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Research Article

Construction of College Physical Education MOOCS Teaching Model Based on Fuzzy Decision Tree Algorithm

Weiwei Yang [1,2] and Jie Yang [1,2]

[1]*Kangda College of Nanjing Medical University, Lianyungang, 235000, China*
[2]*Kyungil University, Gamasil-Gil, Hayang-Eup, Gyeongsan-Si, Gyeongbuk, Republic of Korea*

Correspondence should be addressed to Jie Yang; yangweiwei2006001@njmu.edu.cn

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With the continuous development of the MOOCS model in college physical education, the corresponding teaching evaluation has also been widely concerned by the community. The development of a traditional education mode in college physical education cannot meet the current teaching requirements. In order to solve the problem of narrow application and insufficient accuracy in traditional education, on the basis of the Kohonen fuzzy decision tree algorithm and the MOOCS fuzzy decision tree algorithm, a fuzzy evaluation model of P.E. teaching is proposed. The results show that the fuzzy ID3 algorithm can achieve high accuracy in the four databases, and the classification accuracy of the A-D database is 75.9%, 62.9%, 76.6%, and 95.1%, respectively. Except for database C, the classification accuracy of the minimum classification uncertainty algorithm is lower than the other two clear decision tree algorithms. Compared with the minimum classification uncertainty algorithm, the fuzzy ID3 algorithm has obvious advantages in classification rules. The classification rules of A-D database are 18, 12, 16, and 10, respectively. When the authenticity threshold is about 0.8, the fuzzy ID3 algorithm has the highest classification accuracy. The proposed MOOCS model for college physical education based on the fuzzy decision tree algorithm has strong practicability and high accuracy. This paper studies the MOOCS model of college physical education and introduces the fuzzy decision tree algorithm to evaluate the MOOCS model of college physical education. It solves the problem that traditional sports cannot satisfy the needs of "Internet plus education" at all. Compared with the traditional sports model, it has better applicability and higher accuracy.

1. Introduction

Massive open online course (MOOCS) has become a current online education teaching curriculum mode. It provides diverse and personalized courses to the learning group through the characteristics of convenience and technological innovation. It can help learners get comprehensive and wide information and resources [1]. With the rise of three-course system, udacity and coursera, the goal of students' systematic learning has certain feasibility. Although the online education platform can meet the needs of all kinds of people, the current online education evaluation method still needs further exploration [2]. It is worth noting that decision tree classification has become a very important evaluation classification method, and it is still effective for the uncertain classification problem decision tree algorithm. This fuzzy decision tree has achieved certain research results in many industries such as medical, educational, and energy [2]. In view of the fact that traditional physical education has completely failed to meet the needs of "Internet plus education," a MOOCS model of college physical education is studied and a fuzzy decision tree algorithm is introduced to evaluate the MOOCS mode of physical education in colleges and universities, aiming at providing suggestions for the future development of MOOCS mode in college physical education.

In order to realize intelligent transportation in developed cities, Balta et al. proposed to optimize traffic signals of the SDN (software-defined network) city by using a three-level fuzzy decision tree. The performance test results show that the three-stage fuzzy decision model has better performance than fixed time signaling and webster equation [3]. Nancy et al.

used a fuzzy decision tree and dynamic feature selection to detect the intrusion of wireless sensor networks. The results show that the method can effectively reduce the false positive rate, energy consumption, and delay. At the same time, the system can improve network performance by improving the packet delivery rate. Syryamkin et al. proposed a fuzzy rule set automatic generation algorithm for the fuzzy decision tree and analyzed its performance with the network parameter adaptive hybrid algorithm. The technical efficiency results show that the former has higher performance [4]. Nalinipriya et al. picked up a priority-oriented scheduling algorithm, an enhanced priority scheduling algorithm, which uses job priority measures to generate the fuzzy decision tree. Compared with other scheduling methods, the method improves the execution time and shows better performance [5]. In order to study a general model suitable for prediction and risk, Zhang et al. proposed a generalized membership function model of fuzzy set in fuzzy decision tree and extended it to the fuzzy random forest method. The test results show that the model is practical and effective [6]. Teekaraman et al. pointed out that the fuzzy set and decision tree were used to classify the credibility group of publishers of Book Social Network. The model pruning rules were authenticity, and the evaluation indexes such as classification accuracy, precision, recall rate, rule generation number, and time complexity showed that the proposed learning model had better performance [7].

Ghobaei-Arani et al. proposed a large infrastructure which can support the peak load of the game in order to ensure the QoS requirements of highly variable concurrent players. The workload predicted by the fuzzy decision tree algorithm and user SLA (service level agreement) is used to estimate the appropriate resources allocated to each layer. The test shows that the performance and accuracy of the method are better [8]. Das and Padhy proposed to use fuzzy decision tree to forecast commodity future index in view of the difficult situation of financial time series data analysis and prediction. The experimental results show that the model is very accurate and has high feasibility [9]. Zhai et al. have successfully completed the motivational factors of MOOCS learners in nanotechnology and nano sensors. The results show that the three motivations are occupation, individual, and education, and the college-affiliated students and ordinary participants are all due to common interests and personal growth needs [1]. Lim et al. proposed a semantic network model to measure the different lexical association between teachers and students and the degree of students' participation in MOOCS. According to the data score of the MOOCS forum, the degree of students' participation in MOOCS and students' learning situation showed a positive correlation [10]. Xing et al. comprehensively evaluated some students of computer basic courses for MOOCS by means of investigation and analysis. The test results show that the teaching quality and learning effect have been improved obviously [11].

In conclusion, the fuzzy decision tree algorithm has been widely used in the teaching mode, and the evaluation results are well received by most users. Most scholars have very mature views on the fuzzy decision tree algorithm and the MOOCS model of physical education in colleges and universities. At present, the research data of the MOOCS model of physical education in colleges and universities by using the fuzzy decision tree algorithm are relatively small, and it has not achieved a relatively ideal evaluation and recommendation effect. In view of this, this study proposes a MOOCS model for college physical education based on the fuzzy decision tree algorithm, aiming to make contributions to the future.

