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Research on blended online and offline teaching methods for physical education courses based on fuzzy neural networks

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ABSTRACT
Blended learning typically depends on online platforms and tools for educational delivery, which may lead to decreased student interest and engagement in courses. To enhance student participation and improve performance outcomes in blended learning environments, this study investigates the online and offline (On&Of) blended teaching model for physical education courses using fuzzy neural networks. Initially, On&Of learning data from physical education classes is collected, and the data is preprocessed using the GROUP BY syntax for aggregation. Next, collaborative filtering algorithms are employed to extract key learning features from the On&Of physical education courses. These features are then clustered using fuzzy clustering algorithms and association rules to categorize the learning characteristics of students. Finally, a fuzzy neural network model is developed to integrate the On&Of teaching data for physical education. Based on the fusion of these data sets, specific teaching activities are designed to create an optimized blended learning method for physical education classes. After conducting experimental verification, it is demonstrated that the proposed blended On&Of teaching method leads to an improvement in student grades by more than 20%, with participation rates consistently exceeding 88%. These results indicate that the approach significantly enhances the learning outcomes in physical education courses, showing positive effects for its application.

Keywords: Fuzzy neural network, Physical education class, Blended online and offline teaching, Collaborative filtering, Fuzzy clustering

1. Introduction

With the rapid advancement of information technology, online learning has become a central element in the education sector. The blended learning model, which merges online learning with

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traditional face-to-face teaching, offers significant advantages. Online education removes the constraints of time and location, providing a wealth of learning resources and diverse teaching methods [1]. The hybrid On&Of (online and offline) teaching model maximizes the benefits of information technology and the availability of teaching resources, emphasizing personalized learning and collaborative engagement.

Traditional face-to-face teaching methods, especially in physical education (PE) classes, have inherent limitations, often struggling to meet the diverse learning needs of students within the constraints of time and space. The On&Of blended teaching method combines online and offline resources and tools, enabling innovative teaching approaches and offering a variety of methods to cater to the unique learning needs of students [2]. This model allows students to arrange their learning schedules flexibly, overcoming the time and space barriers of conventional face-to-face instruction [3]. By enabling learning at one's own pace and providing the opportunity to participate in course activities anytime and anywhere, the model significantly enhances the convenience and autonomy of learning.

PE, being a subject that requires individualized attention due to variations in students' physical fitness, skill levels, and interests, benefits greatly from the personalized approach provided by the On&Of blended teaching method. It can address these differences through personalized learning path planning and customized teaching resources, ensuring that each student's needs are effectively met. However, blended learning models depend heavily on the use of online platforms and tools to actively manage and guide the learning process. They also require interaction between teachers and students and peer communication [4]. Some students may struggle with learning autonomy and interactivity, potentially affecting their learning experience and diminishing the overall effectiveness of blended learning. This has led experts in related fields to investigate the challenges and benefits of implementing the On&Of blended teaching method.

Reference [5] designs an On&Of hybrid teaching method based on a multi-level cognitive network. Based on the differences in individual basic cognitive systems, a learning network for MOOC learning and basic knowledge is constructed, with knowledge, abilities, thinking, and values as the four levels of the model. A cognitive network model is established to compensate for the shortcomings of offline learning, and a multi-party complementary architecture for On&Of hybrid learning is constructed, Implement blended On&Of teaching. However, multi-level cognitive networks require both teachers and students to possess certain technical abilities to use online learning platforms and tools. For students who have not been exposed to data mining, it may take a longer time and effort to adapt to new learning modes, learning tools, and data analysis methods. This may lead to confusion and frustration during the learning process, resulting in low student engagement and poor academic performance improvement.

Reference [6] proposed a blended On&Of teaching method based on the MOOC online education platform, mainly through data integration on the MOOC platform, to summarize course knowledge points for students. Combined with the OBE teaching concept of "student-centered and output oriented", a blended On&Of teaching model consisting of three stages: "self-learning before class, offline teaching, and review and consolidation after class" was designed, And using professional data tools to guide students in choosing subjects with weaker grades at the current stage for learning, it has achieved good application results. Although this method can to some extent enhance students' interest in learning, it is limited by the data integration environment and recommendation algorithms, resulting in a slower rate of improvement in student academic performance, and there is still room for improvement in teaching effectiveness.

Reference [7] proposed a blended On&Of teaching method based on desktop cloud laboratory. The cloud open photogrammetry experimental teaching model based on desktop cloud laboratory is improved in teaching mode, homework modularization, economic cost, experimental data and teaching resources, homework achievement management, etc., with a focus on increasing the scope of learning courses and usage time periods, so that students can engage in online learning at any time, Increased student learning time. Although this method can slightly improve students' academic performance, there is no specific recommended course for weak subject projects, which reduces the possibility of students choosing courses and affects the practical application of teaching.

Reference [8] proposed a blended On&Of teaching method based on deep learning theory. Based on the discussion and analysis of the connotation and typical occurrence mechanism of deep learning theory, referring to the "4S" learning content framework model, a thinking oriented teaching mode was designed, and further improved students' divergent thinking in the learning process, which can effectively improve their academic performance. However, there is insufficient data collection for online learning, and there is no complete understanding of students' learning preferences. Therefore, the recommended courses for students cannot gain much recognition, which reduces their participation level.

