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Molecular & Cellular Biomechanics 2025, 22(1), 712.
https://doi.org/10.62617/mcb712

Article

Student physical education teaching achievement test incorporating biomechanics analysis via decision tree algorithm

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CITATION

Zhao N, Wang L, Sun H. Student physical education teaching achievement test incorporating biomechanics analysis via decision tree algorithm. Molecular & Cellular Biomechanics. 2025; 22(1): 712. https://doi.org/10.62617/mcb712

ARTICLE INFO

Received: 4 November 2024
Accepted: 29 November 2024
Available online: 15 January 2025

Abstract: In the context of China's economic growth, building a "sports power" is crucial. With the Internet's development, the nation focuses on physical education curriculum and students' test results. Currently, Chinese students' physical education achievements are mainly evaluated by storage, inquiry, and basic statistics. Digital mining is under - utilized, leaving much data unexplored. But digital education's progress has brought educational data to the fore, enabling schools to find value and patterns for better teaching decisions. In this case, this paper delves into the integration of biomechanics analysis into the assessment of student physical education teaching achievements. Biomechanics offers invaluable insights into the mechanical aspects of human movement during physical activities. By examining biomechanical factors such as joint angles, muscle forces, and movement velocities during various sports, a more profound understanding of students' physical capabilities and performance can be achieved. Taking the physical test results of students in a specific school as a case study, this research employs data mining technology to explore the rich dataset. The optimized decision tree algorithm is then utilized to analyze the biomechanics - related data. This algorithm enables the identification of key factors that influence students' physical test outcomes. For instance, it can pinpoint how a student's running gait mechanics, including stride length, frequency, and leg - muscle activation patterns, affect their performance in track - and - field events. Through this comprehensive approach, the paper not only aims to uncover hidden information within the physical test data but also to elucidate the intricate interplay between biomechanics and students' overall physical education performance. By dissecting the factors that influence physical test results from a biomechanical perspective, this study provides actionable insights for enhancing physical education teaching methods. Educators can leverage these findings to design personalized teaching programs that cater to the unique biomechanical characteristics of each student, thereby optimizing the effectiveness of physical education and promoting students' physical development and athletic performance.

Keywords: decision tree algorithm; students; physical achievement tests; biomechanics analysis

1. Introduction

In recent years, China's youth sports test results have been in a state of decline, in 2021, the relevant personnel to do research on this phenomenon, the results show that students' sports test results in physical fitness, lung capacity, endurance, speed, strength and other aspects have decreased year by year, at the same time, students overweight and obesity phenomenon continues to increase [1]. There are many social and educational factors behind this phenomenon. First of all, with the progress of modernization, great changes have taken place in the lifestyle of teenagers. The excessive emphasis on academic achievement has resulted in students devoting a lot of time to schoolwork, and the time and opportunities for sports activities have been greatly reduced. The high expectations of families and society for academic achievement mean that physical education is often neglected, especially in rapidly urbanizing areas.

Structural problems in the education system are also important reasons for this phenomenon. Although the state has put forward policies to enhance the physical health of adolescents in recent years, physical education still does not receive enough attention and resources in many schools, especially in rural areas. The lack of physical education courses, facilities and teachers makes it impossible for many students to enjoy high-quality physical education. This phenomenon not only affects the physical health of students, but also has a negative impact on the long-term development of national sports. Young people are the foundation of future sports competition, lack of good sports quality will directly restrict the competitiveness of the country in international sports events, and even affect the overall health level of the society.

In 2006, for the first time, China held a meeting on sports matters, and put forward suggestions on sports for young students at the meeting: "To carry out quality education should not only pay attention to the cultivation of students' performance, morality, but also to cultivate students' strong body and healthy body and mind", at the same time, it also emphasized that the physical health of teenagers is related to the future of the country, under the guidance of the education policy, strict attention should be paid to the physical education of teenagers, and the comprehensive implementation and implementation of quality education. The State Council also explained the phenomenon of the decline in the health of the youth system, pointing out that the future of the country and the development of the nation need the health of the youth, and advocated that governments at all levels and relevant units need to support and pay attention to the physical education of the school to improve the physical health of the youth. For the current youth sports test results decline this common phenomenon, it is impossible to carry on a detailed analysis of the reasons, mainly because the way of its performance test can not fully reflect the specific results of students, so as to find out where the problem.

