

$$\phi_i(X) = \frac{\mu_i(X)}{\sum_{l=1}^{R} \mu_l(X)}, \tag{7}$$

The consequent layer involves the vector constraint problem of linear functions, where the output of all variables will be in the fuzzy rule matrix as the normative range, and the feature intensity weighting of the data will also be affected by the linear functions in the process of predicting vector associations. According to the calculation principle of fuzzy rule and linear function, the mathematical equation of the prediction of the feature vector is

$$y_i = a_{i0} + \sum_{j=1}^{n} a_{ij}, x_j, \tag{8}$$

where a_{ij} denotes the correlation coefficient of the i-th fuzzy rule matrix with the j-th eigenvector. Finally, the output layer performs individual neuron reorganization based on the number of feedbacks between each neuron to obtain the prediction trend between feature vectors and then converts the prediction results into indicator results output.

3.3. Learning Strategy. In the network model training experiments, we found that vector features with different evaluation metrics could not complete the traversal task in an orderly manner, for the layer-to-layer specificity led to the variability of feature sharing. Therefore, we replanned the model training strategy. For feature learning fixed fuzzy vectors of the same stratum, we fixed the formal parameters of each stratum and then adjusted the output values of each stratum by adjusting them until the desired range of values was reached. On the data input side, we quantified the prerequisite parameters as error expectations to balance the different values of input and output between different layers. For the case where the feature learning fuzzy vector values are in random variation, we scale down all parameters equally, but none of them exceeds the minimum value range of each parameter. Then the preserial hierarchy parameters are set to constant values, and while keeping the input-output error range consistent between the upper and lower hierarchy levels, we vary the mapping correlation of the fuzzy vectors to accommodate the trend pattern of the output prediction. The detailed flow chart of the model learning strategy is shown in Figure 3.

In addition, we employ the TSK perception mechanism to improve the correlation between networks and to improve the fusion and wholeness of the fuzzy vector features. The TSK perception mechanism takes the output value of the feedforward neural network as a starting point to expand the feature mapping range of each layer under the restriction of minimizing parameters. Although such a means generates a large amount of extremely invalid mapping data, a sizable amount of data can be filtered by simply setting a fixed threshold. If the minimum range of parameters cannot be adjusted for some layers, the fuzzy rule parameters can also be changed so that the fuzzy rule weight parameters of the next layer can be adaptively adjusted according to the difference between the output of the previous layer and the expected value, avoiding the feature rotation between each layer resulting in large feature deviation values. In the parameter adjustment of subsequent layers, the TSK perception mechanism will focus on adjusting the parameter differences of different network layers and improving the output pattern of fuzzy variables in an orderly manner under the premise of coordinating the expected values of the layers so that the output of each layer will share different course indicator features independently. To reasonably optimize the parameter tuning of each network layer, we calculate the expectation value L of the layer parameters in the ideal state, and the expectation value is calculated as .

$$L = \frac{1}{2} \sum_{k=1}^{N} \sum_{i=1}^{R} \left(\phi_{i,k} - \varphi_{i,k}\right)^2 + \sum_{k=1}^{N} \lambda_k \left(\sum_{i=1}^{R} \varphi_{i,k} \left(y_i - y_k^*\right) \right), \tag{9}$$

where λ_k denotes the kth Lagrange constraint coefficient.

3.4. TSK Fuzzy Neural Network Online Course Quality Indication. To ensure the matching of online course quality indexes with a fuzzy neural networks, we add a TSK perception mechanism on top of the fuzzy neural network. The TSK perception mechanism can effectively handle the black-box nonlinear feature vectors of the integrated correlation degree. The echo state network of the fuzzy neural network also belongs to the computational scope of the TSK perception mechanism. We perform fuzzy clustering of the echo state network and then supplement the feature variable values generated by each neuron node with singular value