2. MOOCS Model of College Physical Education

Online and offline hybrid teaching can integrate the group learning advantages of the offline class teaching system with personalized e-learning. It is an effective carrier for the in-depth integration of information technology and education and teaching. This teaching model needs to comprehensively use different learning theories, technical means, and application methods, which puts forward higher requirements for teachers' teaching resource construction, teaching design, and teaching management. Among them, instructional design is the key factor for the success and effectiveness of online and offline hybrid teaching. The integration mode of "MOOCS" and school physical education is shown in Figure 1. In view of the characteristics of school sports technology teaching, MOOCS cannot completely replace traditional school sports teaching. With the advantages of computer technology and Internet platform, it optimizes and integrates the functions of Internet in college sports resources so as to realize the in-depth integration of MOOCS teaching and school sports teaching. MOOCS and college physical education integration is a hybrid teaching form, which achieves the online and offline teaching chain mode. The online and offline centers are questions and tasks, respectively, which are embodied in question answering, communication, learning, evaluation, feedback, and interaction. The MOOCS teaching platform of college physical education can not only complete the evaluation of learning enthusiasm, answering difficult questions, skill video teaching, and online sports knowledge but also ensure that students can actively carry out classroom communication, which greatly reduces the teaching time of classroom teachers and makes students become the real main body of the classroom. Teachers need to design rich and colorful course videos in advance, prepare online interactive Q and A, record students' online learning achievements, carry out formative evaluation, master different students' mastery of skills, and try their best to make students have a certain learning ability of motor skills [12]. For students, in addition to self-learning motor skills and watching videos, they need to participate in offline learning and actively participate in interaction and sharing.

The schematic diagram of MOOCS integration into the school physical education teaching process is shown in Figure 2, covering the production and design of MOOCS video, autonomous online learning, teachers' offline teaching, knowledge consolidation, and practice after class. The course video needs to conform to the theory of cognitive load, reduce the frequency of interference information, and emphasize the relevant content with markers when it

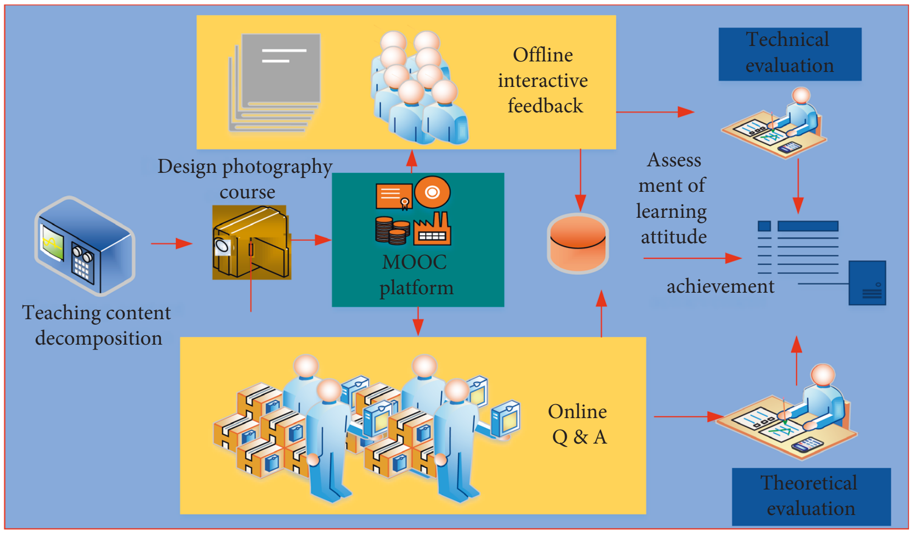

Figure 1: The integration mode of “MOOCS” and school physical education.

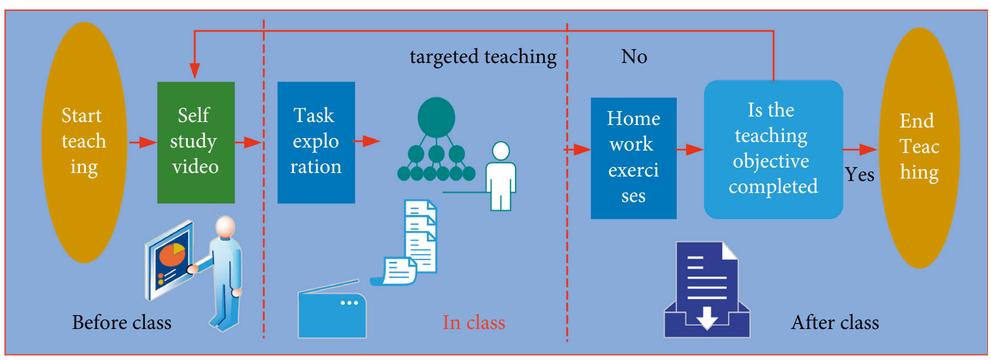

Figure 2: Schematic diagram of MOOCS integration into school physical education teaching process.

appears so as to improve the students’ effective learning time. The best video time is about 6 minutes. The time and place of online autonomous learning should be determined before the next face-to-face teaching. First of all, the food and study are watched, and the questions and related test items set by teachers in advance are completed. On the basis of this, we can have a happy discussion with students. The key step of online classroom teaching is the task-driven method, which can stimulate learners’ interest and give full play to students’ main role and teachers’ leading role. Combined with online and offline mixed teaching, students can truly realize the automation of motor skills and learn to repeat and practice after class.