With the continuous promotion of the strategy of building a sports power in China, the state has continuously increased its attention to the physical education of young people [2]. In this context, the "National Students' Physical health standard Data Management System" (hereinafter referred to as the "physical health data management system") has been established. At the same time, schools are required to conduct physical tests on students every year. After the test according to the "national student physique health standard" (hereinafter referred to as the "standard") the content of the students' scores uploaded to the "physique data management system", so that we can systematically grasp the physique of our students, but the results of the system only excellent, good, pass and fail four aspects, and there is no specific analysis of the students' physical test results [3]. Early sports evaluation mainly relies on quantitative testing methods, such as running, long jump and other standardized physical tests, focusing on assessing students' physical strength level and athletic performance. However, these traditional methods often neglect the comprehensive development of students, including their psychological, social skills and sports interests.

With the change of education concept, especially the idea of "quality education", the evaluation of physical education is gradually developing to a more comprehensive and personalized direction. The new sports evaluation system not only focuses on students' physical fitness level, but also emphasizes students' health status, exercise habits and attitude to participate in sports activities. For example, in recent years, some studies have proposed that physical education teaching evaluation should comprehensively consider multiple dimensions such as students' physical health index (BMI), athletic ability and participation in extra-curricular sports activities, so as to more accurately reflect students' overall health status and sports interest. This multi-dimensional evaluation system helps to fully understand the growth needs of students, so as to provide more targeted improvement suggestions for teaching [4]. At the same time, with the rapid development of big data and information technology, intelligent and data-driven analysis methods have been introduced into PE teaching evaluation. Educators can use data mining technology to analyze students' physical education results, behavioral data, and so on to accurately identify the key factors affecting students' physical education performance, so as to implement personalized teaching strategies and improve education results. This trend promotes the development of the theoretical framework of PE teaching evaluation to meet the needs of modern education.

Physical education teachers are the main body to guide students to carry out sports in school. Scientific, reasonable and targeted physical education courses of physical education are very important for students' physical health. Only by mastering each student's physical condition can we make more effective physical education courses. With the development of the Internet in our country, the campus has also been fully launched the application of computer multimedia teaching mode, for students' physical test results can also use the relevant application of computer to analyze and process the data, but the potential factors in students' physical results can not be found in a deep level [5]. Therefore, it is necessary to refer to the information related to students' physical education test results and system conditions to develop a scientific and reasonable systematic evaluation model for a detailed analysis of the reasons leading to the decline of students' physical education test results. Using this method can enable students to master their own system situation, so as to choose their own method to enhance the system, so as to improve the physical test results. From the perspective of PE teachers, Data-driven decision making can not only help improve the quality of education, but also play an important role in personalized education. For example, analyzing students' sports performance, participation, training frequency and other data can help teachers tailor more effective sports courses for each student and promote the all-round development of students [6].Therefore, by studying the results of students' physical education tests analyzed by data mining technology, this paper promotes the improvement of physical education teaching courses, increases the scientificity, rationality and pertinence of physical education courses, makes the teaching content more effective and the teaching plan more reasonable, and can master the core content of teaching in the process of teaching, so as to improve the teaching vertical and level. So that students can effectively exercise and improve the physical fitness, so that students in the school can be from the moral, intellectual, physical and beautiful all-round development [7].

2. Application status of decision tree algorithm in student achievement analysis

The quality and effectiveness of teaching can be measured by students' scores, and students' scores as an indicator can also measure students' mastery of knowledge. Educational data generated by students can be transformed into effective information for analyzing students' specific conditions through educational data mining technology, and the relationship between students' behaviors and scores in the learning process can be known. By presenting the results of these analyses in the test results of students, teachers can see the shortcomings of each student in the results, so as to formulate and improve the targeted teaching plan, which can comprehensively improve the effectiveness of teaching activities [8].

The decision tree algorithm excels in feature selection and classification, offering distinct advantages in physical education evaluations. By calculating metrics such as information gain or Gini index, decision trees can identify the most significant features in large datasets and construct branches accordingly. This feature selection ability is particularly valuable in assessing factors affecting student physical performance, as it enables the extraction of key variables such as training frequency and BMI that have the most substantial impact on outcomes. By focusing on these influential features, educators can design more targeted instructional content and training regimens that directly address these factors, thereby improving students' physical fitness results. Additionally, the reliability of decision trees in isolating important variables reinforces the scientific rigor of educational evaluations, making it a robust tool for academic assessment.

