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Research on students' physical fitness evaluation based on improved K-means and decision tree algorithm

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ABSTRACT
Introduction: The physical health of students is an indispensable part of the education system. Objectives: The existing methods for evaluating physical fitness and health lack sufficient analysis of test data. Methods: Therefore, the study proposed an improved student physical health evaluation algorithm using K-means and decision tree algorithms. The initial cluster center of K-means was determined using cuckoo optimization, and the median distance of data points was used instead of the mean. The minimum Gini coefficient was used as the optimal binary value for the decision tree algorithm. Results: Experiments showed that the root mean square error of each item in the improved K-means algorithm was on average 0.056 lower than that of the fuzzy C-means algorithm. The recall rate and F1 value were on average 0.084 and 0.093 higher, respectively. The accuracy of clustering analysis was 3.3% and 5.1% higher than that of the FC-MC algorithm and SC algorithm, respectively. The decision tree algorithm approached convergence after 200 iterations, with the maximum values being 1.4%, 6.3%, and 13.5% higher than other algorithms. In the randomly selected class, the contribution of male students' sitting forward bending, long-distance running, and pull-up projects to the total score was relatively low and need to be prioritized for improvement. Conclusion: From this, the proposed physical health evaluation method can effectively minimize the impact of extreme value data on the calculation outcomes, raise the accuracy of clustering analysis and evaluation, and accurately determine the overall and individual physical weakness items of the class.

Keywords: K-means, CART decision tree, Physical health assessment, Cuckoo optimization, Data optimization.

1. Introduction

The state has been monitoring the physical health of college students for a long time, more than 30 years now. As shown by the data on changes in physical fitness and health published by the Ministry of Education, the physical fitness of students has been declining, and they have little interest in physical

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exercise and insufficient awareness of exercise, especially the explosive strength, endurance, speed and flexibility of college students are not optimistic [1-3]. Because of this, the obesity rate of college students is on the rise [4]. Although most colleges and universities regularly conduct physical fitness tests for college students, they do not engage in daily physical exercise to improve their physical fitness through daily physical activities [5-7]. In addition, judging from this year's physical fitness test, most students do not pay enough attention to the physical fitness test. In the face of this situation, China has strengthened the targeted reform efforts of college sports, starting from analyzing the evaluation indexes affecting college students' physical fitness and health, and proposing specific teaching reform programs for the problems existing in the current college sports teaching [8-10].

In order to improve the physical health level of Chinese college students, the requirements for college students' physical health were promulgated at an early stage [11]. The test items of the physical fitness standard for students in higher education still retained the original height, weight, lung capacity, 800/1000m, 50m, sit-up/pull-up, seated body flexion, and standing long jump, but the scoring criteria were adjusted [12-15]. At the same time, a bonus point system for strength and endurance events was implemented to encourage students to develop strength and endurance qualities [16-17]. This seemingly simple reform, in the real situation of testing a large number of students, makes the original monotonous, cumbersome, heavy workload, and error-prone students' physical fitness checklist assessment work more difficult [18-20]. For this reason, the use of big data technology to design a template program for students' physical health evaluation and realize the automatic evaluation of large quantities of students' physical health can not only reduce the work intensity of the teachers and improve the work efficiency, but also reduce the errors caused by the manual form checking and evaluation, and improve the accuracy of students' physical health evaluation [21-25].

Hence, this study introduces an enhanced evaluation approach for student physical health, leveraging the K-means and Decision Tree (DT) algorithms. Innovatively, it employs Cuckoo Optimization to determine the initial cluster center for K-means, utilizing the median distance of data points (rather than the mean), and selects the minimum Gini coefficient as the optimal split criterion for the DT algorithm. The research aimed to raise the accuracy of data analysis and health evaluation, and provide guidance for students' physical exercise.

2. Methodology

Optimization of Student Physical Health Data Grounded on Improved K-means

The aim of evaluating student physical health is to assist students in gaining insight into their physical wellbeing, boosting their enthusiasm for engaging in physical activity, and elevating their fitness levels. Furthermore, it aims to foster well-rounded individuals who excel in moral, intellectual, and athletic development. At present, schools usually set up multiple physical fitness tests including height and weight, lung capacity, 1000 meters, pull-up, and standing long jump to test students' health status. However, due to errors in the testing equipment or differences in the referee's level, the measured data may have significant errors. These errors can easily cause significant interference to the experimental results in subsequent physical health evaluations, so data optimization is needed. The study used the K-means to optimize the data. The K-means divides the data samples into clusters with the same amount of results based on the amount of classifications of the target results, and selects the mean value of data points within each cluster to represent the cluster center. The optimization process for student physical health data using the enhanced K-means involves continuously iterating and updating the cluster centers. This process continues until the positions of the cluster centers remain unchanged or the maximum number of iterations is reached, as illustrated in Figure 1.

In Figure 1, when performing initial cluster selection, data with similar physical fitness scores are grouped based on different test attributes instead of random selection. Based on each initial cluster, the mean of all data points in each cluster is calculated, and in continuous iterations, the algorithm assigns each data point to the nearest cluster center. After all data points are allocated, the mean of all data points in each cluster is recalculated and a new cluster center is selected. The above steps should be repeated until the position of the cluster center changes very little or the max amount of iterations is reached. The mean distance between all data points in the cluster and the cluster center is calculated. Data points with distances less than the mean distance from the cluster center are retained, otherwise the data is removed. To address the issue of K-means algorithm being prone to getting stuck in local optima and improve computational speed, the research studied the use of weighted Euclidean distance, contour coefficient, and cuckoo optimization algorithm to raise the K-means. The weighted Euclidean distance calculation is shown in equation (1).

