THE EFFECT OF ONLINE AND OFFLINE SPORTS SAFETY EDUCATION COMBINED WITH MOOC PLATFORMS IN PHYSICAL EDUCATION TEACHING IN COLLEGES AND UNIVERSITIES

YUAN GAO*

Abstract. In light of Internet+, how to make network technology better serve the educational cause needs more exploration. The online and offline hybrid education model that integrates MOOC is a new attempt. The sports safety of college students is the premise for the smooth development of sports activities. Therefore, a mixed teaching mode of sports safety combined with MOOC is designed to evaluate the teaching effect. However, under this teaching mode, the commonly used teaching effect evaluation methods cannot adhere to formative evaluation standards. Consequently, to better evaluate the MOOC teaching mode, a model for evaluating instructional effects based on RF mixed teaching mode is constructed. Aiming at the defects of RF in data processing, a genetic algorithm and particle swarm algorithm are used to optimize random forest. The outcomes demonstrate that the enhanced PSO-RF evaluation model has a 98.68% accuracy rate, which is 5.44% and 3.49% higher than the RF and GA-RF model respectively. Therefore, the enhanced PSO-RF-based teaching effect assessment model can better assess the mixed teaching mode in sports safety, meeting the evaluation requirements for students' learning effects.

Key words: MOOC; Sports safety; Physical education teaching in colleges and universities; Random Forest

1. Introduction. With the popularization of national fitness awareness, various sports have gradually received widespread attention. Effective physical exercise is an important guarantee for improving the body's constitution and quality of life. As the main force for the future development of society, college students should integrate physical exercise into their daily learning and life. As an important participant in sports activities, college students are also the main group of sports safety accidents. The frequent sports safety accidents in universities not only affect students' enthusiasm for participating in physical exercise, but also have adverse consequences for physical education and daily teaching activities in universities. Sports safety is the prerequisite and foundation for ensuring students' participation in sports activities [3, 4, 5]. However, most of the existing sports safety education is taught orally by teachers before physical exercise, lacking awareness of sports injuries and the ability to handle accidents. Therefore, carrying out sports safety education for college students and improving their safety awareness plays an important role. With the advancement of online education technology, sports safety education in universities has also taken on new development forms. To improve the quality and effectiveness of sports safety teaching in universities, ensure that students have the ability to handle sudden sports safety accidents, and reduce injuries, an online and offline mixed teaching (OAOMT) mode of sports safety education based on the MOOC platform is proposed. Aiming at the sports safety teaching effect under the mixed mode, the evaluation model of sports safety teaching effect based on Random Forest (RF) algorithm is constructed. Then the Particle Swarm Optimization (PSO) is used to improve the evaluation model of Random Forest teaching effect. The teaching effect evaluation model of random forest based on particle swarm optimization (PSO-RF) algorithm is constructed. It is hoped that the problems existing in sports safety education can be corrected in time. The students' sports safety awareness can be improved, and the occurrence of injury accidents in physical exercise can be reduced.

2. Related works. With the frequent occurrence of sports safety accidents, sports safety has received more attention. Teenagers and children may experience cardiac abnormalities or sudden cardiac arrest caused by chest impact. Therefore, Bogue KA et al. proposed that Cardiopulmonary resuscitation training should be carried out to improve the ability of sports personnel to deal with such diseases in an emergency [6]. Jani et

---

*School of Physical Education, Hunan University of Science and Engineering, Yongzhou, 425199, China (Yuan_Gao2023@outlook.com)

al. investigated the quality standards for sports safety and school management. The random sampling method was used to investigate the safety of school sports in some rural and urban areas. When they take action and follow standard operating procedures, good sport management and teacher practice can be ensured [7]. Sun C and others proposed to use Big data and intelligent technology to conduct all-round monitoring and real-time alarm on relevant elements of sports events in view of the injuries that are easy to occur in sports events. The safety of athletes in sports events is ensured [8]. Mai et al. evaluated the safety performance of sports infrastructure based on the level and utilization status of school sports infrastructure [9]. Brown J C et al. believed that conducting curriculum education can reduce the risk of athlete injury. According to the results of the questionnaire survey, the knowledge acquisition rate of participants in the course is relatively low, making it difficult to achieve the goal of reducing athlete injuries effectively [10].

The RF algorithm is suitable for data clustering, data anomaly detection and data pivoting in various environments. The integration technique of artificial intelligence teaching materials is developed to address the difficulties of long running time and low precision. Yang proposed a method for integrating artificial intelligence teaching resources based on behavioral data analysis. The random forest algorithm classifies them and adds rewards and punishments to achieve AI integration of intelligent teaching resources. The findings indicate that this strategy can increase the overall efficiency and accuracy of the method [11]. In view of the impact of evaluation units and non-landslide sample selection methods on landslide susceptibility prediction, Shu H E established a landslide susceptibility evaluation model based on Random Forest tree Bagger classifier. RF and self-organizing feature map network RF are discussed. The results showed that the self-organizing feature map network RF has a high prediction rate and success rate [12]. To improve building energy efficiency, Liu Y et al. proposed a envelope design-based building energy consumption forecast approach. The RF model is used to estimate building energy consumption. The importance of each parameter is ranked, and then the Pearson function is applied to assess the corresponding connection. The findings indicate that the RF model has a significant advantage in building energy consumption prediction [13]. Liang applied the RF algorithm to rural revitalization. The RF method is used in data mining of art services. The significance of the transformation from independent variable to dependent variable in exploring art service strategies in rural revitalization has been determined [14]. Xu et al. used RF algorithm to evaluate the spatiotemporal dynamic characteristics of urban surface thermal environment. Based on the evaluation results, strategies for urban structural adjustment and reasonable layout were proposed to achieve urban structural optimization [15].