3. MOOCS Model of College Physical Education Based on Fuzzy Decision Tree Algorithm

3.1. Fuzzy Decision Tree Algorithm. Decision tree is a widely used machine learning algorithm. Finding the optimal classification features and corresponding classification eigenvalues in the dataset is the key to solve the problem of decision tree, and the division is based on information entropy and information gain. At present, the common decision tree algorithms are CLS, ID3, and C4.5 (classification and regression tree, cart). ID algorithm is a greedy search method from top to bottom in decision tree space. Firstly, the algorithm calculates the information gain of each attribute. By comparing the information gain, it selects the attribute with the maximum value as the splitting node and then forms a branch with the splitting node according to different attribute values. Then, it calculates the information increment of the remaining attributes for each branch according to the above method, calculates and selects the attribute with the maximum value as the splitting node, and then according to each branch, it calculates the information increment of the remaining attributes, generate another branch with different attribute values, and repeat the above steps until the decision tree that can classify training samples is generated. The following is the specific method. For information entropy, it also becomes a classification system, assuming that it is a set of data samples; x is the number of X, C is the attribute category variable, the value is $C = \{C_1, C_2, C_3, \ldots C_n\}$, n is the total number of categories, and x_i is the number of samples contained in C_i. Then, the probability of sample belonging to C_i is $p_i = x_i/x$, and the information entropy of sample classification is $I(x_1, x_2, \ldots x_n) = -\sum_i^n p_i \log_2 p_i$. Suppose that attribute Y has different values of m; m divides X into $\{X_1, X_2, \ldots X_n\}$, and x_{ij} is the number of samples belonging to C_i in the subset X_j; then, the information entropy of Y is

$$E(Y) = \sum_{j=1}^{m} \frac{x_{1j} + x_{2j} + \cdots + x_{nj}}{x} \times I(x_1 + x_2, \ldots x_n). \quad (1)$$

The information gain of attribute Y is as follows:

$$\text{Gain} = I(x_1, x_2, \ldots x_n) - E(Y). \quad (2)$$

Because the ID3 algorithm is complex, it takes up the running memory of the machine and wastes resources and reduces the operation efficiency, this paper proposes to optimize the information entropy formula by using the power expansion of the function, that is, to transform the calculation formula of information entropy into an approximate calculation formula containing the addition, subtraction, multiplication, and division algorithm [13]. The improved process is as follows. According to the demand, p_i can be set as the following equation:

$$p_i = \frac{1 - s_i}{1 + s_i} (0 < p_i \leq 1)(0 \leq s_i < 1). \quad (3)$$

Further processing formula (3) gives the following formula:

$$-\sum_{i=1}^{n} \frac{1 - s_i}{1 + s_i} \log_2 \frac{1 - s_i}{1 + s_i} = -\sum_{i=1}^{n} \frac{1 - s_i}{1 + s_i} \frac{\ln - 1 - s_i/1 + s_i}{\ln 2}. \quad (4)$$

The higher the power of the exponent, the higher the accuracy of the formula, because in the actual operation, only the size is compared, and the approximate calculation formula of the value is as follows:

$$\frac{2}{\ln 2} \sum_{i=1}^{n} \frac{1 - s_i}{1 + s_i} \left(s_i + \frac{1}{3} s_i^3 \right) = \frac{2}{3 \ln 2} \sum_{i=1}^{n} \frac{s_i (1 - s_i)(3 + s_i)}{1 + s_i}. \quad (5)$$

In the above formula, $8/3 \ln 2$ is a constant, which can be ignored in the calculation of comparison size. On this basis, the decision tree is created and generated. For continuous value partition, the expression of information gain can be extended to the equation as follows:

$$\text{Gain}(D, a) = \rho \times \text{Gain}(\widetilde{D}, a) = \rho \times \left(\text{Ent}(\widetilde{D}) - \sum_{v=1}^{V} \widetilde{r}_v \text{Ent}\left(\widetilde{D}^V\right) \right). \quad (6)$$

In the above equation, Ent (D) is the information entropy. In the research, because the complex multisegment partition can achieve better fitting results, which increases the training cost and prediction cost, multiple function combination values are used to partition. Fuzzy set theory refers to the theory of using the concept of membership function and fuzzy set theory. The fuzzy set on the universe can be expressed as follows:

$$\widetilde{A} = \left\{ \langle x, \mu_{\widetilde{A}}(x) \rangle | x \in X \right\}. \quad (7)$$

In the above equation, the membership function of the fuzzy set is $\mu_{\widetilde{A}}(x)$, and the value range is $[0, 1]$, which represents the membership of any element $x \in X$ to $x \in X$. When $\mu_{\widetilde{A}}(x)$ is 0, the element x does not belong to the fuzzy set $\widetilde{A}$. When $\mu_{\widetilde{A}}(x)$ is 1, the element x belongs to the fuzzy set $\widetilde{A}$. There is no clear membership relationship between the set and the element, which is expressed by the membership function. Intersection operation and union operation refer to membership functions of intersection and union of fuzzy subsets $\widetilde{A}$ and $\widetilde{B}$, respectively, which are shown in the equation as follows:

$$\begin{cases} \mu_{\widetilde{A} \cap \widetilde{B}}(x) = \min\left\{\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x)\right\} = \mu_{\widetilde{A}}(x) \wedge \mu_{\widetilde{B}}(x), & \forall x \in X, \\ \mu_{\widetilde{A} \cup \widetilde{B}}(x) = \max\left\{\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x)\right\} = \mu_{\widetilde{A}}(x) \vee \mu_{\widetilde{B}}(x), & \forall x \in X. \end{cases} \quad (8)$$

The related definitions of fuzzy decision tree are as follows: the finite set is represented by U, the set of fuzzy subsets is represented by $F(U)$, in which the fuzzy subset $\widetilde{A}$ can be represented by $\mu_{\widetilde{A}}(x_1)/x_1 + \mu_{\widetilde{A}}(x_2)/x_2 + L\mu_{\widetilde{A}}(x_N)/x_N$, and the sum of membership degrees can be referred to by $M(\widetilde{A}) = \sum_{i=1}^{N} \mu_{\widetilde{A}}(x_I)$. The fuzzy subset given by group m on a finite set can be represented by $M(\widetilde{A}) = \sum_{i=1}^{N} \mu_{\widetilde{A}}(x_I)$, and $M(\Omega_{\text{i}}) > 1$. If the directed tree T satisfies the following four conditions, it can be regarded as a fuzzy decision tree. First, the number of each node is in the set of fuzzy subsets $F(U)$. Second, a set of fuzzy subsets Γ, then $\Gamma = \Omega_i \cap B$, and $1 \leq i \leq m$ are composed of all the children B of nonleaf nodes. Each leaf node of a directed tree has one or more classification decision values. All fuzzy subsets correspond to one attribute, and the construction process of fuzzy decision tree is shown in Figure 3.