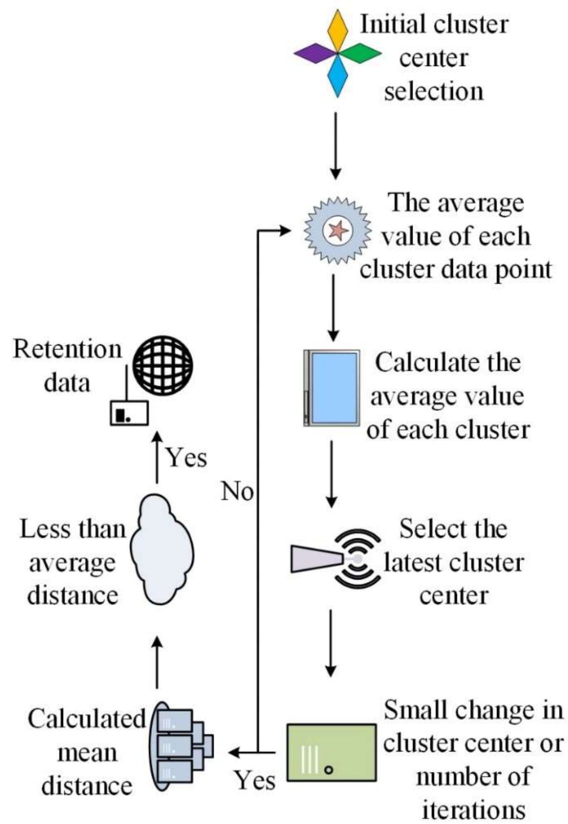

Fig. 1. The Improvement of Student Physical Health Data Optimization with K-means

$$d\left(x_i,x_j\right)=\sqrt{\sum_{i\neq j}^{n}M\left(x_i-x_j\right)^2} \tag{1}$$

In equation (1), $d\left(x_i,x_j\right)$ represents the weighted Euclidean distance calculated based on sample similarity, n means the total amount of samples in the dataset, M n the weighted similarity weight, x_i n the sample set of cluster i, and x_j represents the sample set of cluster j. The K-means usually uses the sum of squared errors as the iteration completion condition, but usually only considers the distance between data points within the cluster, without taking into account the distance between data points between clusters. Therefore, the introduction of contour coefficients in the K-means is studied to effectively demonstrate the similarity of data within clusters and the differences between data between clusters. At the same time, the median distance of data points is used instead of the mean to reduce the impact of extreme value data calculation results. The median distance between data points within and outside the cluster is calculated as denoted in equation (2).

$$\begin{cases} d_1 = med\left[d\left(x_i, x_j\right)\right] \\ d_2 = \min\left[med\left[d\left(x_i, x_j\right)\right]\right] \end{cases} \tag{2}$$

In equation (2), d_1 represents the median distance between data points within the cluster, and d_2 represents the minimum median distance between data points within the cluster and all data points in other clusters. The contour coefficient calculated using the median is shown in equation (3).

$$s = \frac{d_2 - d_1}{\max\left(d_1, d_2\right)} \tag{3}$$

In equation (3), s represents the contour coefficient, and $\max\left(d_1, d_2\right)$ represents taking the maximum value among them. The feature selection of the enhanced K-means grounded on cuckoo optimization algorithm is shown in Figure 2.