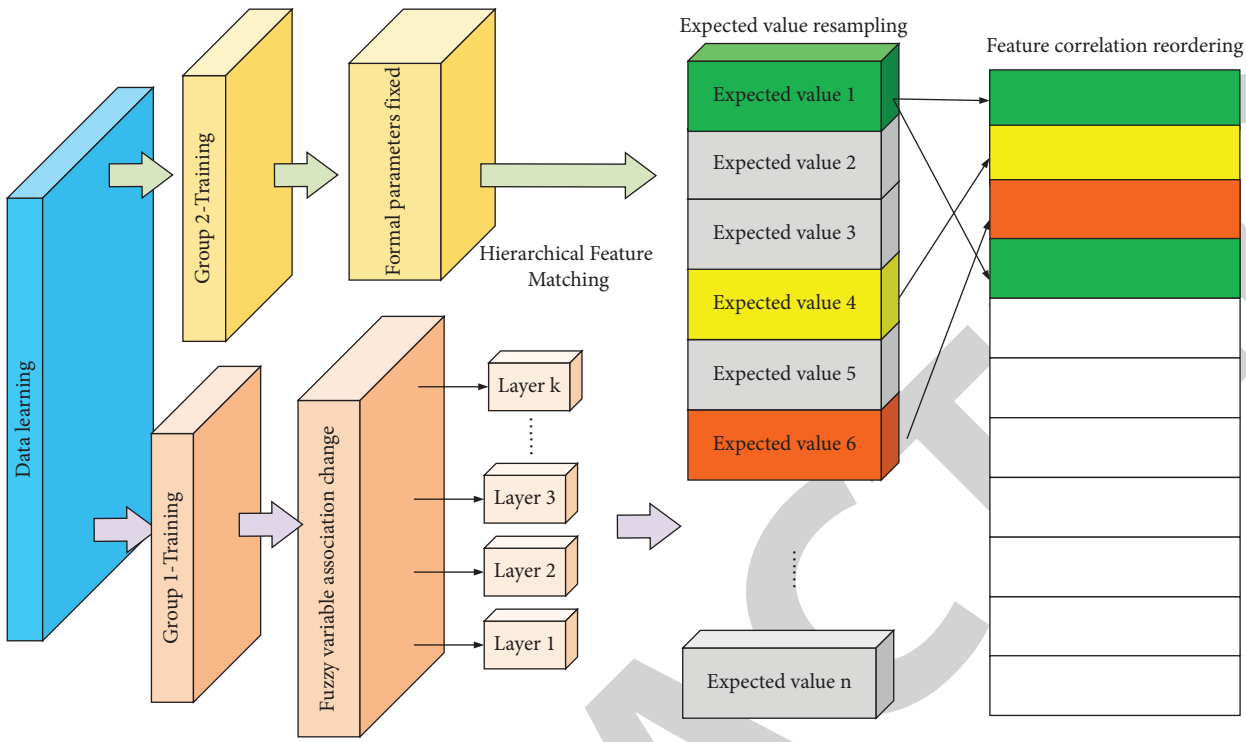

Figure 3: Model learning strategy flow chart.

decomposition so that the randomized mapping association of feature vectors can be realized. According to the fuzzy inference rules, the TSK sensing mechanism can add fuzzy vector simulation value, which is positively correlated with the expected value, under the premise of fuzzy inference. The simulated value is used as the final evaluation result screening threshold, which can effectively improve the prediction accuracy of the fuzzy neural network.

With the assistance of the TSK perception mechanism, the fuzzy neural network can effectively decompose the online course evaluation indexes and extract the feature vectors of different indexes, which can balance all the online course index features through the interaction mapping association between neurons and the calculation of fuzzy rules. The structure of our proposed TSK fuzzy neural network online course feature extraction network is shown in Figure 4. The data on the input side contains four components: online classroom assessment, course schedule evaluation, course test assessment, and course feedback. The data of each part are preprocessed in advance to avoid the problem that the fuzzy rule-based network data cannot be identified. Then the course quality index features calculated by the initial fuzzy rules are input to the fuzzifier layer in turn, then to the TSK perceptual structure layer to enhance the perceptual domain of the fuzzy neural network, and then to the fuzzified layer to defuzzify all the feature vectors, and finally to output the predicted values of the course quality assessment indexes.

4. Experiment

4.1. Data Preprocessing. Online course quality assessment involves different types of data, and as mentioned in the previous sections, there are four categories of input data for our online course assessment metrics. The online classroom assessment part of the data includes teacher-student interaction and student participation in the course, which are often collected in the form of images or videos. In the process of data preprocessing, this part of data will be prioritized for image preprocessing and image recognition operations. Finally, the extracted features are fed into the fuzzy neural network. The course schedule evaluation part of the data contains the rationality and scientificity of the online course schedule by the university's academic affairs office. The preprocessing of this data is based on the logistic regression optimal solution algorithm, which predicts the reasonableness and scientificity of the course and gives weight labels. Finally, the extracted features are fed into the fuzzy neural network.