Fuzzy neural network combines fuzzy clustering and neural network algorithms. The application of fuzzy neural networks can accurately capture the characteristics of students' online learning behavior, perform fuzzy clustering on their online learning characteristics, divide students into groups or categories with similar learning characteristics, use neural networks to analyze the learning characteristics of each group, and customize offline courses according to their sports preferences, which helps to improve their sports performance, Optimize the teaching effectiveness of PE courses. Therefore, based on the advantages of fuzzy neural networks, this article designs a blended On&Of teaching method for PE classes, and verifies the application effect of this teaching method.

2. Design of blended On&Of teaching methods for PE classes

2.1. Data Collection and Preprocessing for On&Of Learning of PE Courses

To achieve the design of a blended On&Of teaching method for PE classes, it is necessary to first collect data on the On&Of learning of PE classes. By collecting On&Of learning data, we can comprehensively understand the situation of students participating in PE courses, including the frequency, forms, and enthusiasm of students participating in PE courses. It can assess students' needs and utilization of On&Of learning resources. This helps teachers and schools to allocate On&Of teaching resources more reasonably, ensuring that students can have balanced learning opportunities [9]. The data collection for On&Of student PE learning is shown in Table 1.

Table 1. Data Collection for On&Of Learning of PE Courses

Teaching methods	Data sources	Data Content
Online collection of PE learning data from students	Online education platform	Utilize the data statistics function provided by the platform. These functions can track indicators such as student login frequency, learning duration, frequency of course participation, as well as the tasks and assignments completed by students during the course.
	Online quizzes and assessments	Conduct PE course tests and evaluations through online platforms. Online questionnaires, practice exercises, or video uploads can be designed to assess students' mastery of motor skills, theoretical knowledge, and other related aspects.
	Student feedback and discussion	Set up discussion areas or message boards on online platforms to encourage students to provide feedback and opinions on the course. Students can share their PE learning experience, difficulties, and solutions, in order to collect their understanding and learning experience of PE courses.
Offline collection of PE learning data for students	Observation records	Teachers can record data by observing students' performance in PE classes. The observed content can include students' level of active participation, sports skill level, cooperation ability, etc. Teachers can use observation forms or record sheets to record the observed data.
	Sports testing	Regularly conduct physical fitness tests to measure students' height, weight, running speed, long jump distance, and other indicators, and record the test results. These indicators can be used to evaluate the physical fitness level and progress of students.
	Student self - evaluation	Allow students to evaluate their own learning situation in PE class. A questionnaire or evaluation form can be designed to allow students to provide ratings or descriptions based on their own feelings. This can gain students' subjective understanding of their learning situation.

After completing the collection of PE On&Of learning data in Table 1, due to the wide range of learning data sources and the variety of types included, it is necessary to preprocess the collected PE On&Of learning data. Data preprocessing is an important step before any data is applied, and the most commonly used method is text cleaning. GROUP BY syntax is a commonly used text cleaning method used to group and summarize text according to specified columns. Through the GROUP BY syntax, the text set can be grouped according to a certain feature, and then each group can be cleaned [10]. Through GROUP BY syntax cleaning, data can be better organized and classified. For example, student PE learning data can be grouped according to grade, gender, physical fitness level, etc., in order to further compare and analyze the differences between different groups, making the data more interpretable and operable, which helps to improve the practical application effect of blended PE teaching methods.

In the constructed MySQL database [11], import the collected On&Of student PE learning data, and use the GROUP BY syntax to deduplicate the PE learning data. According to the On&Of learning data of PE courses, specify column names for grouping, and merge rows with the same column names in the On&Of learning data of PE courses into one data row. Then, summarize the values of this data row and output it. The specific steps are as follows:

1) Add the GROUP BY keyword to the SELECT statement, use the SELECT statement to select the columns that need to be retained, and include the columns for grouping and the columns that need to be aggregated.

2) Use the GROUP BY statement to pass the columns that need to be grouped as parameters to GROUP BY. Use aggregation functions to calculate the corresponding grouping of On&Of learning

data for each PE class.

3) Using the HAVING clause for further filtering, filtering out groups that do not meet certain conditions, and grouping and aggregating them according to specified columns, directly grouping and summarizing, to achieve the cleaning of PE On&Of learning data.

Due to the large amount of redundant and incomplete data in the On&Of learning data of PE courses, in order to improve the application effect of blended learning, it is necessary to remove and filter the redundant and incomplete data contained in the On&Of learning data of PE courses [12].

Assuming that the redundant data contained in the On&Of learning data of PE classes is O_1 and the incomplete data is O_2, $O_{1\varepsilon}$ and $O_{2ò}$ are used to represent the redundant and incomplete data in the ò th PE class On&Of learning data. Q represents the filtered PE class On&Of learning data. The calculation formula for Q is as follows:

$$Q=\frac{o_{1ò}(m)+o_{2ò}(m)}{R\times z_{\min}}-O_{1ò}\left(\sigma L_{ò}\right)-O_{2ò}\left(\psi L_{ò}\right) \tag{1}$$

In the formula, m represents the Pearson correlation coefficient; R represents the feature quantity; $z_{\min}$ represents the minimum variance. σ represents the level of redundancy; L_E represents the effective information of the ò th PE course's On&Of learning data; ψ represents the proportion of missing values.