To sum up, the relevant research on sports safety is relatively rich, covering the safety of school sports facilities and safety issues in sports events. The relevant research content of the RF algorithm involves many fields, which has numerous applications. However, existing research shows that although sports safety education is being implemented, the actual teaching effectiveness and knowledge acquisition rate are very low. Based on this, firstly, a mixed online and offline sports safety teaching model is constructed. Then, the random forest model is constructed to evaluate the teaching effect of the teaching mode. It is expected to find the problems and deficiencies in sports safety teaching, and improve the acquisition rate of sports safety knowledge and teaching quality.

3. Construction of sports safety teaching effect evaluation model based on improved RF algorithm.

3.1. The teaching mode construction of sports safety in colleges and universities combined with MOOC. With the support of network technology, the rapid development of online education based on the MOOC platform enables modern education to break through the limitations of time and place. Physical education has the uniqueness in terms of teaching format and content. In the actual teaching process, more attention is paid to the teaching of motor skills. However, there is relatively little learning about related content, including theoretical knowledge of sports, prevention and handling of sports safety accidents, etc [16]. For the teaching of sports safety awareness, the advantages of MOOC platform is used to build a hybrid education mode for sports safety accidents. Figure 3.1 depicts the specific process.

Specifically, the OAOMT mode is mainly classified into three parts. The first part is the online learning stage before class, including discuss tasks, exercises and assessment content, etc. Students must finish the necessary theoretical knowledge study within the time-frame indicated, and master the related injury treatment skills. The second stage is offline teaching, mainly focusing on physical exercise. Assisted by reviewing relevant
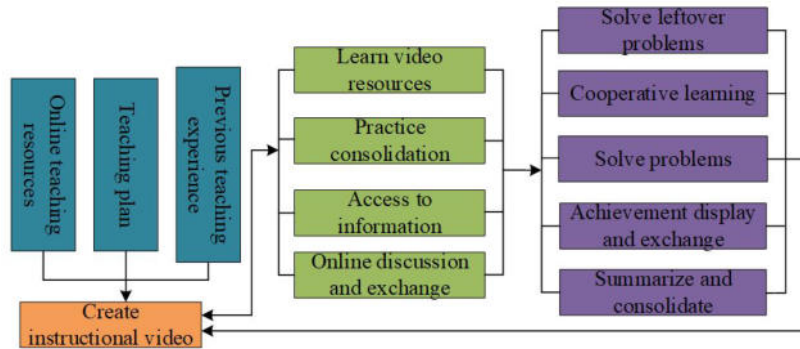
Fig. 3.1: Sports safety teaching mode under mixed mode

theoretical knowledge and answering questions, it helps students improve their safety awareness. In face-to-face communication with students, physical education teachers help students answer questions left over from the previous stage. Some additional knowledge is supplemented to help students consolidate and summarize their skills. The third stage is the application stage of knowledge and skills, which belongs to the stage of long-term benefit. After online and offline learning, students can simulate the injury to consolidate and output what they have learned. In the later stage of physical exercise, safety knowledge in sports should be kept in mind. In a sports injury, the injury can be dealt with urgently to minimize the extent of the injury. The online and offline hybrid teaching mode makes up for the shortcomings of offline physical education teaching. However, this teaching approach places greater demands on both students and teachers. Students need to finish pre-class learning tasks independently and master relevant basic knowledge. The handling of injuries can be proficiently mastered. At the same time, the video content must be learned before class. By publishing appropriate discussion and evaluation assignments, students' mastery of online basic knowledge is checked to ensure the normal teaching process. Relying on the MOOC platform, this mixed teaching mode realizes the teaching process of students' independent learning, discussion and evaluation. Students really become the main participants in the classroom, actively dig for knowledge, build the connection between knowledge, and effectively change traditional classroom teaching. Students receive more participation space. Under this teaching mode, the assessment of educational impact needs to adopt multiple evaluation ways, including the formative evaluation and summative evaluation, to evaluate students' learning effect objectively.