The course test assessment part of the data contains the posttest results of the course, which is more representative of the course quality in terms of species level. This part of the data is mainly based on big data processing analysis to predict the efficiency of the course in each teaching period. Finally, the extracted features are input into the fuzzy neural network. The course feedback is that part of the data which contains students' opinions about the course, students' ratings of the teacher, the school's ratings of the teacher's teaching performance, and the teacher's opinions about the improvement of the classroom, etc. This part of data preprocessing mainly involves text processing. Finally, the extracted feature data are then input into the fuzzy neural network. The detailed data preprocessing process is shown in Figure 5.

4.2. Dataset Distribution. For the quality assessment of online courses, there is no publicly available dataset for online course quality assessment, even though many

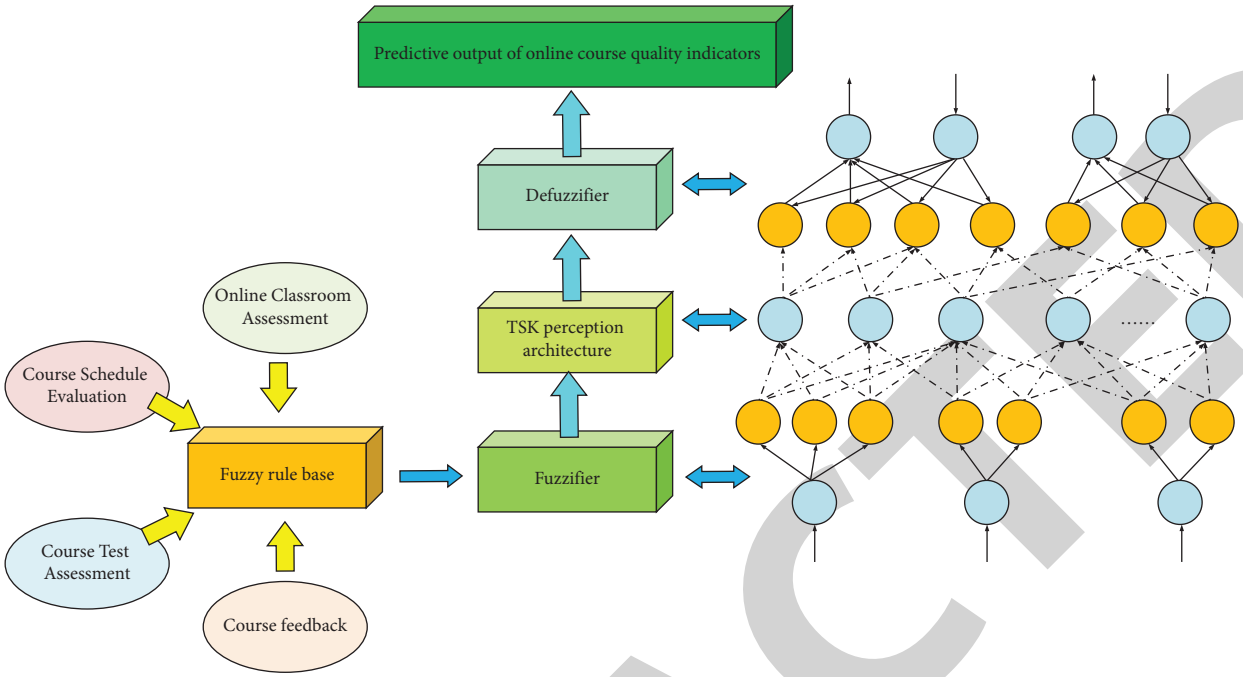

Figure 4: TSK fuzzy neural network online course feature extraction network structure.