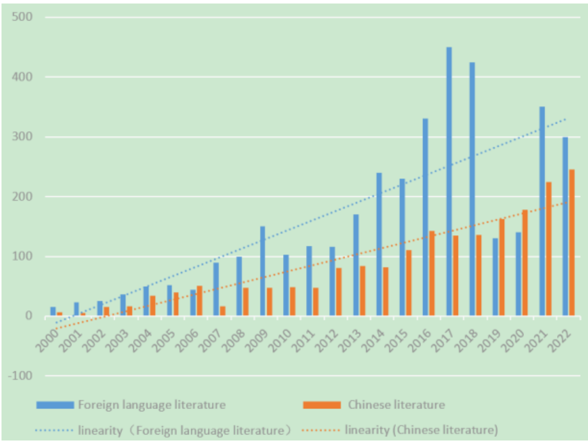

Figure 1. Visual analysis results of literature retrieval metrology.

The author searched relevant literature at home and abroad through eb of science database and CNKI for reference, so as to facilitate the analysis of students' test results by solution tree algorithm. Keywords "Decision tree algorithm", "Performance analysis", "decision tree algorithm" and "achievement analysis" were input to search relevant literature. As of January 2022, the author has found a total of 3489 relevant foreign literatures. 1486 domestic literatures. After continuous research and search, the author has accumulated relevant experience and case list results, which provides the basis and reference for the supervisor to write this paper. The visualization results of literature analysis are shown in **Figure 1**.

Through the above analysis results, it can be seen that the number of researches on decision tree algorithm at home and abroad is on the rise as a whole. In 2017, the total amount of foreign researches on decision tree algorithm is the largest, and in 2022, the total amount of domestic researches on decision tree algorithm is the largest. On the whole, The number of researches on the application of decision tree algorithm in test results has been on the rise from 2000 to 2022.

Some foreign scholars study decision tree algorithm and get conclusions. In 2018, Alemu K. Tegegne and Tamir A. Alemu created and developed A data mining model to analyze and predict the grades of first-year students in some Ethiopian colleges and universities through data mining. In 2019, Khin Khin Lay and San San Nwe created a classification model for the analysis and prediction of students' grades, aiming at students with post-graduate education or less. This classification model uses the original student grades data to classify students' grades through decision tree method. To predict students' grades from information such as attendance, classroom tests, aptitude, performance and homework scores.

In our country, the research of using decision tree algorithm in student achievement data is mainly reflected in the analysis of students' course scores in the process of learning, teachers' teaching evaluation, students' score prediction and score warning, and the system of these aspects is developed and designed. In 2015, He Hong studied the scores of students in a high school, and explored a series of reasons that could affect the scores of students in that school according to the specific situation of China's English college entrance examination reform at that time. In 2016, Wang Furong analyzed students' CET 4 scores and conducted in-depth research on them by applying decision tree algorithm. The analysis results provided a basic basis for the reform and improvement of English teaching, and also put forward effective suggestions for students to prepare for CET 4. In 2018, Yang Lili took a secondary vocational school as a research case, studied the math test results of students there through the decision tree algorithm, obtained the specific situation of students' mastery of knowledge points, and established the decision tree model. In 2019, Hu Mingming took the scores of students in a normal undergraduate college as a case for research and analysis, and built a relevant analysis model by using the decision tree algorithm to analyze students' exam scores, regular scores, course final scores, class setting, gender, subject nature, and teacher titles. In 2020, Xu Chengjun and Zhu Guobin analyzed a series of data generated by the results of China's computer rank examination by using decision tree algorithm, analyzed and studied the aspects of "original knowledge reserve", "pre-class preview", "after-class review" and "level of interest", and created the decision tree model.

To sum up, there are many researches on decision tree algorithm both at home and abroad. The application of decision tree algorithm in education and teaching can grasp the problems existing in students' classroom learning, which is conducive to teachers and education departments to perfect and develop better teaching plans, so as to achieve the purpose of improving teaching level and quality [5]. However, there are few cases of using decision tree algorithm in physical education curriculum in our country, so the application of decision tree algorithm in physical education test results has broad prospects. In addition, data mining technology can also make PE teaching present different information at various levels, and provide effective data information for students and teachers' learning and teaching activities, so as to achieve the purpose of improving students' test scores through future changes and improvements [9].