In the process of constructing fuzzy decision tree, we need to consider the authenticity threshold β_0 and significance level α. Under the significance level, the fuzzy set can be expressed as follows:

$$\widetilde{A}_\alpha = \begin{cases} \mu_{\widetilde{A}}(x,)\mu_{\widetilde{A}}(x) \geq \alpha, \\ 0, \mu_{\widetilde{A}}(x) < \alpha. \end{cases} \quad (9)$$

It can be seen that the higher the α value, the less fuzzy the data training will be, but the larger the value of the training set will become an empty set. Generally, the value range is $(0, 0.5]$. If the training results meet the requirements, the data can be fuzziness without α. Otherwise, α is needed to improve the training effect of the model. β_0 is an indicator used to evaluate whether to stop dividing the nodes. If the node authenticity is greater than β_0, it indicates that the node partition can be stopped [14]. Generally, β_0 is greater than 0.75. The reality degree of a node represents the maximum value of the example in the node in the membership degree of each category, and the expression of the example in the node for the membership degree of the category is as follows:

$$\begin{aligned} \beta_A^C &= \frac{M(A \cap C)}{M(A)} \\ &= \frac{\sum_{x \in X} \min(\mu_A(x), \mu_C(x))}{\sum_{x \in X} \mu_A(x)}. \end{aligned} \quad (10)$$

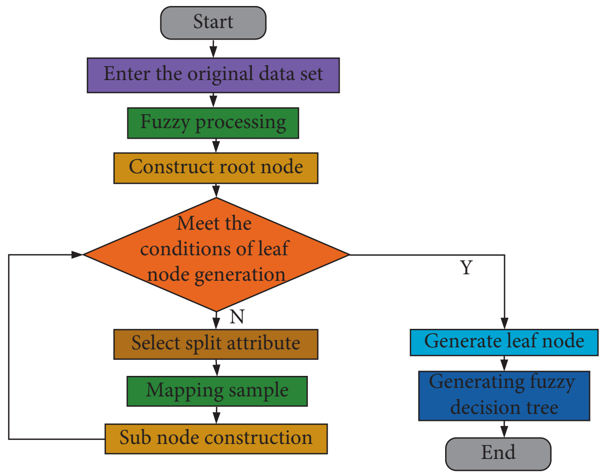

Figure 3: Construction of fuzzy decision tree.

3.2. MOOCS Model of College Physical Education Based on Fuzzy Decision Tree Algorithm. The common fuzzy decision tree algorithms are the fuzzy ID3 algorithm and the minimum classification uncertainty algorithm. The segmentation attribute criteria of the former are fuzzy information gain and fuzzy information entropy. Taking the sample set $X = \{x_1, x_2, \ldots, x_N\}$ as an example, the attribute l of the nonleaf node B can be represented by $A^{(1)}, A^{(2)}, \ldots, A^{(l)}$, in which each fuzzy condition attribute has k_s fuzzy semantic value $A^{(s)} (1 \leq s \leq l)$, which is represented by $T_1^{(s)}, T_2^{(s)}, \ldots, T_{k_s}^{(s)}$. The decision attribute $A^{(l+1)}$ has z values, which can be expressed by $T_1^{(l+1)}, T_2^{(l+1)}, \ldots, T_z^{(l+1)}$. Taking each attribute value $T_l^{(s)}$ as an example, the relevant frequency of its nonleaf node B can be expressed by

$$\begin{aligned} p_{ij}^{s} &= \frac{M\left(T_i^{(s)} \cap T_j^{(l+1)} \cap B\right)}{M\left(T_j^{(l+1)} \cap B\right)} \\ &= \frac{\sum_{x \in X} \min\left(\mu_{T_i^{(s)}}(x), \mu_{T_j^{(l+1)}}, \mu_B(x)\right)}{\sum_{x \in X} \min \mu_{T_j^{(l+1)}}, \mu_B(x)}. \end{aligned} \tag{11}$$

The fuzzy classification entropy of each attribute value $T_i^{(s)}$ in nonleaf nodes can be expressed by formula

$$E_i^s = -\sum_{j=1}^{z} p_{ij}^{(s)} \log_2 p_{ij}^{(s)}. \tag{12}$$

The average fuzzy classification entropy of each attribute on nonleaf nodes can be expressed by

$$E_s = \sum_{i=1}^{k_s} \omega_i E_i^{(s)}. \tag{13}$$

In above formula, the weight of the second attribute of the i attribute is denoted by ω_i. The minimum classification uncertainty algorithm divides the attributes into minimum classification uncertainty. The former is chosen as the classification of the MOOCS model applied in college physical education. In order to construct the MOOCS model of college chysical education teaching based on the fuzzy decision tree algorithm, firstly, we need to calculate k center points by the Kohonen feature mapping algorithm and discretize the continuous attributes by fuzzy semantic value. Then, the triangular membership function is used to fuzzify. The parameter of triangular membership function is the neutral point of attribute. The membership function formula of each semantic value is shown in the equation as follows:

$$\mu_{T_1}(x) = \begin{cases} 1, & x \leq m_1, \\ \dfrac{(m_2 - 1)}{(m_2 - m_1)}, & m_1 \leq x \leq m_2, \\ 0, & x \geq m_2, \end{cases} \tag{14}$$

$$\mu_{T_i}(x)(1 < i < k) = \begin{cases} 0, & x \leq m_{i-1,} \\ \dfrac{(x - m_{i-1})}{(m_i - m_{i-1})}, & m_{i-1} \leq x \leq m_i, \\ \dfrac{(m_{i+1} - x)}{(m_{i+1} - m_i)}, & m_i \leq x \leq m_{i+1}, \\ 0, & x \geq m_{j+1}, \end{cases} \tag{15}$$

$$\mu_{T_k}(x) = \begin{cases} 0, & x \leq m_{k-1}, \\ \dfrac{(x - m_{k-1})}{(m_k - m_{k-1})}, & m_{k-1} \leq x \leq m_k, \\ 1, & x \geq m_k. \end{cases} \tag{16}$$

When the values of k are 2 and 3, the corresponding membership functions are shown in Figures 4(a) and 4(b).