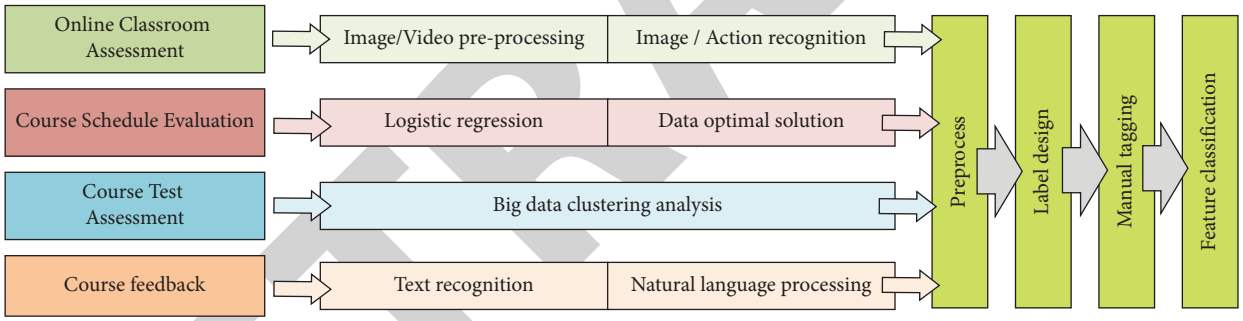

Figure 5: The detailed data preprocessing process.

researchers have presented new results and ideas. To verify the validity of our approach, we collaborated with universities after applying for a research license. Based on the four components involved in online course assessment, we produced four types of datasets. The details of the dataset distribution are shown in Table 1. In the production of the datasets, due to the large labor cost, we used data augmentation processing the datasets, which not only expands the collective amount of data but also enhances the fuzzy neural network's control of global features. In the experimental analysis section, we still use precision, F1 score, and recall to test the performance of our method. In the subsequent analysis, we will refine the dataset and verify the substantial effect of data enhancement.

4.3. Results and Analysis. In the work of dataset production, we used data augmentation to expand the experimental data and enhance the data domain of the model. To verify the effectiveness of data augmentation, we compared the augmented data and the augmented data fused with the original data using the original data as the reference standard. To reflect the efficiency of data augmentation, we used affinity and diversity as validation metrics. Affinity indicates how well the augmented data fit the original data in the model training. Diversity indicates the complexity of the augmented data in the model training. The experimental results are shown in Table 2.

From the experimental results in the above table, it can be seen that the data enhancement results fit more closely with the original data affinity, the diversity differences are small, and the accuracy is maintained above 90%. It proves that data augmentation can effectively expand the dataset and enhance the global data coverage of the model. In addition, the variability of online course quality assessment metrics is obvious, and data type specificity cannot be avoided. To have a basis for weighing the role of each indicator in the quality assessment of courses, we explored the issue of course quality assessment weights. To examine the impact of different data on course quality, we validated four aspects of course efficiency (CE), course pass rate (CPR), course practice satisfaction (CPS), and course retake rate (CRR). The results of the experiment are shown in Table 3.

Table 1: The details of the dataset distribution.

	Dataset			
	Online classroom assessment	Course schedule evaluation	Course test assessment	Course feedback
Group 1 training	1241	1032	1520	1102
Data augmentation	2482	2064	3040	2204
Group 2 training	964	987	1003	992
Data augmentation	1928	1974	2006	1984
Test	231	204	289	274
Total	6846	6261	7858	6556

Table 2: Comparison of data enhancement effects.

	Affinity	Diversity	Accuracy (%)
Group1	1	0.6	100
Augmentation 1	4	0.4	95
Group1 + Augmentation 1	3	0.3	94
Group2	1	0.6	100
Augmentation 2	4	0.5	96
Group2 + Augmentation 2	5	0.3	91

Table 3: Comparison of weighting percentages for quality assessment of course indicators.

	CE (%)	CPR (%)	CPS (%)	CRR (%)	Weight
Online classroom assessment	80	79	75	78	0.3
Course schedule evaluation	43	50	41	40	0.1
Course test assessment	93	90	94	91	0.4
Course feedback	66	60	65	67	0.2

From the experimental results in the above table, it can be seen that course test assessment has the largest proportion of all indicators in the course quality evaluation, followed by online classroom assessment. The total proportion of course schedule evaluation and course feedback is only 0.3. Based on the experimental results of the weighting ratios, we will adjust the model data category parameters to ensure that the datasets with higher quality weighting ratios also maintain the same vector feature ratios in the model training. After the experiments with tuning the parameters for improvement, we test the efficiency of our method in an online course quality assessment. Four indicators such as precision (P), F1 score (F1), recall (R), and course quality assessment matching rate (MR) were assessed in the experimental validation. The detailed experimental results are shown in Table 4.