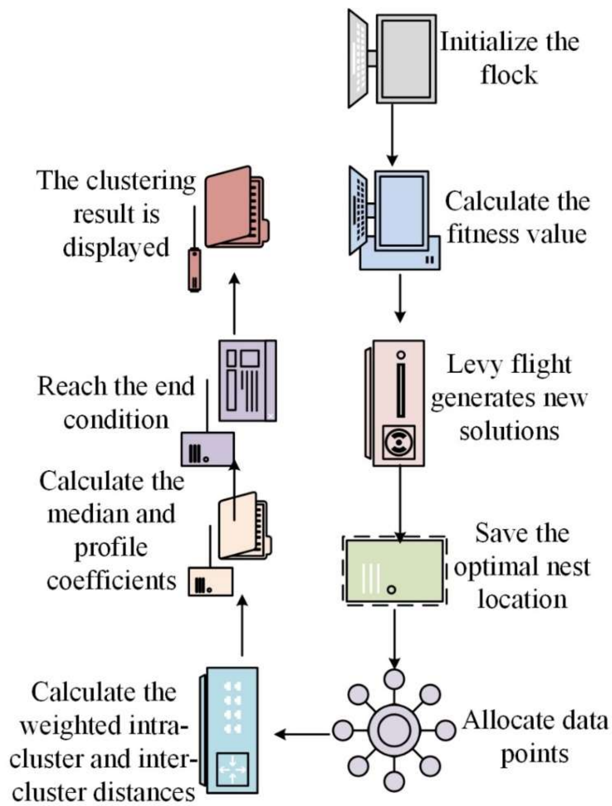

Fig. 2. Feature Selection of K-means with Cuckoo Optimization

In Figure 2, the bird flock is initialized, with the fitness function and maximum iteration count established. A nest is then randomly chosen, and its fitness value is computed. Following this, a new solution is generated using the Levy flight method, and its fitness value is also calculated. If the fitness value of the new solution is greater than that of the bird's nest, the new solution will be used instead of the old solution, and the optimal bird's nest position will be saved after multiple iterations. The initial cluster center is selected based on the optimal bird's nest position, that is, the optimal features, and allocate grounded on the distance between the data points and the cluster center. The weighted intra cluster distance and inter cluster distance will be calculated, then the median distance and silhouette coefficient of data points within and outside the cluster will be calculated. When the change in cluster center position is almost negligible or reaches the max amount of iterations, the clustering and output the clustering result will be completed. Before calculation, it is necessary to standardize the data so that data from different units can be compared with each other. Research is being conducted on using deviation standardization to process the data. Deviation standardization maps the range of raw data to between [0,1] through linear variation, as shown in equation (4).

$$x_m = \frac{x_n - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

In equation (4), x_m represents the data after the change, x_n means the data before the change, $x_{\min}$ means the mini value of the data before the change, and $x_{\max}$ represents the max value of the data before the change. The comparison of physical health test data before and after standardization is indicated in Table 1.

Table 1. Physical Health Test Data before and after Standardized Treatment

Test Data	50m (s)	1000m (s)	Vital capacity (mL)	Standing long jump (cm)	Pull-ups (each)	Sit in a forward bend (cm)	Lv
Initial data	8.9	237	3854	219	8	-16	Good
	9.5	234	3632	212	9	9	Up to standard
	10.3	252	3574	205	6	6	Below standard
Standardized data	0	0.1875	1	1	0.6667	0	Good
	0.4286	0	0.2071	0.5	1	1	Up to standard
	1	1	0	0	0	0.88	Below standard

Overall Evaluation of Students' Physical Health with Decision Tree Algorithm

After optimizing the student test data, the DT algorithm has been broadly utilized in areas such as data mining due to its simplicity, intuitiveness, ease of understanding, and ability to handle various types of data. The study used the Classification and Regression Tree (CART) algorithm to evaluate the physical health of the entire student population in the school, and analyzed the impact of each test item on the evaluation of student health levels. When using the CART DT algorithm to classify data after K-means clustering, there are a total of K items in the processed dataset based on the type of test item. The Gini coefficient of the probability distribution of a certain data belonging to the k item in the dataset is calculated as shown in equation (5).

$$Gini(p_k) = \sum_{k=1}^{k} p_k(1-p_k) \tag{5}$$

In equation (5), $Gini(p_k)$ represents the Gini coefficient of the probability distribution of item k, and p_k represents the probability that a certain data belongs to item k. The Gini coefficient calculation of the standardized dataset is denoted in equation (6).

$$Gini(X) = 1 - \sum_{k=1}^{k}\left(\frac{|C_k|}{|X|}\right)^2 \tag{6}$$

In equation (6), X represents the processed dataset, and C_k represents a subset belonging to item k in dataset X. Dataset X is divided into two parts, X_1 and X_2, based on the value of a certain item k'. The Gini coefficient of dataset X in item k' is calculated as shown in equation (7).

$$Gain\_Gini(X,k') = \frac{|X_1|}{|X|}Gini(X_1) + \frac{|X_2|}{|X|}Gini(X_2) \tag{7}$$

Any attribute value in each item of dataset X is calculated, the dataset is broken into two parts, and the smallest attribute value is selected as the optimal binary value. In the CART DT algorithm, discretization is also required to convert continuous features into discrete features, so that effective splitting can be performed when constructing the DT. Firstly, the values of continuous features are arranged in order of size, and the adjacent elements before and after the continuous feature are averaged. The processed values are used as discrete features, and the discrete features are shown in equation (8).

$$Q_i = \frac{(q_i + q_{i+1})}{2} \tag{8}$$

In equation (8), Q_i represents the binary classification point of the continuous feature, and q_i represents the i-th value in the continuous feature. When evaluating physical fitness and health, the CART DT algorithm performs better for integer order pull-up results than data such as "8.47 seconds for 50 meters". Meanwhile, ordinary CART DT algorithms can only evaluate students' physical health levels based on the calculated total score, and cannot demonstrate the degree of influence of different test items on health levels. Therefore, the study optimized the discretization process of the algorithm, and the optimized continuous feature binary classification point calculation is shown in equation (9).

$$Q_{qi} = \frac{qc_i}{qc_i + bc_i + \ldots + zc_i} \tag{9}$$

In equation (9), Q_{qi} represents the binary classification points of the optimized continuous features, qc_i represents the weighted conversion score of item q, bc_i represents the weighted conversion score of item b, and zc_i represents the weighted conversion score of item z. The operation process of the DT algorithm for student physical health evaluation is denoted in Figure 3.