3.2. Construction of assessment model of sports safety teaching effect based on RF algorithm. RF algorithm is a widely employed machine learning algorithm, which has a positive impact on data classification, regression and other processing. It is mainly consisting of a combination of Bootstrap aggregating (Bagging) and Classification and regression tree (CART) algorithms. The essential building block for the multi-style combination is the decision tree (DT), which uses the voting method to classify the data [17]. When using the RF algorithm for data classification, the Bagging method is used to randomly generate a DT set. Then the best classification features are determined by evaluation indicators such as information gain. The Bootstrap sampling method is used for data classification. A dataset of size D is extracted from dataset n (the total sample size is N) and replace it with K to form a sample set. The probability of each sample being drawn in the training set is shown in Equation 3.1.

$$p = \left(\frac{1}{N}\right)^{N} \tag{3.1}$$

According to the Equation 3.1, the classifier model is constructed using the classification regression tree CART method. A KDT is trained separately. After training the sample set according to CART method, DTs are combined into RF model $\{g_i, i = 1, 2, ..k\}$. The samples q to is used to test the model. The test results are
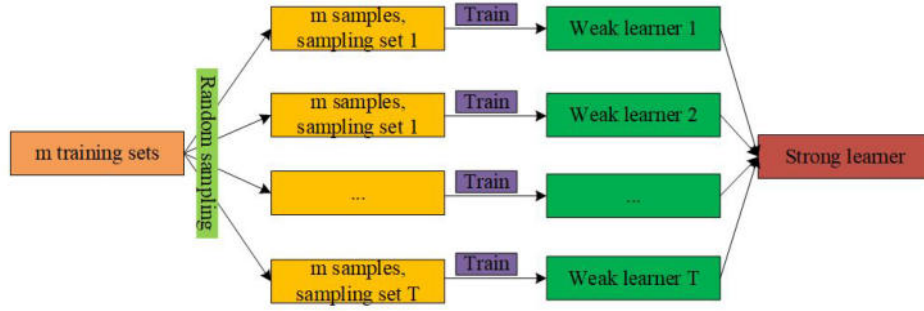
Fig. 3.2: Schematic Diagram of Bagging Method

shown in Equation 3.2.

$$Q = \{g_1(q), g_2(q)....g_k(q)\} \tag{3.2}$$

After the classification results are obtained, the results of each DT are counted. The final regression result is the average value of all the forecast findings, as shown in Equation 3.3.

$$T(q) = \frac{1}{K} \sum_{i=1}^{K} t_i(q) \tag{3.3}$$

In Equation 3.3, q represents the sample data. $t_i(q)$ represents the classification and statistical results of each sample. When the Bagging algorithm regenerates the DT set, it aggregates the operation results after randomly selecting a subset of the original data for independent operation. In Figure 3.2 the calculating procedure is displayed. The Bagging algorithm is used to increase data selection capacity for generalization and reduce overfitting problems that may occur in decision trees (DTs). When the DT node position is split, the CART algorithm mostly chooses the attribute with the Gini index (Gini) as the split attribute [18]. The impurity of the data collection is represented by the Gini index. The definition is shown in Equation 3.4.

$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2 \tag{3.4}$$

In Equation 3.4, D represents the data sample. K represents the scale of the DT. p_i represents C_j the probability that the sample data in sample set belongs to D. Taking an attribute A in the sample set D as an example, the sample is based on the sum of two data subsets divided by the attribute D_1 and D_2. The Gini index obtained by dividing the two subsets is the weighted sum of the impurity in subsets. Equation 3.5displays the computation process.

$$Gini_A(D) = \frac{|D_1|}{D} Gini(D_1) + \frac{|D_2|}{D} Gini(D_2) \tag{3.5}$$

The impurity of the attribute -based subset can be obtained from Equation 3.5, as shown in Equation 3.6.

$$\Delta Gini(A) = Gini(D) - Gini_A(D) \tag{3.6}$$

When generating a regression tree, it is necessary to select the data set attribute with the smallest Gini index as the node splitting attribute [19, 20]. After completing the Bagging process and the CART algorithm, the random forest model can be constructed. The specific operation process is shown in Figure 3.3 From the figure
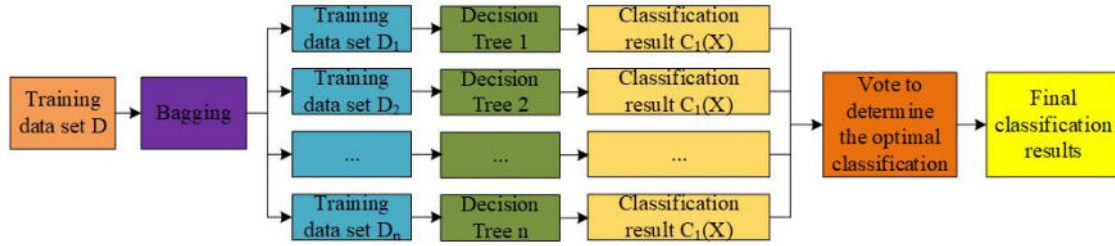
Fig. 3.3: Schematic Diagram of Random Forest

above, for classification results of the DT, the weighted voting method is used to perform weighted calculations on the classification outcomes of each DT. The final classification result is determined. If the classification result of the sample data is a, the total number of votes belonging to the X class is S_a. Equation 3.7 shows the calculation process of voting results.

$$S_a = \sum_{t=1}^{K} (T_{a,X})(X)W_t \tag{3.7}$$

In formula (7), K represents the scale of the DT. W_t represents the decision weight. T represents the scale of the sampling data set. If the value is 1, it means that the classification result $T_{c,X}(X)$ of the sample a belongs to the class X. If the value is 0, it means it does not belong to the class. The generalization error of the RF is affected by correlation and strength of the DT. Generalization error has an upper limit, as shown in Equation 3.8.

$$PE^* \leq \overline{\rho}(1 - s^2)/s^2 \tag{3.8}$$

In Equation 3.8, $\overline{\rho}$ represents the average value of the correlation between DTs. After the classification results are calculated by the weighted voting method, the category X with the highest number of votes is output as the final classification result of the sample.