Table 4: The efficiency of online course quality assessment.

	Online classroom assessment	Course schedule evaluation	Course test assessment	Course feedback
Precision	91%	92%	90%	95%
F1 score	0.87	0.81	0.79	0.83
Recall	0.93	0.89	0.91	0.92
Matching rate	95.4%	96.6%	97.1%	95.2%

From the experimental results in Table 4, it is clear that our proposed methods all maintain above 90% in terms of accuracy. The large difference in F1 scores is due to the specificity between different categories of datasets, but considering the diversity of online course assessment metrics, the F1 scores have little effect on the quality assessment grade. The matching rate shows that our method matches the results of online course quality assessment with the actual assessment results by more than 95%, which proves the excellent applicability of our method in this field of study.

5. Conclusion

This paper explores the factors influencing the quality assessment of online courses and analyzes the current research proposal of online course quality indexes with online courses as the research object. To make the online course quality assessment more intelligent, we propose an online course quality assessment method based on a fuzzy neural network.

The method uses fuzzy rules as the baseline and adds a TSK perception mechanism to expand the perception domain of fuzzy neural network and improve the course quality index prediction accuracy. At the input side of the fuzzy neural network, we preclassify the online course data into four parts, and each part of the data represents a different assessment domain. Due to the large data cost, we expanded the collective amount of data using data augmentation methods. In addition, we parse the structure of the fuzzy neural network hierarchy and introduce the construction and role of the TSK perception mechanism in the fuzzy rules. An optimal learning strategy is proposed in the fuzzy neural network training. Finally, in the experimental session, we verify the effectiveness of data augmentation and explore the distribution of course quality assessment weights. In the experimental validation of accuracy testing, our method maintains accuracy of over 90% in online course quality assessment and achieves a 95% matching rate with actual assessment over, which proves that our method has excellent applicability in practice.

Although our study has achieved high matching rate and accuracy in practical applications, there is still a gap in the specificity of our method between different disciplines. In our future work, we will use a transfer learning approach to find shared parameters in course evaluation between different disciplines and enhance the disciplinary generalization of our method.

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 there are no conflicts of interest.

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References

[1] Y. Guo, J. Huang, M. Xiong, X Hu, and J Wang, "Facial expressions recognition with multi-region divided attention networks for smart education cloud applications," *Neurocomputing*, vol. 493, pp. 119–128, 2022.

[2] Z. Han and A. Xu, "Ecological evolution path of smart education platform based on deep learning and image detection," *Microprocessors and Microsystems*, vol. 80, Article ID 103343, 2021.

[3] T. Chen, "Smart campus and innovative education based on wireless sensor," *Microprocessors and Microsystems*, vol. 81, Article ID 103678, 2021.

[4] D. Kraľovičová, "Online vs. Face to face teaching in university background," *Megatrendy a médiá*, vol. 7, no. 1, pp. 199–205, 2020.

[5] A. M. Maatuk, E. K. Elberkawi, S. Aljawarneh, H. Rashaideh, and H. Alharbi, "The COVID-19 pandemic and E-learning: challenges and opportunities from the perspective of students and instructors," *Journal of Computing in Higher Education*, vol. 34, no. 1, pp. 21–38, 2022.

[6] J. Frederick and S. Van Gelderen, "Revolutionizing simulation education with smart glass technology," *Clinical Simulation in Nursing*, vol. 52, pp. 43–49, 2021.

[7] B. Bruggeman, A. Garone, K. Struyven, B. Pynoo, and J. Tondeur, "Exploring university teachers' online education during COVID-19: t," *Computers and Education Open*, vol. 3, Article ID 100095, 2022.

[8] S. A. Nikou, "A snapshot of university students' perceptions about online learning during the covid-19 pandemic," *Ludic, Co-design And Tools Supporting Smart Learning Ecosystems and Smart Education*, pp. 123–134, Springer, Singapore, 2022.

[9] S. Zhang, R. Ma, Z. Wang, G. Li, and T Fa, "Academic self-concept mediates the effect of online learning engagement on deep learning in online courses for Chinese nursing students: a cross-sectional study," *Nurse Education Today*, vol. 117, Article ID 105481, 2022.

[10] Y. Chandra, "Online Education during COVID-19: Perception of Academic Stress and Emotional Intelligence Coping Strategies Among College students," *Asian education and development studies*, vol. 10, no. 2, pp. 229–238, 2020.