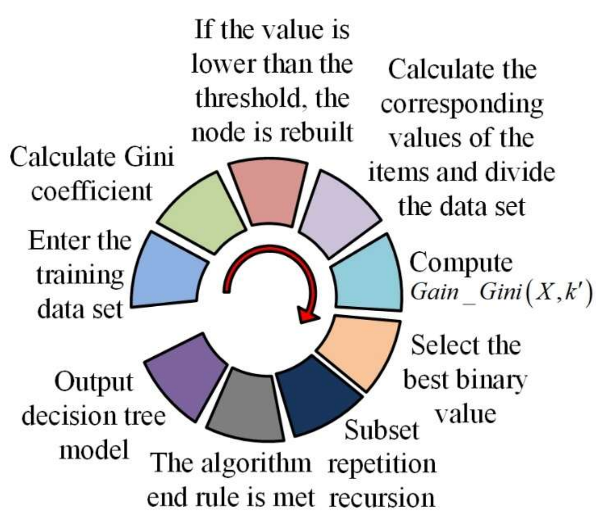

Fig. 3. Operation Flow of Decision Tree Algorithm for Students' Physical Health Evaluation

In Figure 3, the termination condition for the algorithm is when the input dataset either contains 0 features or the total number of data points falls below the specified threshold. The training dataset is input, the Gini coefficient of the dataset is calculated, and if the Gini coefficient is less than the threshold, the decision branch of the node will be rebuilt. The values corresponding to all items in the dataset will be calculated, all values are divided into two parts, and the value of $Gain\_Gini(X,k')$ will be calculated according to equation (7). The minimum Gini coefficient is selected as the optimal binary value among all the values corresponding to each item. The dataset is broken into two parts based on the best binary score, the above steps should be recursively repeated until the algorithm interpretation rules are met, and the DT model is output. According to the above algorithm, the designed individual health assessment of students and the overall health assessment of the class are shown in Figure 4.

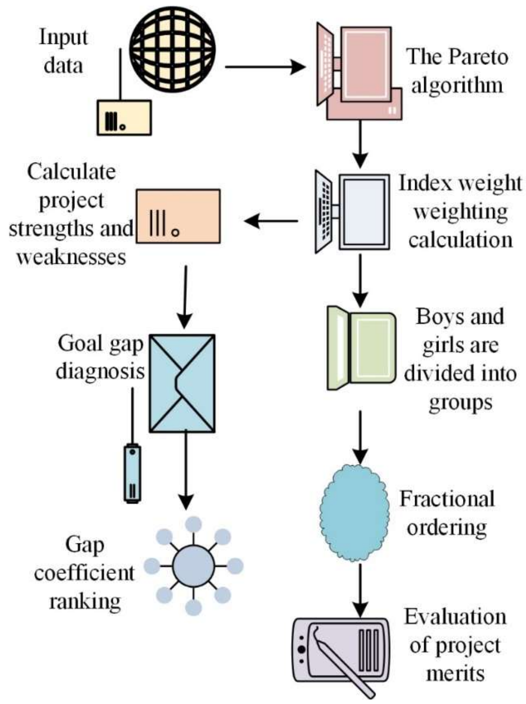

Fig. 4. Individual Student Health Evaluation and Class Overall Health Evaluation Process

In Figure 4, the overall health evaluation of the class uses the Pareto algorithm to calculate the contribution of the total score of each test item to the class rating. The class rating is divided into male and female groups and calculated separately. The test scores are weighted using weight indicators. Using the Pareto algorithm for score sorting, items ranked at the bottom 0.3 are considered unqualified. In the individual health evaluation of students, the advantage items are scored by adding the standard deviation to the mean score of each indicator. Conversely, the disadvantage items are scored by subtracting the standard deviation from the mean score of each indicator. Then, the target gap diagnosis algorithm is used to calculate the scores of each item, such as the target gap. The priority category for improvement is determined based on the ranking of the gap coefficient.

3. Results

Analysis of Optimization Results of Student Physical Health Data with Improved K-means

The study analyzed the physical examination data of a university from freshman to senior year in 2022, with a total of 12432 students participating in the test, including 7436 males and 4996 females. The test items included height, weight, 50 meters, 1000 meters, or 800 meters, lung capacity, standing long jump, pull up, and sitting forward bend. The comparative data clustering methods used in the study are Fuzzy C-Means Clustering (FC-MC) and Spectral Clustering (SC). The clustering analysis results of college students' physical health data are shown in Table 2.

Table 2. Results of Cluster Analysis of Students' Physical Health Data

Test item	K-means	FC-MC	F	P

	RMSE	Recall	F1	RMSE	Recall	F1		
Height	0.16	0.84	0.92	0.22	0.76	0.80	104.18	0
Weight	0.14	0.86	0.89	0.25	0.74	0.76	274.30	0
50m	0.21	0.82	0.87	0.23	0.75	0.77	125.62	0
Long-distance running	0.25	0.85	0.90	0.32	0.77	0.82	306.51	0.02
Spirometry	0.15	0.83	0.86	0.18	0.76	0.79	219.32	0
Broad jump	0.16	0.88	0.91	0.26	0.80	0.83	198.68	0
Chin-up	0.18	0.92	0.95	0.19	0.83	0.86	327.62	0.03
Sit-up-and-bend	0.19	0.84	0.88	0.24	0.76	0.81	64.35	0

In Table 1, the significance P values of each item were all less than 0.05, indicating that the statistical results of cluster analysis were significant and had significant differences. According to the F value, the importance of the test items on cluster analysis could be determined. The larger the F value, the more important it was for cluster analysis. The three most important items were pull-up, long-distance running, and body weight, while the least important item was sitting and bending forward. In different test project data, the root mean square error of K-means algorithm was lower than that of FC-MC algorithm, with an average decrease of 0.056. The recall rate and F1 value of K-means algorithm were superior to FC-MC algorithm, with an average recall rate 0.084 higher and an average F1 value 0.093 higher. The accuracy comparison of clustering analysis using different algorithms is denoted in Figure 5.