3.3. Construction of sports safety teaching effect evaluation model based on improved RF algorithm. RF algorithm has a good effect in data classification. It needs to perform optimization calculations in parameter selection. This process takes a long time, which has a direct impact on categorization efficiency [21, 22]. Given the flaws in the execution method, the parameter values obtained by the traditional method cannot make the performance of the algorithm reach the optimum. Therefore, an intelligent approach is proposed to determine the appropriate RF technique settings. Genetic Algorithm (GA) is a non-linear optimization intelligent algorithm based on natural selection and genetic mechanism, which has good applications in the fields of parameter optimization, signal processing and machine learning [23, 24]. Firstly, the GA-RF evaluation model is constructed. After initializing the population, the crossover probability and mutation probability are determined. If F_{max} is the maximum population fitness, F_{avg} is the population average fitness, the probability of chromosome crossover P_c and mutation P_m will change with the fitness of the population. Then, the relationship between the initial probability of crossing P_{ci} and the probability of crossing P_{c2} is shown in Equation 3.9.

$$Pc = \begin{cases} P_{c1}(P_{c1} - P_{c2})\frac{F - F_{avg}}{F_{max} - F_{avg}}, F \geq F_{avg} \\ P_{c1}, F < F_{avg} \end{cases} \tag{3.9}$$

Initial probability of mutation $Pm1$ and the probability of mutation progress $Pm2$ are shown in Equation 3.10.

$$Pm = \begin{cases} P_{m1}(P_{m1} - P_{m2})\frac{F_{max} - F}{F_{max} - F_{avg}}, F \geq F_{avg} \\ P_{m1}, F < F_{avg} \end{cases} \tag{3.10}$$

Usually, mutation probabilities P_m are achieved very small. The mutation operation needs to cooperate with the crossover operation, aiming at mining the diversity of individuals in the population. Two individuals are randomly selected from the primary selection group for crossover. The obtained expression is as Equation 3.11.

$$\begin{cases} \alpha_1 = \lambda\alpha_2 + (1-\lambda)\alpha_1 \\ \alpha_2 = \lambda\alpha_1 + (1-\lambda)\alpha_2 \end{cases} \tag{3.11}$$

In Equation 3.11, $\lambda \in \{0,1\}$ is any random number generated. After crossing, the chromosomes of α_1 and α_2 offspring are recalculated and optimized in the original population. In the genetic algorithm, the operators for crossover and mutation are the core of the algorithm. The crossover rate P_c and mutation rate P_m are key parameters for the convergence and stability. The P_c and P_m reflects the probability of the algorithm's crossover and mutation operations, which determines the convergence of the algorithm. Another commonly used intelligent algorithm is particle swarm optimization (PSO), which is a swarm intelligence-based random evolution method with distinct advantages in finding optimal solutions [25]. If there are particles in a population, the spatial position of each particle is Z, denoted by V, indicating the moving direction of the particle in the feasible region. The running speed of particles needs to be limited by the maximum speed and the minimum speed. The relationship between the two is obtained as shown in Equation 3.12.

$$V_{min} = -V_{max} \tag{3.12}$$

In Equation 3.12, V_{min} and V_{max} represent the particle velocity's highest and minimum values, respectively. When searching for the optimal solution, each particle will get the optimal position that each particle passes through after iterations $p_{best}(t)$. The solution of the minimum optimization problem is shown in Equation 3.13.

$$gbest(t) = min\{pbest_1(t), pbest_2(t), ..., pbest_N(t)\} \tag{3.13}$$

When the algorithm advances to the next generation, the particles in the space will update the speed and position based on previous generation information and present information. The speed update method is shown in Equation 3.14.

$$V_a^{t+1} = V_a^t + c_1 r_1 pbest_a^t - Z_a^t + c_2 r_2 (gbest_a^t - Z_a^t) \tag{3.14}$$

In Equation 3.14, α represents the particle. c_1 and c_2 represents the learning factor of the particle. r_1 and r_2 are random number between 0-1. V_a^t represents the speed of the particle α. Z_a^t represents the space vector t at the first iteration. The method is shown in Equation 3.15.

$$Z_a^{t+1} = Z_a^t + V_a^{t+1} \tag{3.15}$$

The new position and velocity are constantly updated through Equation 3.13 and Equation 3.14. The best positional solution is identified. Figure 3.4 depicts the specific operating process.

A larger weight coefficient is used to search the global. After obtaining the optimal solution, a smaller weight coefficient is used to search the local optimal solution to achieve the optimization effect of the particle swarm optimization algorithm.