3. Decision tree achievement test model based on improved ID3 algorithm

3.1. Decision tree algorithm—ID3

ID3 in the decision tree algorithm is computed in a top-down recursive manner during construction [10]. As a greedy algorithm, ID3 determines the split attribute based on the information gain. The specific calculation process is as follows: First, while determining the information gain, the split node is the attribute with the maximum information gain compared with its value, and the branch is generated for the node according to the attribute; Then, the branches of other split nodes are determined, and the information gain of the branches is determined. Repeat the above process until a decision tree for classifying training samples can be generated, the formation steps are as follows:

Step 1: Calculate the information entropy by Equation (1)

Hypothesis: the set of data samples is represented by the number of, the attribute category variable is represented by, the total number of categories is represented by, the number of samples contained in the class is represented by, $AAaCC = \{C_1, C_2, \ldots, C_n\}n \quad C_i\, a_i$

$$P_i = \frac{a_i}{a} \tag{1}$$

The information entropy of sample classification is represented by Equation (2).

$$I(a_1, a_2, \ldots, a_n) = -\sum_{i=1}^{n} p_i \, log_2 \, P_i \tag{2}$$

Step 2: Calculate the properties by Equation (3)

Assumption: attributes have different values, according to which can be divided into, is the number of samples belonging to the subset, then the information entropy is:$BxAx \quad A = \{A_1, A_2, A_3, \ldots, A_n\} A_{ij}\, A_j\, C_i B$

$$E(B) = \sum_{j=1}^{x} \frac{a_1 j + a_2 j + \ldots + a_n j}{a} \times I(a_1 j + a_2 j + \ldots + a_n j) \tag{3}$$

Step 3: Calculate information gain by company (4)

The information gain for the property is:B

$$G_{ain} = I(a_1, a_2, \ldots, a_n) - E(B) \tag{4}$$

3.2. Sports performance test based on improved ID3 algorithm

3.2.1. Sports performance test index

The content of sports test is to assess the physical function, physical form and physical quality of students, and their scores can also be measured according to these three aspects. Differentiated test items can be formulated according to the age and physical development of students. This paper will study the hypocrisy of college students, the height, weight, vital capacity, 50 m running, 1000 m running (men)/800 m running (women), standing long jump, sitting forward bend and other physical test items are analyzed, according to the content requirements of the "standard", the students' scores of each test item are calculated and the total score is obtained. Through this way to evaluate the students' sports test results. **Table 1** below is a table of indicators that should be achieved in various items of physical education test.

Table 1. College sports achievement test index evaluation table.

Items	Grade grade	Grades	Boys' standard score	Girls standard score
Body mass index (BMI)	Low body weight	80	≤ 16.4	≤ 16.4
	Normal weight	100	16.5–23.2	16.5–23.2
	Over weight	800	233–26.5	23.3–26.5
	Obese weight	60	≥ 26.6	≥ 26.6
Vital Capacity Index (VCI)	optimal	90–100	4300–4540	3050–3150
	good	80–89	3800–4050	2750–2900
	In the	60–79	2600–3680	1750–2650
	poor	10–59	1950–2470	1550–1700
50 m run	optimal	90–100	7.1–7.3	7.8–8.0
	good	80–89	7.4–7.5	8.3–8.6
	In the	60–79	7.7–9.5	8.8–10.6
	poor	10–59	9.7–10.5	10.8–11.6
Standing long jump	optimal	90–100	2.5–2.6	1.92–2.04
	good	80–89	2.35–2.43	1.78–1.85
	In the	60–79	1.95–2.31	1.48–1.75
	poor	10–59	1.70–1.90	1.23–1.43
Sitting position Forward bend	optimal	90–100	19.4–23.6	20.8–24.4
	good	80–89	1.0–13.6	4.4–16.1
	In the	60–79	1.95–2.31	1.48–1.75
	poor	10–59	−4.0–0	0.4–3.6

The content presented in **Table 1** above is the requirements of the sports test items and scoring criteria in the "Standards". Together, the tests provide an idea of a student's overall physical fitness. Each of the tests in the table provides an idea of a student's physical performance. In different cases, some students are unable to complete the physical education test because of special medical reasons, so the final data result may not be a complete test score for all students.

3.2.2. Improving the ID3 algorithm

ID3 algorithm is a classic decision tree algorithm, widely used in data classification and regression analysis. It selects the optimal split attribute by calculating the information gain and recursively generates the decision tree. However, the traditional ID3 algorithm has the problem of low computational efficiency when dealing with large-scale data sets, especially when a large number of features and attributes are involved, the calculation process of information gain is complicated, and it is easy to be interfered by data noise and outliers [11]. In this study, we proposed a sports performance test model based on improved ID3 algorithm, and made several key improvements to ID3 algorithm to improve the efficiency and accuracy of sports test data analysis, such as Equations (5)–(8). The specific steps are as follows:

Step 1: Re-determine the actual physical achievement test demand value by Equation (5):P_i

$$P_i = \frac{1-a_i}{1+a_i} \tag{5}$$

The information entropy of sample classification is represented by Equation (6):

$$-\sum_{i=1}^{n} \frac{1-a_i}{1+a_i} log_2 \frac{1-a_i}{1+a_i} = -\sum_{i=1}^{n} \frac{1-a_i}{1+a_i} \frac{ln \frac{1-a_i}{1+a_i}}{ln\, 2} \tag{6}$$

Step 2: Equation (7) Compute a function with a power series of two:

$$\frac{2}{ln\, 2} \sum_{i=1}^{n} \frac{1-a_i}{1+a_i} \left(a_i + \frac{1}{3} {a_i}^3\right) = \frac{2}{3\, ln\, 2} \sum_{i=1}^{n} \frac{a_i(1-a_i)(3+{a_i}^2)}{1+a_i} \tag{7}$$

Equation (8) is the calculation of information gain:

$$\frac{1}{a} \sum_{i=1}^{n} \frac{a_i(a^3 - {a_i}^3)}{(a+a_i)^3} \tag{8}$$

The improved ID3 algorithm shows higher efficiency and accuracy in sports performance data analysis. Specifically, compared with the inherent ID3 algorithm, the advantages and innovations of this research are as follows:

(1) Improve computing efficiency

The traditional ID3 algorithm needs to calculate the logarithmic function many times, which leads to its low computational efficiency when dealing with large-scale data. In order to solve this problem, we use the power series expansion to simplify the logarithmic function operation in the information gain calculation, and instead use the operators such as addition, subtraction, multiplication and division, which significantly improves the computational efficiency. This improvement enables the algorithm to process large amounts of data more quickly, especially in the analysis of large-scale sports performance data, which can effectively reduce the calculation time.

(2) Outlier processing

The traditional ID3 algorithm is more sensitive to outliers and is prone to bias in the process of decision tree construction. We introduce an outlier detection mechanism to identify and process abnormal data in the data preprocessing stage, which reduces the negative impact of these data on decision tree construction. In this way, the improved algorithm can more accurately reflect the students' real athletic performance and avoid misleading analysis results due to data noise.

(3) Information gain optimization

The traditional ID3 algorithm mainly relies on information gain to make decision when selecting split nodes. However, when there is a strong correlation between features, the information gain can lead to overfitting. In order to avoid this problem, we introduce regularization mechanism on the basis of information gain. By smoothing the gain value, we avoid overfitting phenomenon and improve the generalization ability of the model. In this way, the improved algorithm can still maintain high accuracy and stability on complex data sets.

4. Based on the improved ID3 algorithm sports performance test evaluation

4.1. Data source and processing

Data collection is the most basic work of data analysis and research, which is mainly to select the data that meet the conditions in the previous database [12]. Through communication with the physical education teachers, the author collected some students' physical education performance data information, including weight, height, vital capacity, 50 m running, standing long jump and sitting forward bend, a total of 1147 pieces of data information, the data information is the physical education results of the students tested under the strict supervision of the physical education teachers, and the test content of these students is complete. Students' grade, class, basic information, test data and other information are available. After collecting the information, the data needs to be cleaned. In this paper, the related work of data cleaning includes the following contents: Fill in the blank of the unrecorded attribute value with the average; The data of some students who did not participate in the physical education test due to various reasons were deleted. The data table obtained after cleaning the data by these two methods is the effective data information, which has a total of 1078 pieces of information. By referring to the content of the National Student Health System standards, the scores of each attribute and the overall score were calculated. Since there are many contents in the overall data table, the following **Table 2** shows the data fields of the achievement test results.

Table 2. Sports performance test result data fields.

Weight	Lung capacity	50 m run	Standing long jump	Sit forward bend
95	56	64	84	76
90	89	75	62	78
95	84	69	91	69
75	80	74	55	65
100	90	81	42	71
100	60	97	23	78
....				

4.2. Outlier handling and impact analysis

When analyzing sports performance data, the presence of outliers may adversely affect the analysis results. To improve the accuracy and reliability of the data analysis, outliers were handled in this study. Outliers are defined as data points that significantly deviate from the other observations in the dataset, which may be caused by recording errors, extreme cases, or data noise. To ensure the accuracy of the data, we adopted the following methods:

Step 1: Statistical Method

We identified outliers using box plots and standard deviation methods. Suppose the mean of a variable X is μ_X and the standard deviation is σ_X, then outliers are defined as:

$$\text{Outlier} \quad X_i \quad \text{if} \quad X_i > \mu_X + 3\sigma_X \quad \text{or} \quad X_i < \mu_X - 3\sigma_X \tag{9}$$

where μ_X and σ_X are the mean and standard deviation of the variable, and X_i is each observation in the dataset. Any data point that exceeds three standard deviations from the mean is considered an outlier. This method was applied to all features (e.g., 50-meter run, long jump, weight) in the dataset. We removed all outliers to ensure the stability of model training.