The evaluation of the MOOCS model in college physical education teaching is based on students' learning behavior, including teaching resources browsing, forum data, online notes, and online test. According to the final test times and comprehensive score, it can be divided into four levels: A, B, C, and D. The behavior description of the students is shown in Table 1. In view of the attributes that affect the effectiveness of the model in the integrated information, it is necessary to reduce the attributes. Finally, the input data are student number and four kinds of final learning behavior data.

Finally, the evaluation structure of the MOOCS mode of college physical education teaching oriented to fuzzy decision tree is shown in Figure 5, and the classification model represents a series of if-then rules [15]. If a new data is introduced, the root node testScore (A4) is used to judge the attribute and content of the test data, and then browsertime (A3), onlinenotes (A2) and bbspost (A1) are used to get the final evaluation result. The learning behavior of the educated is a series of vectors, and finally, four scoring rules are obtained. The evaluation criteria of the classification model are classification accuracy and the scale of decision tree model [16].

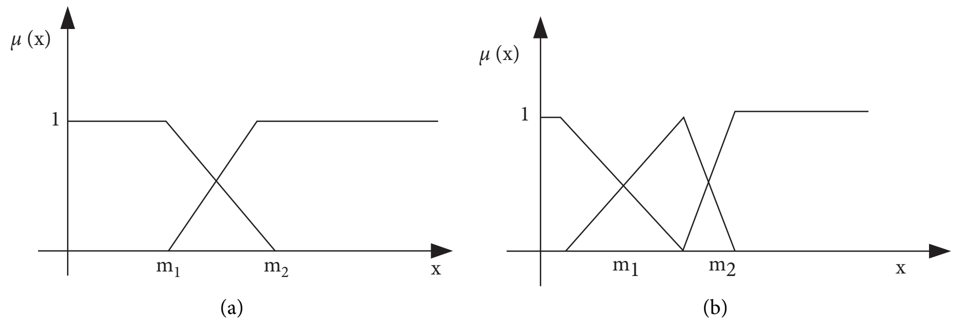

Figure 4: Schematic diagram of membership function ($k = 2, 3$). (a) Schematic diagram of membership function ($k = 2$). (b) Schematic diagram of membership function ($k = 3$).

Table 1: Description of related behaviors.

No	Data name	Meaning	Specific description
1	Browsertime	Browse teaching resources	Length of learning time of teaching resources
2	Browservideo	Browse video resources	Learning time length of video resources
3	BBSPost	Forum posting data	Forum post number, post ranking, and reply times
4	BBSReply	Forum reply data	Forum reply number and reply times
5	OnlineNotes	Online notes	Completeness and length of online notes
6	OnlineTest1	Online self testing	Number and score of online self tests
7	OnlineTest2	Online unified test	Online unified test results

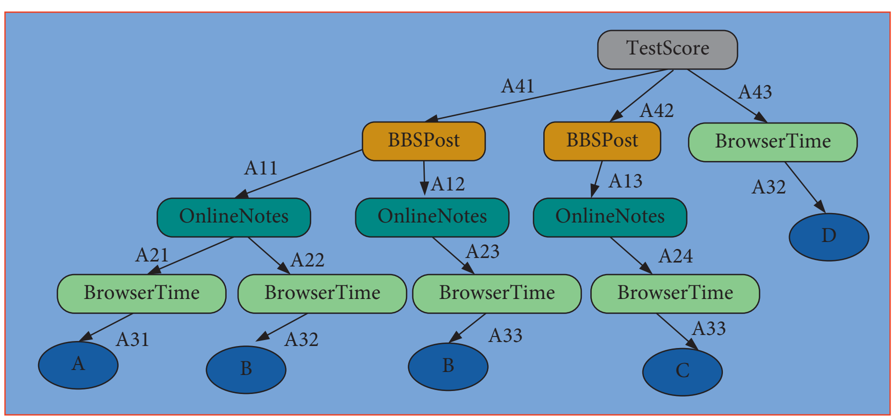

Figure 5: Evaluation structure of MOOCS model in college physical education oriented to fuzzy decision tree.

4. Evaluation and Analysis of MOOCS Model in College Physical Education

In the experiment, the rules extracted from the fuzzy decision tree are predicted, and the data examples are shown in Table 2. The membership degrees of A11 and A12 are 0.2 and 0.8, respectively, the membership degrees of A21, A22, A23, and A24 are 0.0, 0.7, 0.1, and 0.2, respectively, the membership degrees of A31 and A32 are 0.1 and 0.9, respectively, and the membership degrees of A41, A42, and A43 are 0.0, 0.7, and 0.3, respectively.

The matching result of instance and rule is shown in Figure 6. The two rules of instance classification B are rule 2 and rule 5, respectively. The maximum matching membership is 0.3, and the authenticity of the corresponding rule is 89%. There is only one rule in the other case classification. The matching membership and rule true degree of A are 0.0 and 86%, respectively, the matching membership and rule true degree of C are 0.1 and 89%, respectively [17], and the matching membership and rule true degree of D are 0.2 and 88%, respectively.

In the experiment, the database table of the corresponding system of university A entity is selected to evaluate the classification performance of the MOOCS mode. The database includes three parts: comprehensive scoring, data integration management, and query statistics. When the learning rate is set to 0.5 and the number of center points is 2 and 3, respectively, the center points of the four attributes of the dataset are shown in Figure 7. It can be seen that there is a big difference between the four major attributes under different numbers of center points [18]. The maximum and minimum number of center points of browsertime are 7.1 and 9.58, respectively, the maximum and minimum number of center points of onlinenotes are 0.1 and 43.75, respectively, the maximum and minimum number of center points of bbspost are 25.37 and 43.85, respectively, and the

Table 2: Basic information of data examples.