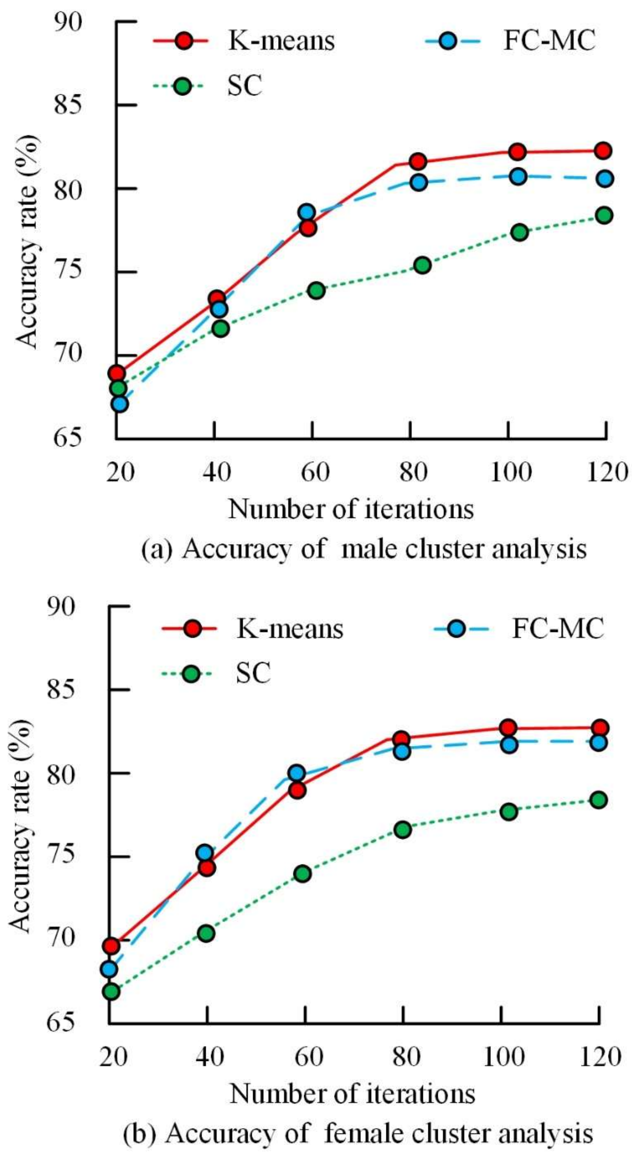

Fig. 5. Comparison of Data Clustering Analysis Accuracy of Different Algorithms

In Figure 5 (a), the clustering analysis accuracy of K-means grew slightly slower than FC-MC algorithm in the early stage, but the maximum accuracy value was 83.4%, which was 3.3% and 5.1% higher than FC-MC algorithm and SC algorithm, respectively. Because using the median instead of the mean when calculating distance could minimize the influence of extreme data on the calculation outcomes and raise the accuracy of clustering analysis. In Figure 5 (b), the trend of accuracy changes in clustering analysis of the three algorithms was basically the same as that in Figure 5 (a). The K-means algorithm accelerated its growth rate in the first 80 iterations, and the maximum value increased slightly. The maximum clustering analysis accuracy of K-means algorithm was 84.6%, which was 1.2% and 7.8% higher than the other two algorithms, respectively, because the test data of the female group were more evenly distributed.

Analysis of Student Physical Health Evaluation Results Grounded on Decision Tree Algorithm

After constructing the DT model, the study divided the test data of male and female students into training set, validation set, and testing set in a ratio of 7:2:1. The comparative algorithms selected for the experiment included Iterative Dictatorship 3 (ID3), eXtreme Gradient Boosting (XGBoost), and Chi-Square Automatic Interaction Detector (CHAID). The prediction accuracy comparison of different algorithms is shown in Figure 6.