Through the above content, complete the collection and preprocessing of On&Of learning data for PE classes.

2.2. Feature extraction for On&Of PE course learning

After collecting student On&Of learning data, it is necessary to extract the learning features of PE courses On&Of. Behavioral characteristics can effectively reflect the sports fields that students are interested in on online education platforms, and can be obtained through statistical analysis of student search tags, keywords, or browsing webpage categories [13]. The collaborative filtering algorithm can discover the correlation information between the potential sports interests and actual offline sports behaviors of students on online education platforms based on their interest content and behavior history. By mining the On&Of learning behavior patterns and data of students, more accurate learning characteristics of On&Of PE courses can be extracted, which helps to improve the effectiveness of blended On&OfPE teaching methods.

Therefore, this article combines collaborative filtering algorithms and assumes that the total time series of students browsing sports related courses on online education platforms [14] is T. The time spent browsing U sports content within t is $t(U)$, and different categories of sports content are labeled as $I=\left\{I_1,I_2,\ldots,I_U\right\}$. The probability of interest for the student browsing I tag sports in U sports is inferred, and the probability of interest is expressed as P_I^U. The calculation formula for P_I^U is:

$$P_I^U=\frac{t(U)}{T\times Q(r)}\sum_{u=1}^{U}B\left(I_\omega^h\right)\times Q(1-t(U)) \tag{2}$$

In the formula, B represents the student's duration of stay in the I tag exercise in U class sports; I_ω^h represents the weight of the keyword h in I tag sports events; $H(h)$ represents the frequency of the keyword h appearing.

The information area and duration of student stay on the online education platform can reflect their interest in different sports labels and behavioral habits in different fields. By calculating the information area and duration of student stay on the online education platform, it is possible to gain a deeper understanding of student online learning behavior, identify the behavioral characteristics of student online learning of PE courses, and improve the effectiveness of blended PE teaching [15].

Therefore, assuming that the number of effective information regions that a student stays in on the online education platform is Z, and the search frequency for I tag sports in U sports is $q_{(I)}$, then the student's interest in I tag sports is $D(I)$:

$$D(I)=\frac{1}{Z\times P_I^U}\sum_{u=1}^{U}q_{(I)}^{\varepsilon}\times\theta_{(l_1-l_0)} \tag{3}$$

In the formula, ε represents the search period coefficient; θ represents the area of stay; l_1 represents the start time of the stay behavior; l_0 represents the end time of the stay behavior.

Based on the student's level of interest in the I tag sports project, a cross comparison is made between the student's stay time B when browsing the I tag sports project in the U class in all areas of the online education platform. Using a collaborative filtering algorithm, the student's preference features for browsing the I tag sports project in the U class are extracted, which is the student's online PE course learning feature F_1. The calculation formula is:

$$F_1=P_I^U\frac{B\left(l_1-l_0\right)}{\theta}\times\frac{l_1-l_0}{Z}+D(I)\sum_{u=1}^{U}\frac{\left|\varphi_1+\varphi_0\right|}{2q(I)} \tag{4}$$

In the formula, φ_1 and φ_0 represent the long-term preference characteristics and short-term preference characteristics of students browsing I labeled sports items in U class, respectively.

After obtaining the learning characteristics of students in online PE courses, combined with the data of students participating in actual PE courses offline, the F_2 of students learning characteristics in offline PE courses is extracted, and the calculation formula is as follows:

$$F_2=\frac{1}{Q}\times\frac{E}{c\left(d_1\times d_2\right)}\times G \tag{5}$$

In the formula, E represents the actual time of participating in sports training in offline PE courses; c stands for the category of sports activities in offline PE courses; d_1 and d_2 represent the intensity and selection rate of offline PE courses, respectively; G represents the weight of sports events.

The learning characteristics of students in On&Of PE courses can be obtained through $F=F_1+F_2$, laying the hybrid teaching method for PE courses On&Of.

2.3. Learning feature clustering based on a fuzzy clustering algorithm

To achieve better results in blended teaching of PE courses, it is necessary to cluster the extracted learning features [16]. Fuzzy clustering algorithm is a clustering method used to divide a dataset into fuzzy and uncertain classes or clusters. Student learning behavior data has diversity and complexity, and fuzzy clustering algorithm can flexibly handle situations where data points may belong to multiple student groups or interest categories. By dividing data points into fuzzy categories, potential similarities between different students are discovered, and students are divided into different groups or categories, Each group has similar learning characteristics. Based on the similarity of online learning characteristics among students, PE teachers can develop personalized offline learning plans for each group or category in offline PE classes, and provide targeted physical training programs and activities for different groups according to their physical fitness, skill level, and interest preferences [17].

Therefore, for each learning feature sample, a membership value needs to be assigned to it, indicating the degree to which the sample belongs to each cluster. Therefore, when initializing sample data, membership values can be assigned to learning feature samples through random allocation. Set the extracted feature samples of online PE course learning for students i as F_i, and after multiple iterations of random allocation, the membership value of F_i is F_i^e. Calculate the distance S between the F_i feature samples of On&Of PE course learning for students and the clustering center of the feature samples, and obtain the new membership value F_i^e for the On&Of PE course learning feature samples of students i. The calculation formula is:

$$S = \frac{q_{(l)}^{\varepsilon} \times D(l)}{F(b)} \times B\left(l_1 - l_0\right) \tag{6}$$

$$\Delta F_i^e = \frac{1}{b} \sum_{u=1}^{U} \frac{q_{(I)}^{\varepsilon} \times D(I)}{F_i(S)} \tag{7}$$

where b is the number of iterations.