Step 2: Data Imputation

For missing data caused by special circumstances, the mean imputation method was used. Suppose the variable X has missing values, and the imputed value for the missing data is:

$$X_i^{\text{imputed}} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (\text{where} n is the number of non-missing values) \tag{10}$$

For example, in the analysis of the "50-m run" scores, for missing student data, we filled in the missing values with the mean of that feature. After data imputation, the research showed that the imputation did not significantly affect the model's prediction accuracy.

After handling the outliers and missing values, we retrained the model and performed an impact analysis by altering the dataset with and without outliers to observe the effect on the decision tree model's results. The results indicated that after removing outliers, the model's accuracy improved by approximately 5%, with the prediction error decreasing from 0.25 to 0.22.

4.3. Feature importance analysis

Feature importance analysis is a crucial step in evaluating the contribution of each feature to the prediction of sports performance. In this study, we calculated the importance of each feature using the information gain of the decision tree model. Information gain IG is a measure of the reduction in uncertainty when a feature is used to split the data, and it is calculated by the following formula:

$$IG(S, A) = H(S) - \sum_{v \in A} \frac{|S_v|}{|S|} H(S_v) \tag{11}$$

where $H(S)$ is the entropy of the dataset S, and $H(S_v)$ is the entropy of the subset S_v when the feature A takes the value v. The larger the information gain, the more important the feature is in predicting the outcome.

We performed feature importance analysis on the following key features and calculated their information gains:

Training Frequency: Training frequency has a significant effect on student physical test scores. The analysis showed that students with higher training frequency performed better in most test items. The average information gain of training frequency was 0.35, significantly higher than other features.

BMI (Body Mass Index): BMI is closely related to students' physical performance. The average information gain of BMI was 0.28, indicating its importance in physical performance. Specifically, students with lower BMI performed better in tests such as running and long jump.

Extracurricular Sports Participation: Extracurricular sports participation is another important factor. The average information gain of this feature was 0.21, indicating that students who actively participate in extracurricular sports tend to achieve better results in physical tests.

Through the feature importance analysis, we identified that training frequency and BMI are the key factors influencing students' physical performance. Based on this analysis, teachers can prioritize these key factors when designing physical education courses to improve students' physical performance.

4.4. Calculating the entropy of the various attributes of the sports performance test

The training frequency in the following table, 1 represents high frequency training, 3 represents low frequency training; In the gender attribute, 1 is male and 2 is female; In the age attribute, 1 is 17 to 19 years old, and 2 is a student of other ages; In addition, in order to make the data more convenient to mine the information, the height and weight of students are also discretized, that is, overweight, obese and low weight groups are classified as abnormal weight, so that the weight can be divided into normal and abnormal; At the same time, it also discretizes the total score of physical test. After a series of processing, the data in **Table 3** below are presented.

Table 3. Sports performance test data after processing.

Training frequency	Gender	Age	Height/weight	Class
1	2	1	Normal	Qualified
3	1	2	Normal	Qualified
1	1	2	Normal	Qualified
1	2	1	normal	Qualified
3	2	2	Abnormal	Unqualified
3	2	1	Abnormal	Unqualified
....				

As can be seen from **Table 3** above, there are five attributes of decision tree, namely training frequency, gender, age, height, weight and grade. The split attribute is calculated according to these five attributes, and the decision tree model is established to analyze and study the required result information, which can be used as the basis for teaching design.

Since Equation (7) in the above content has calculated the information entropy of the student's gender, age, weight and training frequency, we can first take the training frequency as an example. Among all the data, there are 661 pieces of information about high-intensity training. Among the 661 pieces, there are 538 pieces of information that pass the physical test and 124 pieces of information that fail. The training frequency in the data is 3, that is, there are 468 pieces of information data of low-frequency training, and 371 pieces of data in the total physical test score are qualified, and the number of failing is 97; So the following formula can be listed:

$$E(a_{\text{training intensity}=1}) = \frac{1}{661} \times \left[\frac{538 \times (661^3 - 538^3)}{(661+538)} + \frac{124 \times (661^3 - 124^3)}{(661+124)}\right] = 0.1754 \quad (12)$$

$$E(a_{\text{training intensity}=3}) = \frac{1}{468} \times \left[\frac{371 \times (468^3 - 371^3)}{(468+371)} + \frac{97 \times (468^3 - 97^3)}{(468+97)}\right] = 0.1857 \quad (13)$$