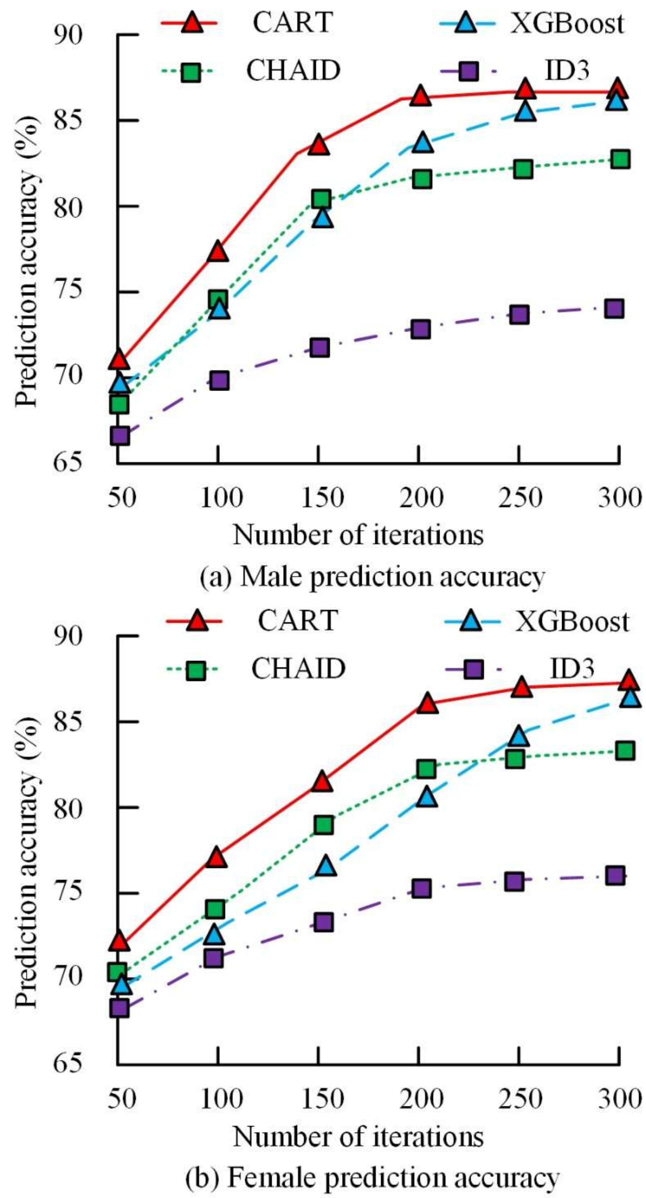

Fig. 6. Comparison of Prediction Accuracy of Different Algorithms

In Figure 6 (a), the prediction accuracy of each algorithm gradually increased with the increase of iteration times. The CART DT algorithm approached convergence at 200 iterations, with a maximum value of 86.7%, which was 1.4%, 6.3%, and 13.5% higher than XGBoost, CHAID, and ID3 algorithms, respectively. The difference in maximum values between CART and XGBoost was small, but required fewer iterations, effectively improving computational efficiency. In Figure 6 (b), the maximum value of CART DT algorithm was 87.2%, which was 0.9%, 4.2%, and 13.1% higher than XGBoost, CHAID, and ID3 algorithms, respectively. The impact of different algorithm DT depths on prediction accuracy is shown in Figure 7.

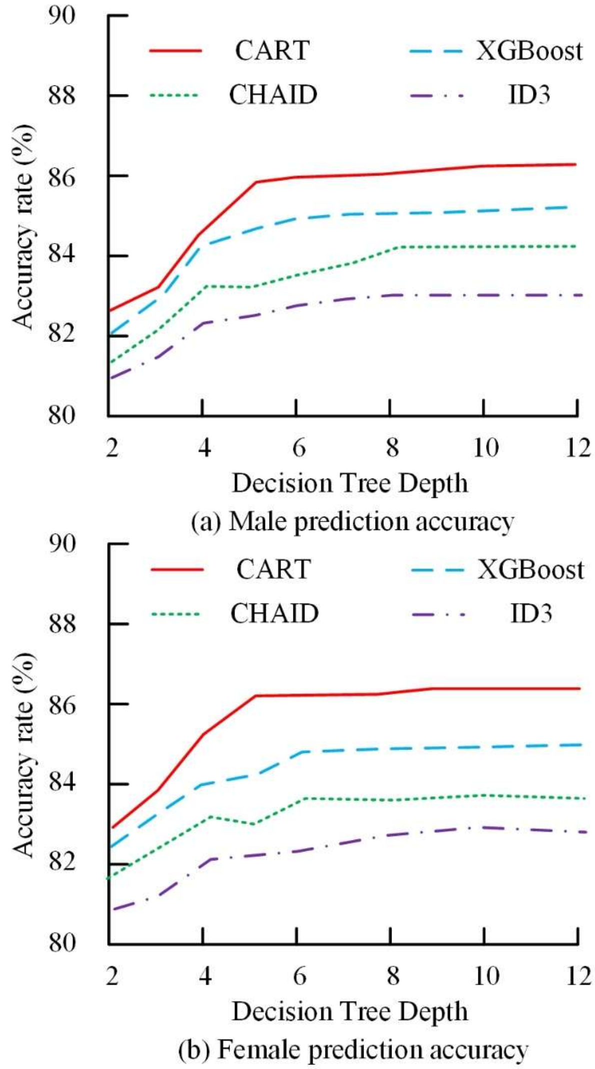

Fig. 7. Influence of Different Decision Tree Depth on Prediction Accuracy

In Figure 7 (a), the prediction accuracy of CART increased the fastest when the tree depth was 2-5. After the tree depth was 5, the prediction accuracy remained basically unchanged because the algorithm overfitted, which reduced the performance of the DT. When the tree depth was 5, CART's prediction accuracy was higher than other algorithms by 1.5%, 3.4%, and 3.8%, respectively. In Figure 7 (b), the changing trends of each algorithm were basically the same. When the tree depth was 5, CART's prediction accuracy was 2.4%, 3.2%, and 4.1% higher than other algorithms, respectively. The overall and individual physical health scores of the class are shown in Figure 8.