A1		A2			
A11	A12	A21	A22	A23	A24
0.2	0.8	0.0	0.7	0.1	0.2
A3		A4			—
A31	A32	A41	A42	A43	—
0.1	0.9	0.0	0.7	0.3	—

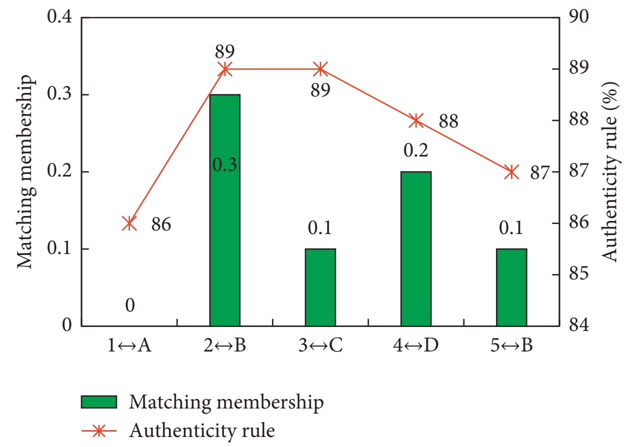

Figure 6: Matching results of examples and rules.

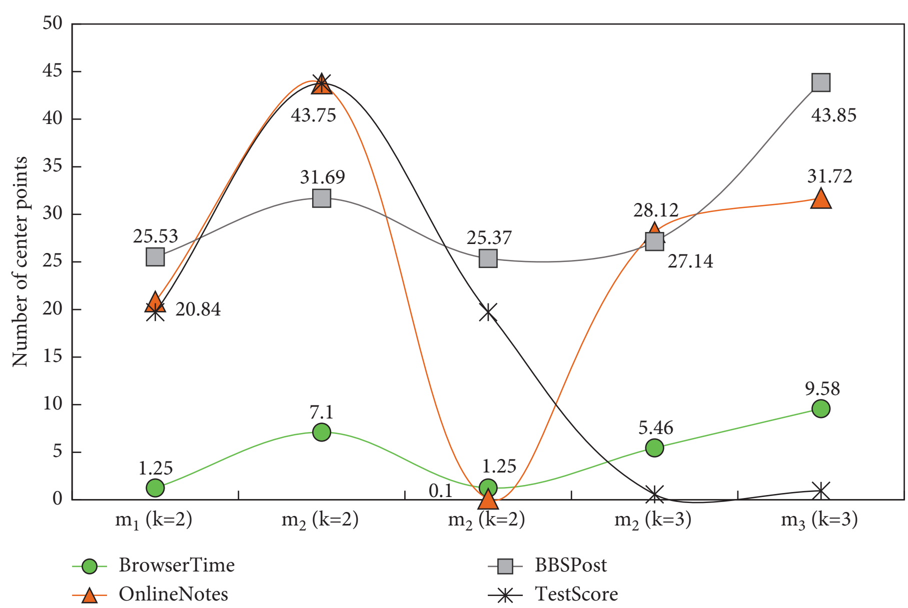

Figure 7: The central point of four attributes in university A dataset.

maximum and minimum number of center points of testScore are 0.57 and 43.75, respectively.

The fuzzy results of the university data set are shown in Figure 8. There are great differences between browsertime's fuzzy long and short attribute membership degrees, the biggest differences are 0.997 and 0.006. There are great differences between onlinenotes's fuzzy long and short attribute membership degrees, the biggest differences are 0 and 1, and there are seven groups of data. There is a big difference in the membership degree of bbspost's fuzzy long short attribute, the biggest difference is 0 and 1, and there are three groups of data. There is a big difference between the membership degree of fuzzy long and short attributes of testScore, the biggest difference is 0 and 1, and there are 8 groups of data.

The experiment further selects the system database table of the other three schools B-D for the MOOCS mode classification evaluation. The algorithms used are C4.5, cart, fuzzy ID3, and minimum classification uncertainty. The classification accuracy is shown in Figure 9. The classification model constructed by the fuzzy ID3 algorithm can get

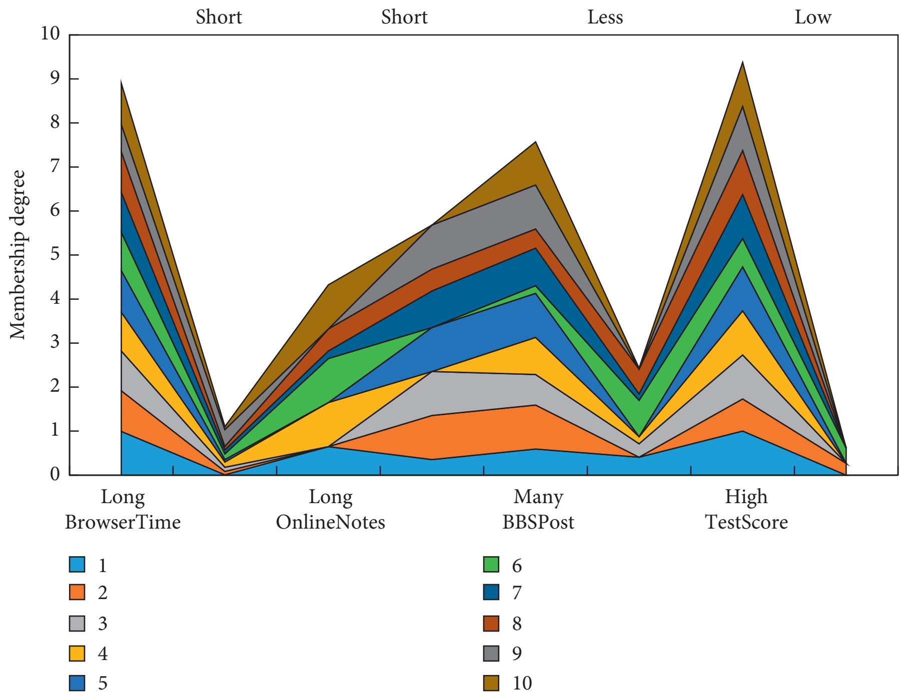

Figure 8: Dataset fuzzification results.