Based on the new membership value FDF of the feature samples of student i 's On&Of PE course learning, update the position of the clustering center, set the maximum iteration number to V, and determine the position of the clustering center K:

$$K = \frac{q_{(I)}^{\varepsilon} \times D(I)}{V(g)} \times \Delta F_i^e(S) \tag{8}$$

In the formula, g represents the update rate of cluster centers.

Due to the large number of feature quantities contained in the learning feature samples of On&Of PE courses, the process of clustering the learning features of On&Of PE courses can be represented through fuzzy clustering transformation. Cluster the On&Of PE course learning feature samples in each fuzzy grid through association rule attributes. Set the data storage nodes of the fuzzy grid to be represented as $\alpha = \left(\alpha_1, \alpha_2, \ldots, \alpha_{n-1}, \alpha_n\right)$, and describe the overall network structure as $\beta = \left(\beta_1, \beta_2, \ldots, \beta_{n-1}, \beta_n\right)$. The fuzzy clustering transformation process is shown in Figure 1.

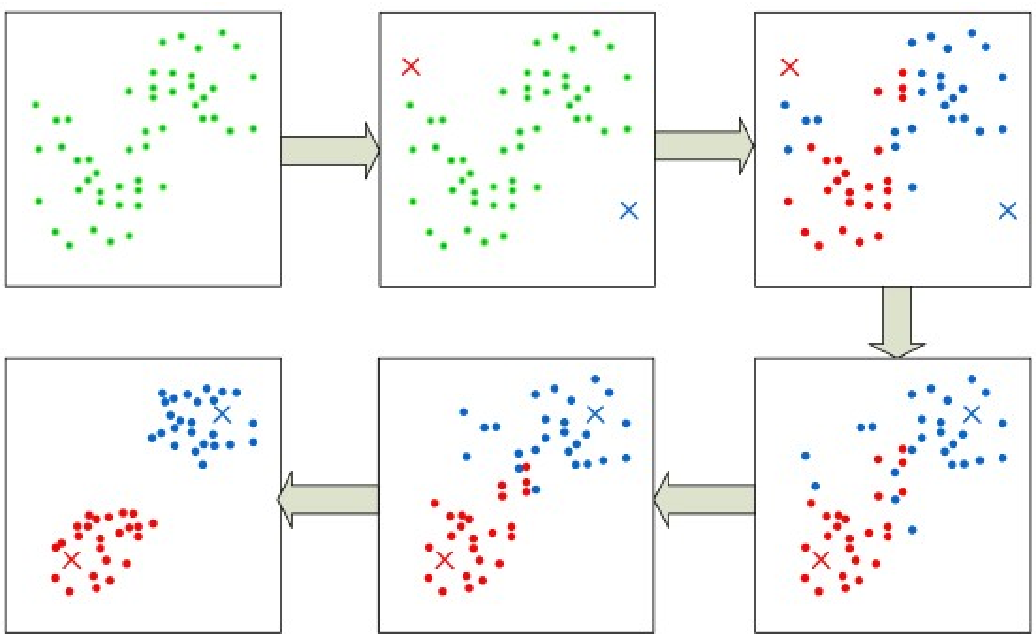

Fig. 1. Fuzzy clustering transformation process

So in the process of clustering feature samples for On&Of PE course learning, the set of samples distributed in the cluster center after clustering association can be expressed as:

$$\delta = \left\{C_{\alpha_1}^{\beta}, C_{\alpha_2}^{\beta}, \ldots, C_{\alpha_{n-1}}^{\beta}, C_{\alpha_n}^{\beta}\right\} \tag{9}$$

Assuming that the first layer of On&Of PE course learning feature sample nodes in the fuzzy clustering grid sample are clustered according to their weights [18], and the associated variable object is A. The number of variable objects is represented by ∂. Based on the On&Of PE course learning characteristics of students, the distribution of On&Of PE course learning characteristics that can be mined through association rules can be expressed as:

$$W = \frac{v(A) \times A(\partial)}{\varpi} \times \sum_{i}^{N} \delta \times \Delta F_i^e(S) K \tag{10}$$

In the formula, $v(A)$ represents the v th variable object in the fuzzy clustering grid; ϖ represents the weight of the sample node.

Based on the new membership value ΔF_i^e, determine the membership function ζ, and implement On&Of PE course learning feature clustering based on fuzzy clustering in the storage space of the fuzzy clustering sample grid. The specific calculation formula is as follows:

$$\vartheta = -\sum_{i}^{N} \zeta(\delta) \times \frac{v(A) \times A(\partial)}{V(g) \times \tilde{n}} + \Delta F_i^e(\lambda) \xi \tag{11}$$

In the formula, ϑ represents the clustering results of the learning characteristics of On&Of PE courses; λ represents the fuzzy correlation coefficient; ξ represents the relevance of learning features; $\tilde{n}$ represents the convergence coefficient.