[11] D. Kang and M. J. Park, "Interaction and online courses for satisfactory university learning during the COVID-19 pandemic," *International Journal of Management in Education*, vol. 20, no. 3, Article ID 100678, 2022.

[12] Z. M. Han, C. Q. Huang, J. H. Yu, and C. C. Tsai, "Identifying patterns of epistemic emotions with respect to interactions in massive online open courses using deep learning and social network analysis," *Computers in Human Behavior*, vol. 122, Article ID 106843, 2021.

[13] Y. Feldman-Maggor, R. Blonder, and I. Tuvi-Arad, "Let Them Choose: Optional Assignments and Online Learning Patterns as Predictors of success in Online General Chemistry courses," *The Internet and Higher Education*, vol. 55, Article ID 100867, 2022.

[14] S. Na and H. Jung, "Exploring university instructors' challenges in online teaching and design opportunities during the COVID-19 pandemic: a systematic review," *International Journal of Learning, Teaching and Educational Research*, vol. 20, no. 9, pp. 308–327, 2021.

[15] M. Nilashi, B. Minaei-Bidgoli, A. Alghamdi et al., "Knowledge discovery for course choice decision in Massive Open Online Courses using machine learning approaches," *Expert Systems with Applications*, vol. 199, Article ID 117092, 2022.

[16] F. Ari and I. Arslan-Ari, "Examining nontraditional graduate students' experiences with video feedback in a fully online course," *The Internet and Higher Education*, vol. 55, Article ID 100858, 2022.

[17] J. Jacqmin, "Why are some Massive Open Online Courses more open than others?" *Technovation*, vol. 112, Article ID 102395, 2022.

[18] H. Tang, "Teaching teachers to use technology through massive open online course: p," *Computers & Education*, vol. 174, Article ID 104307, 2021.

[19] O. Poquet, Q. Nguyen, V. Kovanovic, C Brooks, S Dawson, and A Biotteau, "Grade-based Similarity Prevails in Online Course Forums at Scale," *Computers & Education*, vol. 178, 2021.

[20] B. R. Daubman, P. E. Pérez-Cruz, O. Leiva, A Wong, and S Mark, "Furthering palliative care training in Latin America:

development and assessment of an advanced diploma course in palliative care in Chile," *Journal of Pain and Symptom Management*, 2022.

[21] M. Ma and G. Bui, "Implementing continuous assessment in an academic English writing course: an exploratory study," *Assessing Writing*, vol. 53, Article ID 100629, 2022.

[22] D. Carless, *Excellence in university Assessment: Learning from Award-Winning practice*, Routledge, England, UK, 2015.

[23] J. Y. Choi, S. E. Lee, S. Choi et al., "Integration of visual thinking strategies to undergraduate health assessment course: a mixed-method feasibility study," *Nurse Education Today*, vol. 113, Article ID 105374, 2022.

[24] M. E. Ray, L. DuBrava, and M. Jacks, "Leveraging a required e-portfolio course to meet multiple needs: student assessment, curriculum improvement, and accreditation," *Currents in Pharmacy Teaching and Learning*, vol. 12, no. 12, pp. 1437–1446, 2020.

[25] K. Sethi and V. Jaiswal, "PSU-CNN: prediction of student understanding in the classroom through student facial images using convolutional neural network," *Materials Today Proceedings*, vol. 62, pp. 4957–4964, 2022.

[26] N. K. Sharma, D. K. Gautam, S. Rathore, and M. Khan, "CNN implementation for detect cheating in online exams during COVID-19 pandemic : a cvru perspective," *Materials Today Proceedings*, 2021.

[27] M. Xenos, "Prediction and assessment of student behaviour in open and distance education in computers using Bayesian networks," *Computers & Education*, vol. 43, no. 4, pp. 345–359, 2004.

[28] A. A. Mubarak, H. Cao, and I. M. Hezam, "Deep analytic model for student dropout prediction in massive open online courses," *Computers & Electrical Engineering*, vol. 93, Article ID 107271, 2021.

[29] E. Kim, "Output feedback tracking control of robot manipulators with model uncertainty via adaptive fuzzy logic," *IEEE Transactions on Fuzzy Systems*, vol. 12, no. 3, pp. 368–378, 2004.