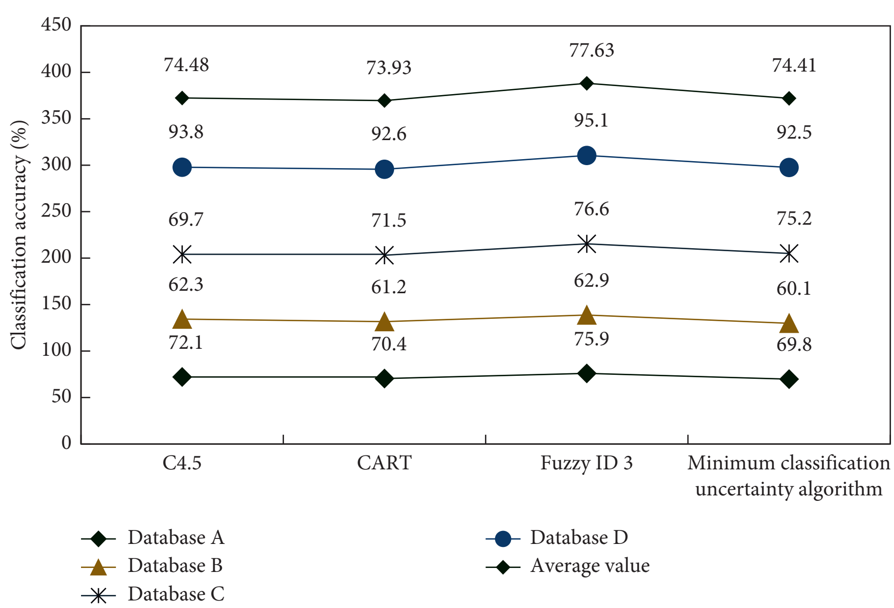

Figure 9: Classification accuracy of four algorithms in four databases.

the highest accuracy among the four databases. The classification accuracy of A-D database is 75.9%, 62.9%, 76.6%, and 95.1%, respectively. Therefore, the algorithm has strong practicability. The accuracy of the minimum classification uncertainty algorithm is far lower than that of the fuzzy ID3 algorithm, and the classification accuracy of *A*, *B*, and *D* databases is lower than C4.5 and cart. The least classification uncertainty algorithm does not get higher classification accuracy than the clear decision tree, which may be related to the probability of the distribution of the research results. C4.5 and cart have an average classification accuracy of 74%, which can process data continuously and have better classification accuracy. The accuracy of database *D* classification is higher than that of the other three groups of databases, and the four algorithms have obtained more than 90% of the data in the database, which shows that there are significant differences among different individuals in the database. The accuracy of database *B* classification is about 60%, which shows that there is no difference between different individuals in the database.

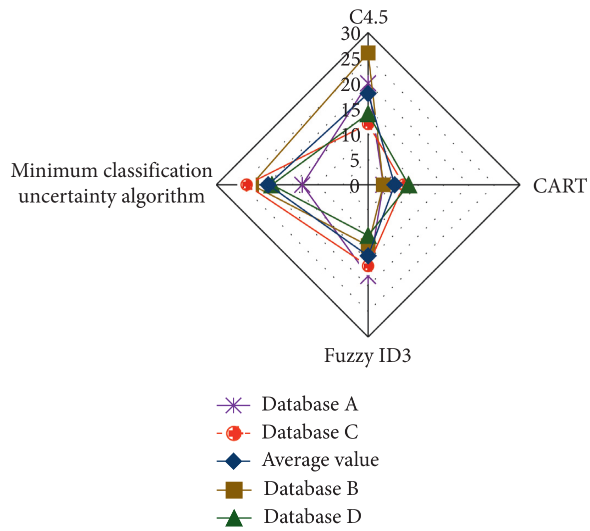

Figure 10: Comparison of the number of classification rules of four algorithms in four groups of databases.

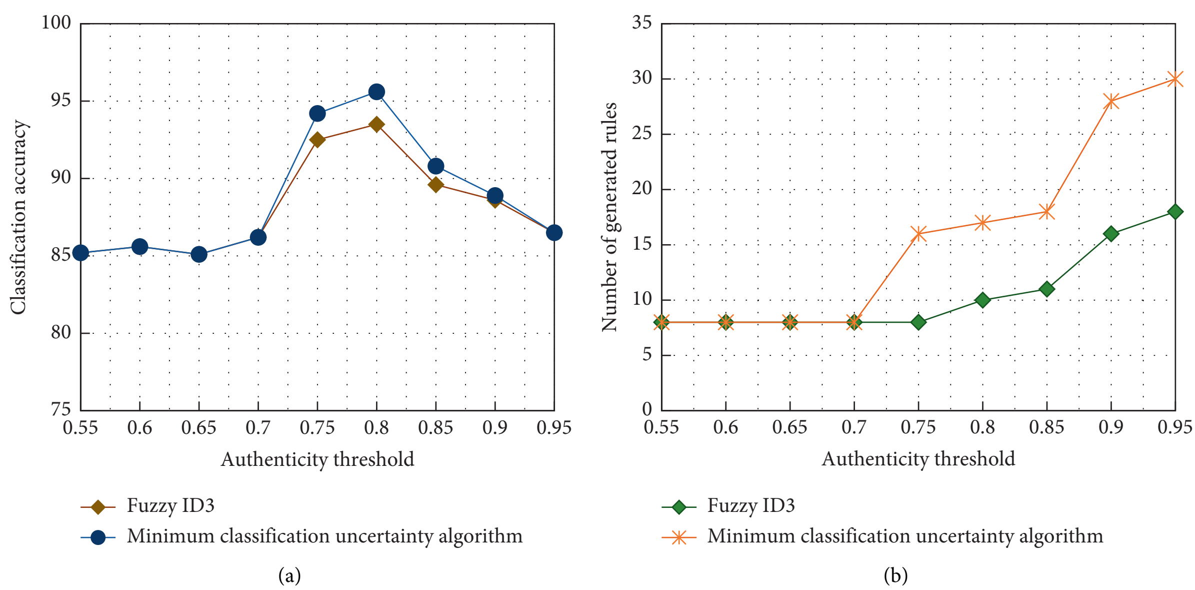

Figure 11: The influence of authenticity threshold on classification accuracy and classification rules. (a) The influence of authenticity threshold on classification accuracy. (b) The influence of authenticity threshold on classification rules.