2.4. A teaching data fusion model based on a fuzzy neural network

Clustering the learning characteristics of On&Of physical education courses provides valuable insights into how students engage with the material in different learning environments. However, relying solely on the clustering analysis of either online or offline data may not offer a complete picture of students' learning experiences. To address this, the design ofa blended On&Of teaching approach can be effectively achieved by integrating both online and offline teaching data. This integration allows for a more comprehensive understanding of student performance and engagement, leading to more tailored and effective teaching strategies.

By combining fuzzy theory with neural networks, a fuzzy neural network model [19] is constructed to integrate the On&Of PE course teaching data and output the fused results through the input layer, fuzzification layer, fuzzy rule layer, and output layer.

The first layer fuzzy input of the fuzzy neural network model is x_j, which is the On\&Of teaching resource data of PE courses. The formula is as follows:

$$x_j = \left[x_1, x_2, \ldots, x_M\right]^k \tag{12}$$

where M is a natural integer; k is the number of iterations.

Then, generate the output of the first layer network:

$$Y_j = x_j(y), j = 1, 2, \ldots, r \tag{13}$$

where Y_j represents the dataset of teaching resources after dimensionality reduction operation; y represents the learning rate.

Transfer the processed Y_j to the second layer, and combine it with a Gaussian function to analyze the fuzzy set of input feature quantities in the second layer, as shown in formula (14):

$$\mu = \exp\left|-\vartheta\left(x_j - wx_j\right)^2 / 2f^2\right| \tag{14}$$

where μ represents the fuzzy set of input features; The Gaussian membership function core with wx_j of x_j; f is the function width.

Output is:

$$X_j = f\left(\sum_j^M p \times x_j + J\right) + \mu(\pi) \tag{15}$$

where p is the weight coefficient; J is the threshold; π is the weight coefficient of the objective function.

Design fuzzy rules in the third layer of the fuzzy neural network model, and describe each rule through nodes. The fuzzy rules are represented by formula (16):

$$s = \min\left(\vartheta_{1j}, \vartheta_{2j}, \ldots, \vartheta_{Mj}, 1\right), \vartheta_{1j} = a_1, \ldots, a_M \tag{16}$$

where ϑ_{Mj} represents the fuzzy feature set.

$$\Delta Y_j = \rho\left(\sum_j^M wx_j \times X_j + \eta\right) \times \frac{1}{s(\gamma)} \tag{17}$$

where ΔY_j represents the On\&Of teaching dataset after completing the training of the fuzzy neural network model; ρ represents the local weights; η is the speed of deblurring; γ represents the fuzzy median.

Based on the above content, a fuzzy neural network model is constructed to take On&Of teaching data as input samples. After processing through each layer, the teaching data is compared with the clustering results of On&Of PE course learning features, and the weights of each layer are adjusted. This iterative process continues until the error is minimized, with each training cycle refining the model. The process is repeated until all On&Of teaching data are fused, resulting in the best-integrated teaching data for On&OfPE courses.

2.5. Mixed teaching activity design

Combined with the fusion results of On&Of teaching data, specific teaching activities are designed, mainly for video resources and discussion, remote real-time guidance, online experiments and simulation training, cooperative projects and training programs, so as to stimulate students' interest in learning and promote the mastery and application of knowledge and skills.details are as follows:

1) Video resources and discussion: PE teachers can cluster the results according to the characteristics of On&Of PE course learning, search for the demonstration video resources of PE skill training matching with the characteristics, and share them through secondary production or editing, and through online courses. After watching the video, students can discuss and communicate their understanding and feelings about action skills and training methods online. PE teachers, as discussion guides, provide guidance and feedback, and encourage students to explore and think about.

2) Remote real-time guidance: PE teachers can use the live broadcast tools of online courses to provide remote real-time guidance. Through real-time video interaction, teachers can supervise students 'movement execution, posture correctness, etc., and give timely guidance and adjustment to improve students' skills.

3) Online experiment and simulation training: withthe help ofonline virtual laboratory or simulation training software. Students conduct online training, under the guidance of PE teachers, simulate actual physical exercise and training through virtual environment, exercise related skills and deepen their understanding of sports rules and strategies.

4) Cooperation programs and training programs: PE teachers can organize students to work in groups offline and jointly develop sports programs or training plans. Each sports project team will arrange 2 students with excellent skills and 2 students with weak skills. Through the cooperation within the group, they will make training plans and design competition strategies to jointly achieve performance improvement. PE teachers regularly guide and evaluate each group to help students

understand the importance of teamwork, in order to improve the competitive ability ofsome students' weak sports projects in practice.

So far, the research on the On&Of mixed teaching method of PE class based on the fuzzy neural network has been completed. The method flow of this paper is shown in Figure 2.