Therefore, the information entropy of training intensity can be obtained, and the calculated information entropy is 0.1796. By comparing the information entropy of training intensity (0.1796) with that of gender (0.1761), age (0.1794) and weight (0.1773), we can know that the information entropy of gender attribute is the smallest, so gender can be used as the root node of differentiation. According to the above method, the information entropy of other split attributes can be calculated, and the decision tree can be built by comparing their sizes. When the decision tree is built, a pass rate calculation function can be added.

4.5. Analysis of test results in real cases

4.5.1. Accuracy rate

Based on the above research steps, the data of male and female training values, predicted values and verification values are obtained as shown in **Figure 2**:

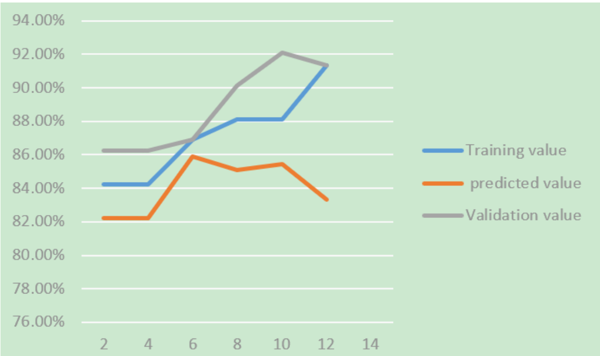

Figure 2. Prediction accuracy curve.

In order to improve the classification accuracy, the training set was trained, and the accuracy rate of the final calculation result exceeded 86% by optimizing the depth, but the expectation did not meet the expectation. While continuously optimizing the depth, the accuracy rate of the three values was improved, and there was overfitting of the model, which would affect the pan-Chinese ability. In view of this, the coordinated decision tree pruning method was continuously optimized. Determine the prediction accuracy curve of the optimized decision tree model, and then understand the relevant data of male and female samples as a whole, determine the depth of 5, carry out the visual output of the decision tree model, and understand the impact of the project on the classification of students' institutional grades.

4.5.2. Analysis of operation results

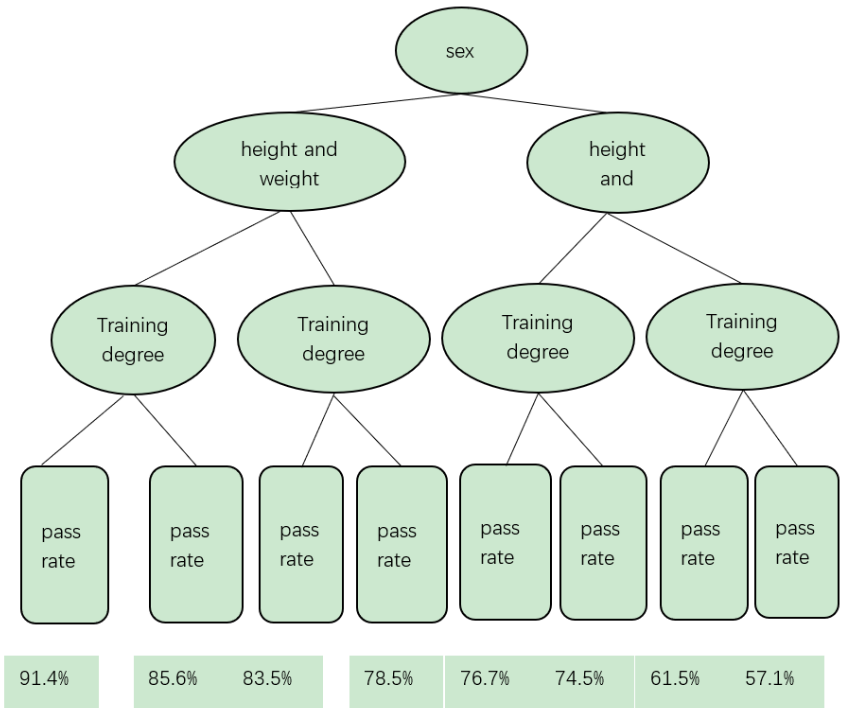

Figure 3. Decision tree run results.