The comparison of the number of classification rules of the four algorithms under the four groups of databases is shown in Figure 10. The number of rules is closely related to the efficiency of decision tree. Too many rules can easily lead to over fitting. Compared with the minimum classification uncertainty algorithm, the classification rules of the fuzzy ID3 algorithm have obvious advantages. Except for database *A*, the rules generated by the fuzzy ID3 algorithm are less, which shows that the fuzzy ID3 algorithm has higher applicability. The cart algorithm generates the least number of rules, and the number of classification rules of database *A*-*D* is 3, 3, 7, and 8, respectively. Moreover, the algorithm is quite different from other algorithms, which is closely related to the principle of the algorithm.

The experiment takes the database *D* with a strong classification effect as an example to explore the influence of authenticity threshold on classification accuracy and classification rules. The results are shown in Figures 11(a) and 11(b), respectively. With the increase of authenticity threshold, the classification accuracy first increases and then gradually decreases, and the maximum classification accuracy is about 0.8. The number of classification rules of the two algorithms increases with the increase of the authenticity threshold. Therefore, it is necessary to select the appropriate authenticity threshold in the construction of the MOOCS classification evaluation model.

At the end of the experiment, the MOOCS model of physical education teaching in colleges and universities was evaluated and analyzed, including online theoretical

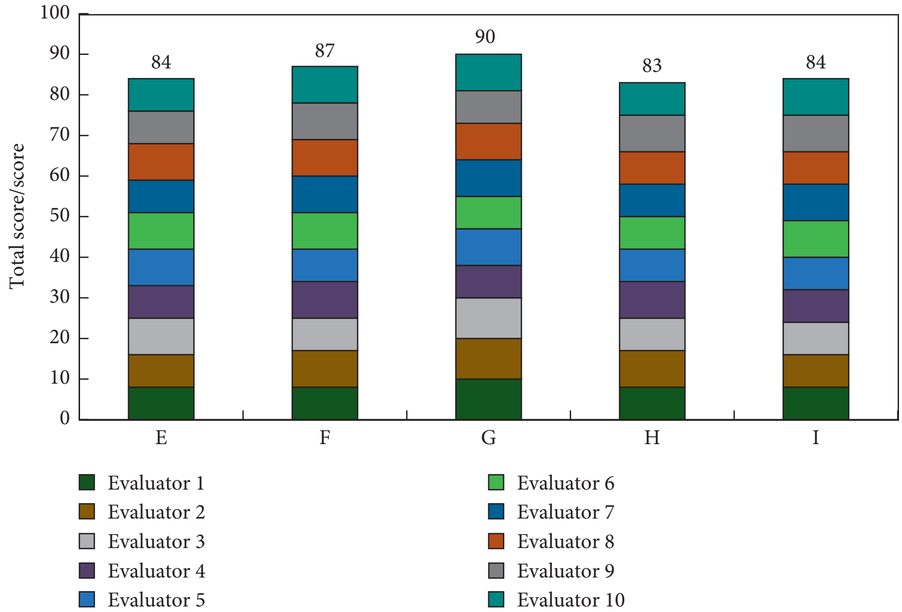

Figure 12: Evaluation of MOOCS model in college physical education.

assessment, offline skills assessment, platform learning, students' learning ability, progress, and growth. The letter E-I was used to refer to each aspect. The full score of each aspect was 10 points, and the evaluators were 10 professional MOOCS researchers. The overall situation is shown in Figure 12. It can be seen that all the 10 evaluators have a high evaluation on the five aspects of the MOOCS mode of college physical education, the score of each item is about 9 points, the total score of five items is more than 80 points, and the total score of platform learning is the highest, with a value of 90 points.

5. Conclusion

The classification and evaluation of MOOCS mode in college physical education teaching is a topic of common concern of many scholars and experts in the field of education. In view of the problems existing in the traditional teaching evaluation, this paper puts forward a classification evaluation model of the MOOCS mode of college physical education oriented to the fuzzy decision tree algorithm, constructs the fuzzy ID3 algorithm combined with fuzzy theory and decision tree algorithm, and applies it to the classification evaluation of the MOOCS mode of college physical education. The classification accuracy of the minimum classification uncertainty algorithm in the four databases is lower than that of the fuzzy ID3 algorithm, and the fuzzy ID3 algorithm has higher practicability than the minimum classification uncertainty algorithm and the other two clear decision tree algorithms. The average classification accuracy of C4.5 and cart is about 74%. In the four databases, the cart algorithm generates the least number of rules, and the classification rules of the A-D database are 3, 3, 7, and 8, respectively. Except that database A generates fewer rules, the fuzzy ID3 algorithm has obvious advantages over the minimum classification uncertainty algorithm. The number of classification rules of the fuzzy ID3 algorithm is positively related to the authenticity threshold, and the classification accuracy is obtained when the authenticity threshold is about 0.8. In view of the fact that the cart algorithm has a small number of classification rules, it can be combined with other methods to improve the accuracy of MOOCS classification evaluation in college physical education. However, this paper does not discuss the classification accuracy of the minimum classification uncertainty algorithm in the database. The minimum classification uncertainty algorithm has obvious advantages and is not obvious enough, which makes the research need to be further improved.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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