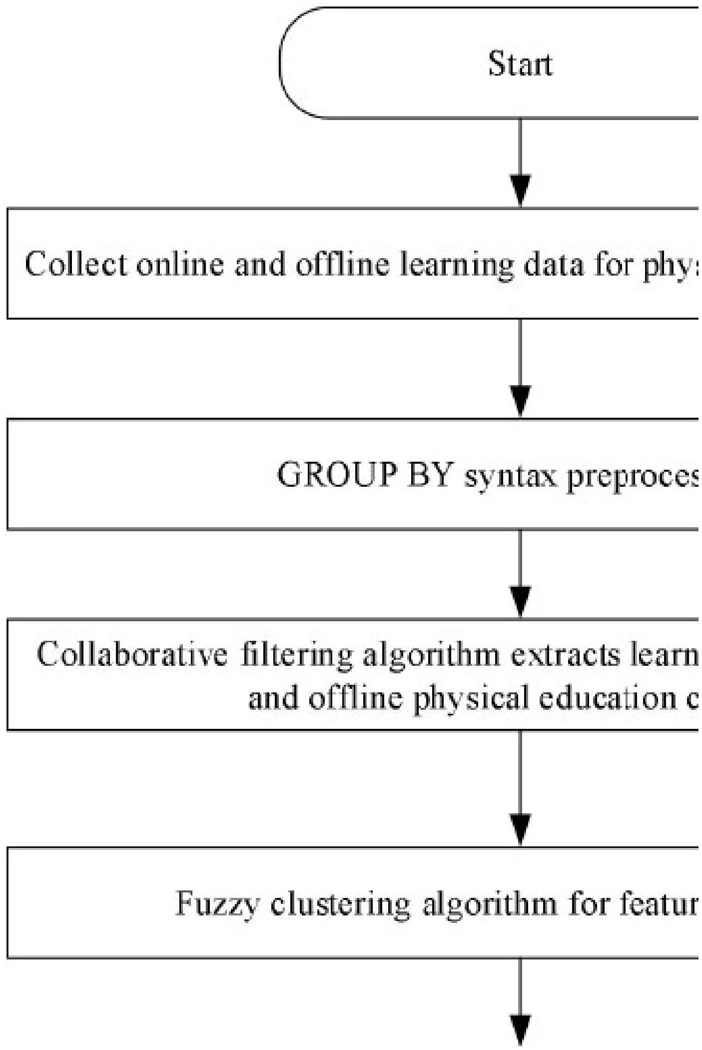

Fig. 2. Mixed On&Of teaching process of PE class

3. Experimental analysis

3.1. Experimental setup

Take junior students from a certain university as the experimental subjects. The university adopted a blended On&Of teaching mode from September 2021 to July 2022, and chose the MOOC platform for online teaching. Therefore, 100 students in this grade were randomly selected for testing. Collect data on online education learning for these 100 students during this academic year. Set the sampling sample length of MOOC English online education learning effectiveness evaluation data to 1200, the sample set size to 200, and the training sample set size to 20. Use MATLAB simulation software for assistance. The method proposed in reference [5] and the method proposed in reference [6] will be used as comparative methods for this experiment, and will be compared with the method proposed in this paper to verify its feasibility. The environmental settings for this experiment are shown in Table 2.

Table 2. Experimental environment configuration

Serial Number	Project	configuration
(1)	Operating system	Ubuntu 18.04 LTS
(2)	Deep learning framework	TensorFlow 2.5.0 + Keras 2.4.3
(3)	Python edition	Python 3.7.9
(4)	GPU	NVIDIA Tesla V100(32GBGraphics memory)
(5)	CuDNN edition	cuDNN 8.0.5(Used for GPU acceleration)
(6)	CPU	Intel Xeon Silver 4216(2.1GHz, 16 Cores)
(7)	Data processing tools	OpenCV 4.5.1

The required badminton course in the PE course of the university is taken as the experimental course, and the online badminton teaching data set is shown in Table 3.

Table 3. Online teaching datasets

Data type	Data quantity/piece
Teaching video dataset	210895
Teaching dataset	345224
Speech Teaching Dataset	403322
Teaching courseware dataset	342344
Course Dataset	245644
This course will discuss various datasets	201220

The schematic diagram of online PE teaching is shown in Figure 3.