4. Performance analysis of the sports safety teaching effect assessment model based on the improved RF algorithm.

4.1. Analysis of the training effect of the evaluation model. To explore the teaching effect of the sports safety course in the mixed teaching mode, the teaching effect of the OAOMT mode integrated with MOOC is verified. The assessment model based on RF, the Random forest based on genetic algorithm (GA-RF) evaluation and the PSO-RF assessment model are compared and analyzed. Experimental data utilized for the research comes from the statistical data of 2500 students in the " University Physical Education" course in the initial semester of the 2017-2018 school year in a university. After preprocessing the data, 2000 pieces of data are used for model training. During the training process, the iteration times of the three models are shown in Figure 4.1.
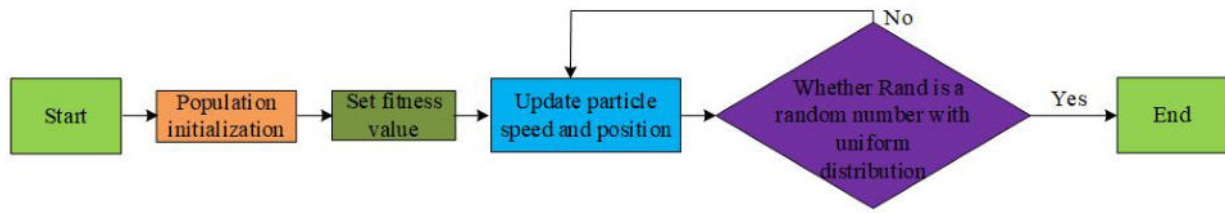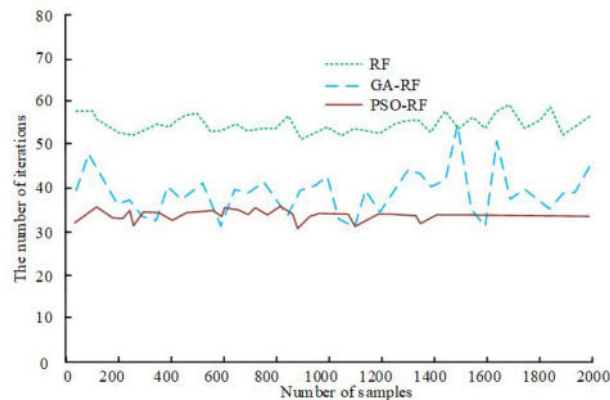
Fig. 3.4: PSO-RF algorithm flow

Fig. 4.1: Comparison of Iterations of Three Models

From Figure 4.1, the iteration numbers of the three models are significantly different. The RF model has undergone a significant number of iterations. The entire training process is unstable, and multiple maximum and minimum values appear. The maximum number of iterations is 60 when there are 1700 samples. The number of iterations is 52 when there are 900 samples. The average iteration is 55 times. The GA-RF model has a limited number of iterations. The rate of change is rapid, and performance stability is low. The minimal number of iterations is 32 when there are 1600 samples. The maximum iteration is 55 when there are 1500 samples. The range of iterations is 23 times, and the average number of iterations for the entire model is 42 times. The PSO-RF model has small fluctuations in the early stage of training. The number of iterations does not dramatically vary after there are 1400 samples. The average value is 34, and the convergence is good. Compared with the RF and the GA-RF, the average number of times of the PSO-RF model is 21 and 8 times lower respectively. The convergence is significantly better than the other two evaluation models. From the running results of the above model, the convergence of the improved RF model proposed in the study is significantly better than the other two methods. It has better performance in model training and can achieve convergence in fewer samples. The running time of the three models during training is shown in Figure 4.2.

From Figure 4.2, the running time of the three models diverge significantly. Specifically, the running time of the RF fluctuates greatly under different samples. The maximum running duration is 1.2s when there are 1400 samples. The minimal running time is 0.8s when there are 1500 samples. There are multiple maxima and minima throughout the test. The model performance is highly unstable. During the running process, the GA-RF model is more stable than the RF model. The running time is the smallest and the running efficiency is the best. When the number of samples is 1450, the maximum running time is 0.8s. The lowest running time is 0.56s when there are 1350 samples. The model performance is poor, with an average run time of 0.59s. The
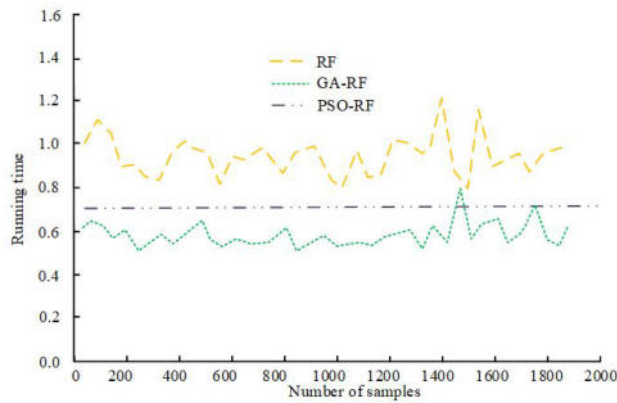
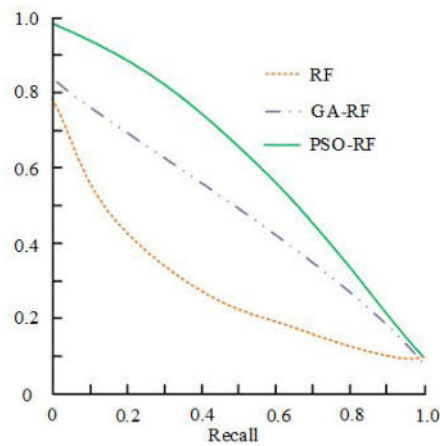Fig. 4.2: Running time comparison of three models

Fig. 4.3: PR comparison chart of three models

running time of the PSO-RF has no obvious fluctuation. The whole process is kept at about 0.7s. Compared with the RF model, the average running time of the PSO-RF model is 0.2s lower. Compared to the GA-RF, the average running time of the PSO-RF is slightly higher by 0.11s, but the stability of this model is completely better than that of the RF and the GA-RF.