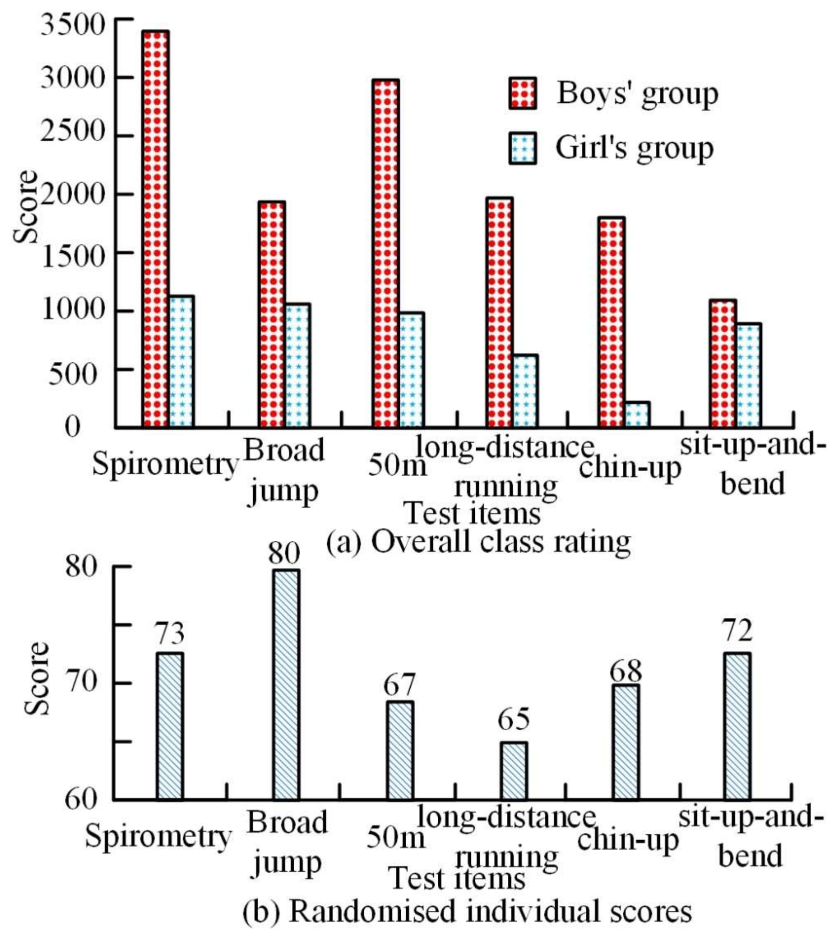

Fig. 8. Overall Physical Health Scores of the Class and Individuals

In Figure 8 (a), there were 49 boys and 15 girls in the randomly selected class. After calculating the total score of the class, the project scores were sorted. It can be seen that in the male group, the sitting and forward bending project had the lowest contribution to the total score of the class and was a disadvantaged project. Other projects such as long-distance running and pull-up also had relatively low scores and needed to be improved first. In the female group, the pull up project had the lowest contribution to the total score of the class, and the long-distance running project also ranked last in terms of score. In Figure 8 (b), the student's weaknesses were 50m, long-distance running, and pull-up, all of which did not reach the passing line. Their strengths were sitting forward bending, and they should prioritize exercising their body strength and endurance. The total score was 70, which meant they had just reached the passing line and need to strengthen their exercise.

4. Conclusion

Regarding the existing methods for evaluating students' physical health, there are issues such as insufficient data mining depth, inaccurate data analysis and evaluation results. The study proposed an improved method for evaluating students' physical fitness and health using K-means and DT algorithms. The experiment outcomes showed that the root mean square error of each item using the improved K-means clustering analysis was lower than that of the FC-MC algorithm, with an average decrease of 0.056. The recall rate and F1 value were on average 0.084 and 0.093 higher, respectively. The P values of each item were all less than 0.05, indicating that the statistical results of cluster analysis were significant. According to the F value, the three items with the highest importance for health evaluation were pull-up, long-distance running, and weight. The maximum accuracy of K-means algorithm in clustering analysis was 83.4%, which was 3.3% and 5.1% higher than FC-MC algorithm and SC algorithm respectively. Using median instead of mean could minimize the impact of extreme data on the calculation outcomes and raise the accuracy of clustering analysis. The CART DT algorithm approached convergence after 200 iterations, with maximum values 1.4%, 6.3%, and 13.5% higher than XGBoost, CHAID, and ID3 algorithms, respectively. CART had the best predictive performance when the DT depth was 5. Continuing to increase the tree depth would not only increase the model complexity, but might also lead to overfitting and reduce algorithm performance. In the randomly selected classes, the contribution of boys' sitting forward bending, long-distance running, and pull up events to the total score was relatively low and needed to be prioritized for improvement, while girls' pull up and long-distance running needed to be prioritized for improvement. There were still some issues with this study, as it chose science and engineering colleges with a higher number of male students. In the future, different regions and categories of schools can be added to establish a comprehensive evaluation model and improve its generalization performance.

References

[1] Manchester, R. (2020). How has the health of college students changed in the last 50 years?. Journal of American College Health, 68(8), 795-797.