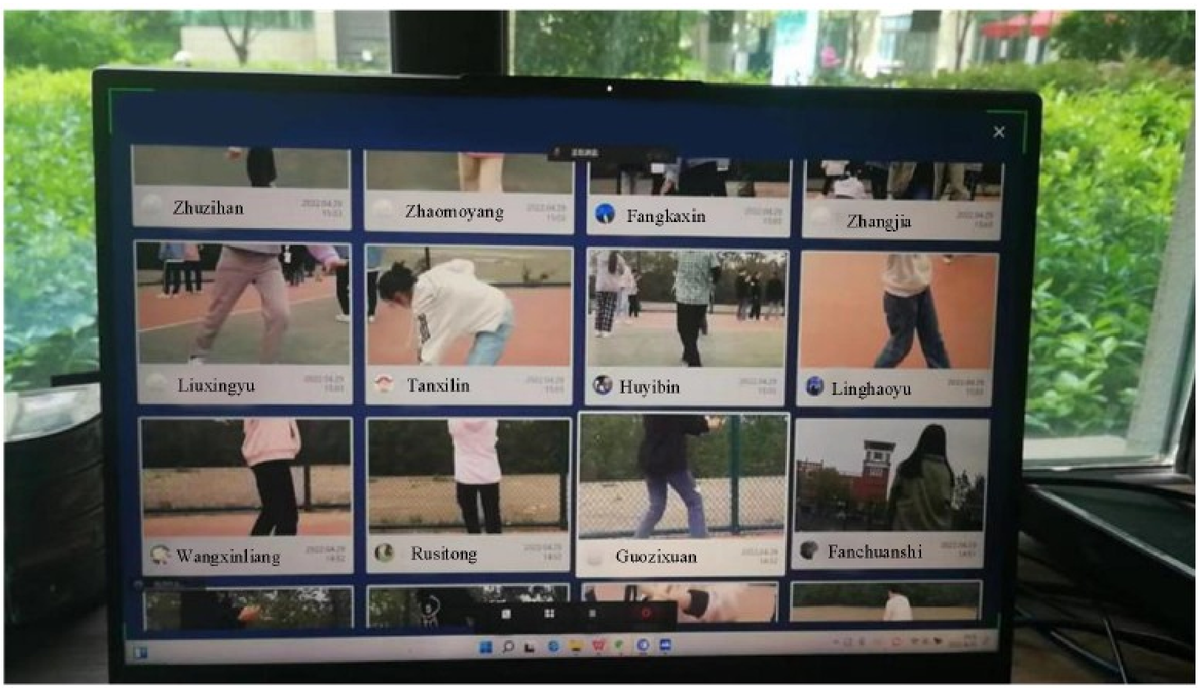

Fig. 3. Schematic diagram of online PE teaching

3.2. Experimental indicators

Scoring level: One of the core goals of PE teaching is to cultivate students' sports skills and abilities. By evaluating the score levels of students in different projects, we can understand their mastery and practical application ability of the learned skills, and thus determine whether teaching methods can effectively improve students' technical level.

Performance improvement effect: By comparing the changes in student academic performance before and after blended On&Of teaching, the impact of teaching methods on student performance can be evaluated. The improvement of grades can reflect the degree of improvement in students' knowledge understanding, skill mastery, and sports performance.

Participation: PE teaching emphasizes active participation and self-directed learning among students. By observing the level of student participation and activity in the classroom, including questioning, answering questions, and discussing, one can evaluate whether teaching methods can stimulate student interest and participation, promote their learning motivation and effectiveness.

Therefore, this article takes the level of project scores, the effectiveness of grade improvement, and participation as indicators to evaluate the effectiveness of blended On&Of PE teaching methods, comprehensively evaluating the effectiveness of blended On&Of PE teaching.

3.3. Experimental Results and Analysis

3.3.1. Scoring level of sports events. Choose the badminton course in PE as the comprehensive score level course for the sports project, and randomly select 10 students from 100 students with numbers T1 to T10. Before conducting blended learning On&Of, the badminton course scores of these 10 students were numbered 8.0, 7.7, 7.4, 7.2, 6.9, 6.7, 6.5, 6.4, 6.2, and 6.0, respectively. During the application of blended learning mentioned in this article, tests were conducted every two weeks, and a total of 8 tests were conducted until the end of the semester. Record the badminton course scores of these 10 students and draw a schematic diagram of the changes in sports score levels, as shown in Figure 4.

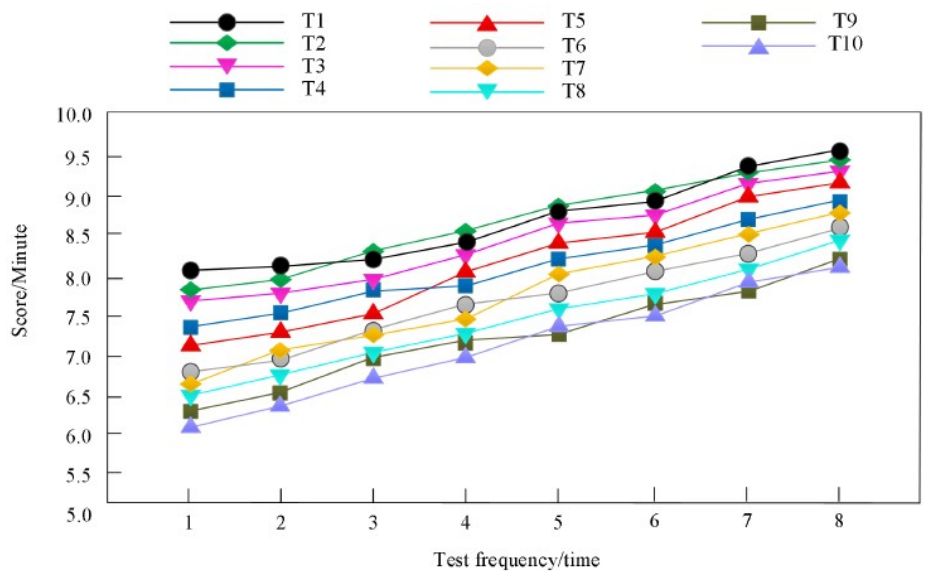

Fig. 4. Schematic diagram of changes in sports score levels

According to Figure 4, it can be seen that after the blended On&Of teaching, the badminton course grades of these 10 students are 9.6, 9.5, 9.4, 9.0, 9.2, 8.6, 8.8, 8.4, 8.3, and 8.2 points respectively. Compared with before the blended On&Of teaching, they have improved by 1.6, 1.8, 2.0, 1.8, 2.3, 1.9, 2.3, 2.0, 2.1, and 2.2 points respectively. This indicates that after the application of the fuzzy neural network-based blended On&Of PE teaching method proposed in this article, The teaching method has a certain effect on effectively improving the academic performance of PE curriculum projects.