4.2. Analysis of the PR effect of the evaluation model. To measure the capacity of each model, the evaluation results are evaluated by PR curves. The precision - recall (PR) curves of the three evaluation models are shown in Figure 4.3.

From Figure 4.3, when the recall rate approaches 0, the precision rate of RF is 0.78. The precision rate of GA-RF evaluation model is 0.82. The precision rate of PSO-RF model is 0.98. PSO-RF has a far greater accuracy than the other two assessment models. This indicates that the improved RF model has higher accuracy and recall rate. The performance of the model is better. Reflected in the evaluation of teaching effectiveness, the proposed model can more accurately evaluate students' learning effectiveness.

4.3. Analysis of the application effect of the evaluation model. The model proposed in the study is used to evaluate the actual teaching effectiveness. The actual scores of students are fitted with the evaluation scores. The results are shown in Figure 4.4.
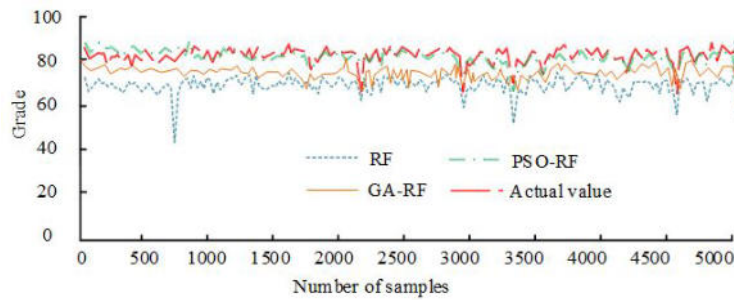
Fig. 4.4: Fitting of two models

Table 4.1: Student Performance Evaluation Results

	N	Min. Value	Max. Value	Mean Value	Standard Deviation
Online Learning	100	15	100	86.13	9.420
Online Discussion	100	35	100	91.24	5.093
Examination	100	50	99	92.35	7.573
Group Work	100	45	99	83.68	9.652
Classroom Performance	100	55	100	78.65	15.791
Total Score	100	58	97	82.74	7.106

In Figure 4.4 there is a large error between the student grades obtained by the RF evaluation model and the actual course grades. When the student sample is roughly between [5001000], the maximum error occurs. The score is only 45. The student achievement obtained under the model is significantly lower than the actual achievement. The extreme value of the GA-RF evaluation model changes slightly, but the grades obtained are slightly smaller than the actual grades. When the sample size of the PSO-RF model is small, the results are slightly higher than the actual results. However, as the sample size increases, the error between the evaluation results of the model and the actual results gradually decreases. From this analysis result, the optimized RF model proposed in the study has relatively small errors. During the entire evaluation period, it has a high degree of stability and accuracy, which can better reflect students' actual learning situation and achieve learning effects on sports safety courses. The performance of 5000 students who received combined physical teaching is rated. The statistical results are shown in Table 4.1.

From Table 4.1, under the OAOAMT mode, the highest score of students in online video learning of sports safety is 100 points, the lowest score is only 15 points, the average score is 86.13 points, and the standard deviation is 9.420. This indicates that students have a higher level of learning in online video courses. Online MOOC resources are more attractive to students. In the online discussion part, the highest score is 100 points, the standard deviation is 5.093, the lowest score is 35, the average is 91.24, and the lowest score is 35. The standard deviation of this learning content is the smallest and the learning level is the highest. The standard deviation of student classroom performance is 15.791, indicating a significant difference in academic performance. The polarization of students' classroom performance is evident, with some students having weaker classroom performance abilities. The standard deviation of the total student score is 7.106, indicating that there is a small difference in final grades among all students. The blended teaching mode that integrates MOOC can meet the real needs of various students. The accuracy rate of the trained evaluation model in student activism safety performance is shown Figure 4.5.