According to the data in **Figure 3**:

First of all, gender is the main factor affecting the performance of sports test. Through comparing the data of passing rate of male and female sports test results, it is found that the passing rate of female is significantly lower than that of male. Reason analysis: Men have more outdoor activities (basketball, football, etc.) than women, and their exercise is greater than that of women, resulting in a higher proportion of passing rate than that of women [13–15].

Secondly, according to the operation result of decision tree, through comparing the physical education test results of students with height and weight, it is found that the passing rate of students in normal state is greater than that of students in abnormal state. Reason analysis: Due to the influence of factors such as weight and rest habits, the students in the abnormal state have a gap between their usual living habits and those in the normal state, and their comprehensive physical fitness is low, resulting in a low pass rate of the abnormal height and weight.

Thirdly, high-intensity forest patrol is also a factor that affects test scores. Students with low training degree have lower physical fitness than students with strong training degree due to the influence of factors such as the number of exercises and intensity. Reason analysis: After the exercise, the students' physical fitness is obviously improved, resulting in the degree of training affecting the test results of the decision tree [16].

Finally, according to the analysis of the operation results of the decision tree, age has little influence on the results of students' physical fitness.

4.5.3. Applicability of the model and transformation of research results into teaching improvement measures

When discussing the advantages and applications of the decision tree model, it is necessary to further explore the applicability of the model to different types of schools and different age groups of students. First, the decision tree algorithm has high flexibility and can adjust its classification criteria according to different school types (such as urban schools, rural schools, public schools and private schools). This flexibility allows the model to be adapted to a variety of educational Settings, ensuring that a diverse group of students from different backgrounds can benefit from it. For example, urban schools and rural schools may have significant differences in resource allocation, students' physical fitness, and participation in sports activities, and decision trees can formulate more targeted teaching strategies according to these differences.

Secondly, decision tree model also has strong applicability to students of different ages. Students of different ages have significant differences in physical fitness, athletic ability and sports interest. Therefore, decision tree can provide personalized physical education programs for students of different grades according to their age, physical development stage and athletic ability. For primary school students, the emphasis can be placed on the cultivation of basic physical fitness and sports interest, while for middle school students, more attention can be paid to the improvement of motor skills and physical fitness. By introducing the relevant variables of student age and physical fitness into the decision tree, it can be ensured that the physical education curriculum and evaluation model can better adapt to the growth needs of students.

Based on the results of decision tree analysis, educators can take various measures to translate the research results into concrete teaching improvements. First, decision trees can identify key factors that affect students' athletic performance, such as BMI, training frequency, and so on. Teachers can adjust teaching strategies for these factors, such as designing weight loss training for students with higher BMIs, or increasing extracurricular exercise opportunities for students with low training frequency. In addition, decision trees can help teachers identify weak points in students' physical tests, thus providing personalized reinforcement training. Second, decision trees contribute to personalized and differentiated teaching. By analyzing students' athletic performance, teachers can design targeted training programs for students of different ages and fitness levels, ensuring that each student is able to progress within his or her ability. Finally, the decision tree model can provide a basis for schools to make PE teaching policies. For example, if the analysis results show that students' physical fitness levels are generally low, schools can increase physical education classes or optimize facilities to improve students' physical fitness and participation.

5. Conclusions

This paper studies the relevant data of college students' physical education test results, hoping to find the reasons that affect the decline of students' physical education, and provide basis for the design plan to improve students' physical education test results to meet the national standards and requirements. By improving the ID3 algorithm, the author analyzes and studies the students' physical education test results and analyzes the relevant reasons that can affect physical education test results. From the perspective of physical education teachers, it can improve the quality and level of teaching, and from the perspective of students, it can enhance their physical health. Although the decision tree calculation method in this paper has a certain efficiency, its application in sports test results is still in the initial stage, and further research is still needed.

Despite the great potential of data-driven decision making, its practical application in education systems still faces many challenges, such as data quality issues, privacy protection issues, and how to correctly interpret and apply the results of data analysis. On the other hand, students' subjective feedback and perceptions should also be regarded as critical factors. Such feedback offers valuable insights into students' engagement in physical activities, their attitudes toward training, and their overall physical condition—elements that are often challenging to quantify through conventional fitness assessments. Despite their difficulty in measurement, these factors can significantly influence the outcomes of physical education programs. Future research should aim to integrate both subjective feedback and objective test data, utilizing a multidimensional analytical approach to enhance the comprehensiveness and applicability of the findings.

Author contributions: Conceptualization, NZ and HS; methodology, HS; software, LW; formal analysis, NZ; investigation, NZ and HS; writing—original draft preparation, NZ; writing—review and editing, HS; visualization, LW; supervision, HS. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

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