3.3.2. Comparison of performance improvement effects. Then, additional 20 students numbered D1~D10 and G1~G10 were selected, and the methods in reference [5] and [6] were applied for teaching, respectively. The comparison was made with the improvement effect of the badminton course grades of students under the application of the method in this article, as shown in Figure 5.

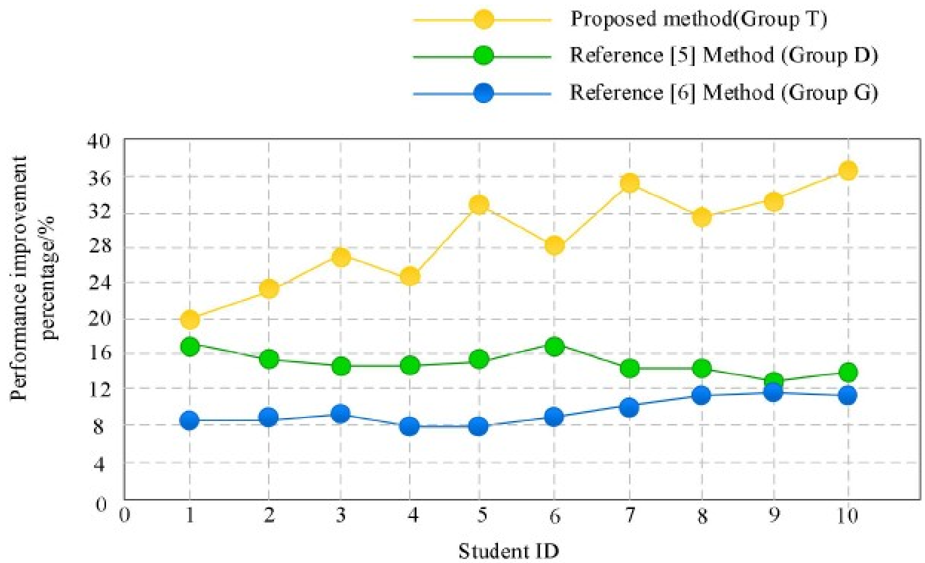

Fig. 5. Comparison of the improvement effects of student grades under different methods

According to Figure 5, it is observed that the improvement in badminton course grades for Group D students who applied the method in reference [5] after completing blended On&Of teaching ranged from 13% to 17%. Similarly, for Group G students who applied the method in reference [6], the improvement in badminton course grades ranged from 8% to 12%. In both cases, the grade improvement did not exceed 20%. However, after applying the method proposed in this study, the improvement in badminton course grades for T group students ranged from 20% to 37%, with improvements consistently above 20%. This result demonstrates that the fuzzy neural network-based blended On&Of PE course teaching method introduced in this paper significantly enhances academic performance in PE courses, with a notably positive application outcome.

3.3.3. Participation comparison. The methods proposed in this article, reference [5], and reference [6] were used for teaching, and the participation of students numbered D1~D10, G1~G10, and T1~T10 were compared. The comparison results are shown in Table 4.

Table 4. Comparison of Student Participation under Different Methods

User ID	Proposed method (Group T)	Participation rate/% Reference [5] Method (Group D)	Reference [6] Method (Group G)
1	93.27	78.56	76.54
2	90.56	77.56	79.65
3	91.76	76.45	79.76
4	92.76	79.67	78.35
5	90.35	82.34	77.67
6	89.54	84.56	80.78
7	88.90	81.76	81.65
8	89.91	78.45	73.56
9	93.76	74.65	74.67
10	92.45	80.65	79.45
Average value	91.33	79.47	78.21

According to Table 4, it can be observed that after applying the method from literature [5] for blended On&Of teaching, Group D students had a participation rate in badminton courses ranging from 74.65% to 84.56%, with an average participation rate of79.47%. For Group G students, who applied the method from literature [6], the participation rate ranged from 73.56% to 81.65%, with an average of 78.21%. In contrast, after applying the method proposed in this study, the participation rate for T group students ranged from 88.90% to 93.76%, with an average participation rate of 91.33%, significantly higher than the two compared methods. The participation rate remained consistently above 88%, demonstrating that the fuzzy neural network-based blended On&Of teaching method for PE courses can effectively boost students' enthusiasm for engaging in PE projects, showing strong application performance.

4. Conclusion

To address the limitations of low course participation and inadequate performance improvement in existing blended On&Of teaching methods, this paper proposes a new blended On&OfPE teaching method based on fuzzy neural networks.

The first step involves collecting On&Oflearning data for PE courses, preprocessing the data using GROUP BY syntax, and extracting learning features through collaborative filtering algorithms. These features are then clustered using fuzzy clustering algorithms. A fuzzy neural network model is constructed to integrate the On&Of PE teaching data. Based on the fused teaching data, specific teaching activities are designed, completing the development ofthe blended On&Ofteaching method for PE courses.

Experimental verification demonstrates that the method proposed in this paper leads to an improvement in student grades by more than 20%, with a participation rate consistently above 88%. This method effectively enhances the learning performance of PE curriculum projects, showing positive application results.

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