From Figure 4.5, the accuracy rates of the three models in the application process are quite different. The accuracy of the three evaluation models increases with the test sample. Among them, the RF model's accuracy
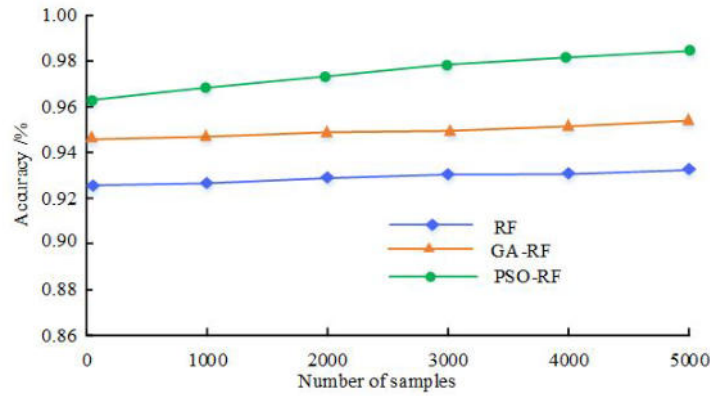
Fig. 4.5: Comparison of accuracy of three evaluation models in application
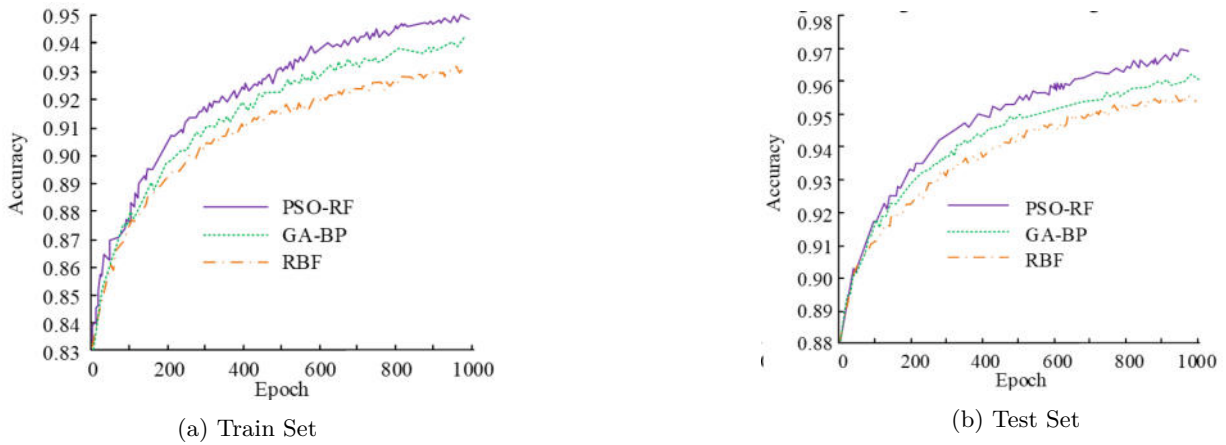

(a) Train Set

(b) Test Set

Fig. 4.6: Accuracy comparison of commonly used evaluation models

is 93.24%, and the GA-RF model is 95.19%. The PSO-RF model varies greatly. The accuracy in equilibrium state reaches 98.68%. Compared to the RF and GA-RF model, the PSO-RF model is greater 5.44% and 3.49%, respectively. The PSO-RF has a good application impact, which satisfies the assessment requirements of sports safety courses in the mixed teaching ways. It achieves a reasonable and objective evaluation of students' grades. In the intelligent evaluation of data, the commonly used K-means based radial basis function model (RBF), and genetic algorithm based optimization BP (GA-BP) are compared with PSO-RF model. The F1 values of the three models on the training and testing sets are shown in Figure 4.6. In Figure 4.6(a), on the training set, the accuracy of the PSO-RF model is 94.86%. The accuracy of the GA-BP and RBF models are 93.57% and 92.94%, respectively. In Figure 4.6(b), on the test set, the accuracy of the PSO-RF model reached 97.15%, which is higher than the GA-BP model and RBF model. This indicates that the evaluation model proposed in the study has significant advantages over similar methods.

5. Conclusion. Online education is in high demand due to the Internet's rapid development in the field of education. The OAOMT mode that integrates MOOC not only conforms to the development of teaching reform, but also can meet the shortcomings of sports safety education in physical education courses. Aiming at the mixed teaching mode of sports safety integrated with MOOC, an assessment methodology is constructed

for educational effects based on RF. However, the traditional RF has certain defects in the data processing process. Therefore, an assessment model based on PSPO algorithm is proposed to enhance the sports safety teaching effect assessment model. The outcomes of the trial indicate the average running time of the PSO-RF is only 0.7s. The accuracy rate reaches 0.98. the fitting degree between the assessment results and the actual results is basically consistent. The standard deviation of the total score for students is 7.106, which means that the difference in final grades for all students is very small. From the above analysis, the teaching effectiveness evaluation model based on improved RF proposed in the study has high accuracy and significantly outperforms other commonly used teaching effectiveness evaluation models. By using this evaluation method, students' grades can be objectively evaluated. Their learning situation and academic achievements in sports safety courses are well presented. From the application situation, the teaching effect of the online and offline sports safety mixed teaching mode that integrates MOOC is relatively ideal. This teaching mode can meet the actual needs of different students, which has high practical application performance. However, there are still shortcomings in the research. This model is only tested in physical education safety teaching in universities. In future research, the model should be tested in different educational and disciplinary fields to improve the applicability.

REFERENCES

[1] Chao, Y., Guo, X. & Wang, R. Exploration of Teaching and Education: Integration of Sports and Medicine in Physical Education in Colleges and Universities. *Journal Of Contemporary Education Research.* **6**, 63-67 (2022)

[2] Huang, C. The Current Situation and Improvement Strategy of Physical Education in Colleges and Universities. *Journal Of Contemporary Education Research.* **5**, 1-4 (2021)

[3] Lee, K., Won, Y. & Kim, S. The Effect of Sports Instructor's Safety Awareness and Safety Accident Prevention Activities on Sports Safety Culture. *Korean Journal Of Sports Science.* **28**, 49-59 (2019)

[4] Slater, L., Wasserman, E. & Hart, J. Trends in Recurrent Anterior Cruciate Ligament Injuries Differ from New Anterior Cruciate Ligament Injuries in College and High School Sports: 2009-2010 Through 2016-2017: Orthopedic Journal of Sports 2019. (0)