[2] Downes, L. (2015). Physical activity and dietary habits of college students. The Journal for Nurse Practitioners, 11(2), 192-198.

[3] O'Brien, M. W., Shivgulam, M. E., Wojcik, W. R., Barron, B. A., Seaman, R. E., & Fowles, J. R. (2022). 30 year trends of reduced physical fitness in undergraduate students studying human movement. International Journal of Environmental Research and Public Health, 19(21), 14099.

[4] de Vos, P., Hanck, C., Neisingh, M., Prak, D., Groen, H., & Faas, M. M. (2015). Weight gain in freshman college students and perceived health. Preventive medicine reports, 2, 229-234.

[5] Calamidas, E. G., & Crowell, T. L. (2018). A content analysis of college students' health behaviors. American Journal of Health Education, 49(3), 133-146.

[6] Kim, M. Y., & Kim, Y. J. (2018). What causes health promotion behaviors in college students?. The Open Nursing Journal, 12, 106.

[7] Prontenko, K., Griban, G. P., Dovgan, N., Loiko, O., Andreychuk, V., Tkachenko, P., ... & Bloshchynskyi, I. (2019). Students' health and its interrelation with physical fitness level. Sport Mont. International Scientifi c Journal, (17 (3)), 41-46.

[8] Wang, J., Xie, Z., Li, Y., Song, Y., Yan, J., Bai, W., ... & Qin, J. (2020). Relationship between health status and physical fitness of college students from south china: An empirical study by data mining approach. IEEE access, 8, 67466-67473.

[9] Gula, L. P. (2024). Health and skill-related physical fitness tests: An assessment in determining the students' physical fitness level. Retos: nuevas tendencias en educación física, deporte y recreación, (58), 1014-1021.

[10] Meng, X., Horrell, A., McMillan, P., & Chai, G. (2021). 'Health First'and curriculum reform in China: The experiences of physical education teachers in one city. European Physical Education Review, 27(3), 595-612.

[11] Zhang, C., Liu, Y., Xu, S., Sum, R. K. W., Ma, R., Zhong, P., ... & Li, M. (2022). Exploring the level of physical fitness on physical activity and physical literacy among Chinese university students: a cross-sectional study. Frontiers in psychology, 13, 833461.

[12] Calestine, J., Bopp, M., Bopp, C. M., & Papalia, Z. (2017). College student work habits are related to physical activity and fitness. International journal of exercise science, 10(7), 1009.

[13] Han, S. S., Li, B., Wang, G. X., Ke, Y. Z., Meng, S. Q., Li, Y. X., ... & Tong, W. X. (2022). Physical fitness, exercise behaviors, and sense of self-efficacy among college students: a descriptive correlational study. Frontiers in Psychology, 13, 932014.

[14] Zhamardiy, V. O., Donchenko, V. I., Yemets, A. V., & Skrinnik, Y. O. (2019). Physical development by means of fitness technologies as one of general aspects of student's health. Wiadomości Lekarskie, 72(5), 1074-1078.

[15] Jessop, D. C., Reid, M., & Solomon, L. (2020). Financial concern predicts deteriorations in mental and physical health among university students. Psychology & health, 35(2), 196-209.

[16] Prontenko, K., Griban, G. P., Aloshyna, A., Bezpalyi, S., Yavorska, T., Hryshchuk, S., ... & Bloshchynskyi, I. (2019). The physical development and functional state as the important components of the students' health. Wiadomości Lekarskie, (12 (1)), 2348-2353.

[17] Guo, Q., & Li, B. (2021). Role of AI physical education based on application of functional sports training. Journal of Intelligent & Fuzzy Systems, 40(2), 3337-3345.

[18] Yan, W., Nie, M., Ma, R., Guo, Q., & Li, H. (2024). The influence of physical literacy of student with different obesity levels on physical fitness: the mediating effect of MVPA. Frontiers in public health, 12, 1463108.

[19] Büyükvesek, E., & Shahidi, S. H. (2024). Cross-Faculty Analysis of Physical Fitness and Health Metrics among Turkish University Students. International Journal of Physical Education, Fitness and Sports, 13(3), 22-33.

[20] Xiangli, F., & Xiujun, H. (2024). Multimodal sensing and decision-making for evaluating the physical fitness of university students using body area network. Wireless Networks, 30(3), 1465-1478.

[21] Li, H. C., & Shen, S. F. (2021). Construction of college students' physical health data sharing system based on django framework. Journal of Sensors, 2021(1), 3859351.

[22] Xue, B., & Liu, T. (2018). Physical health data mining of college students based on DRF algorithm. Wireless Personal Communications, 102, 3791-3801.

[23] Wang, J., Wu, B., Jiang, Y., & Yuan, Y. (2022). Research on prediction of physical fitness test results in colleges and universities based on deep learning. Mathematical problems in engineering, 2022(1), 6758684.

[24] Tang, P., Wang, Y., & Shen, N. (2020). Prediction of college students' physical fitness based on K-means clustering and SVR. Computer Systems Science and Engineering, 35(4), 237-246.

[25] Suo, J., Guo, C., & Wang, G. (2022). Analysis of physical test indexes of college students based on data mining model. Mathematical Problems in Engineering, 2022(1), 7393986.