[5] Maat, S., Luppino, F., Schipper, I., Krijnen, P. & KA., B. Injury patterns after skiing and snowboarding sports accidents. *The Journal Of Sports Medicine And Physical Fitness.* **60**, 119-124 (2020)

[6] Bogue, K., Idriss, S., Sturkey, D. & Derouin, A. Improving youth sports safety: Implementing an emergency action plan for sudden cardiac arrest. *Journal Of Pediatric Nursing.* **59**, 81-88 (2021)

[7] Jani, M., Shahril, J., Muszali, M., Adnan, R. & Mai, S. Administrative Management Quality Standard and Teachers' Practices Compliance on School Sports Safety. *International Journal Of Academic Research In Progressive Education And Development.* **10**, 648-664 (2021)

[8] Sun, C., Li, J. & Gao, Q. Study on the Early Warning of Athletes' Safety in Sport Events Based on the "Fusion of Data and Intelligence". *Open Journal Of Social Sciences.* **9**, 299-304 (2021)

[9] Mai, S., Jani, J., Shahril, M., Muszali, R. & Context, B. Audit, and Index (CAI) Model Approach in Determining the Safety of Sports Infrastructure in Malaysia Schools. *IOSR Journal Of Sports And Physical Education.* **7**, 49-56 (2020)

[10] Brown, J., Hendricks, S., Lambert, M. & Van Mw, V. BokSmart rugby safety education courses are associated with improvements in behavioral determinants in attending coaches and referees: presurvey-postsurvey study. *Injury Prevention.* **27**, 363-368 (2021)

[11] Yang, X. Research on Integration Method of AI Teaching Resources Based on Learning Behavior Data Analysis. *International Journal Of Continuing Engineering Education And Life-Long Learning.* **30**, 492-508 (2020)

[12] Shu, H., Abudikesimu, X., Meng, H. & Chen, K. Evaluation on landslide susceptibility based on self-organizing feature map network and random forest model: A case study of Dayu County of Jiangxi Province. *The Chinese Journal Of Geological Hazard And Control.* **33**, 132-140 (2022)

[13] Liu, Y., Chen, H., Zhang, L. & Feng, Z. Enhancing building energy efficiency using a random forest model: A hybrid prediction approach. *Energy Reports.* **2021** pp. 7-5003 (2019)

[14] And, L. and Solutions of Art Professional Service Rural Revitalization Strategy Based on Random Forest Algorithm. *Wireless Communications And Mobile Computing.* **2022**, 1-11 (2022)

[15] Xu, N., Deng, F., Liu, B., Li, C., Fu, H., Yang, H. & Zhang, J. Changes in the Urban Surface Thermal Environment of a Chinese Coastal City Revealed by Downscaling MODIS LST with Random Forest Algorithm. *Journal Of Meteorological Recearch.* **35**, 759-774 (2021)

[16] Kim, G. & Gurvitch, R. The effect of Sports-based Physical Activity program on teachers' relatedness, stress and exercise motivation. *Health Education Journal.* **79**, 658-670 (2020)

[17] An, A. & Bpabc, D. Spatial landslide susceptibility assessment using machine learning techniques assisted by additional data created with generative adversarial networks. *Geoscience Frontiers.* **12**, 625-637 (2021)

[18] Papineni, S., Reddy, A., Yarlagadda, S. & Akkinen, H. An Extensive Analytical Approach on Human Resources using Random Forest Algorithm. *International Journal Of Engineering Trends And Technology.* **69**, 119-127 (2021)

[19] Xia, G., Chen, J., Tang, X., Zhao, L. & Sun, B. Shift quality optimization control of power shift transmission based on particle

swarm optimization–genetic algorithm. *Proceedings Of The Institution Of Mechanical Engineers*. pp. 872-892 (2022)

[20] Teer, B. Performance analysis of sports training based on random forest algorithm and infrared motion capture. *Journal Of Intelligent & Fuzzy Systems: Applications In Engineering And Technology*. **40**, 6853-6863 (2021)

[21] Alatawi, M., Alsubaie, N., Ullah, K., Sadad, T., Alwageed, H., Ali, S. & Zada, I. Cyber Security against Intrusion Detection Using Ensemble-Based Approaches. *Security And Communication Networks*. **2023** pp. 2023

[22] Arbogast Kristy B, M. Sport Safety for Adolescents: Linking Biomechanics of Repetitive Head Impacts With Health and Wellbeing. *The Journal Of Adolescent Health: Official Publication Of The Society For Adolescent Medicine*. **72**, 2023

[23] Donnelly Peter, K. Contesting the autonomy of sport to realize the right to safe sport: a Canadian case study. *The International Sports Law Journal*. **22**, 2022

[24] Sae Hyung Kim, H. Development of physical education safety awareness scale for middle school students using multi-facets Rasch model and group classification through latent profile analysis. *Korean Journal Of Sports Science*. **29**, 2020

[25] Wang Yan, Z. Wei,Ge Ziyang,Wang Junliang,Xu Haoyu,Jiang Chao. Pressure sensing recognition of FBG array based on random forest algorithm. *Optoelectronics Letters*. **19**, 2023