SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(2), 503.
https://doi.org/10.62617/mcb503

Article

Enhancing college students physical education using artificial intelligence-optimized teaching system based on biomechanics

Zixuan Gao[1], Hongjing Guan[2], Zhi Tan[1,*]

[1] Chaoyang Normal University, Chaoyang City 122000, China
[2] Graduate School, José Rizal University, Manila 0900, Philippines
*** Corresponding author:** Zhi Tan, qwassawq666@163.com

CITATION

Gao Z, Guan H, Tan Z. Enhancing college students physical education using artificial intelligence-optimized teaching system based on biomechanics. Molecular & Cellular Biomechanics. 2024; 22(2): 503. https://doi.org/10.62617/mcb503

ARTICLE INFO

Received: 10 October 2024
Accepted: 5 November 2024
Available online: 17 January 2025

Abstract: Physical Education Teaching concerns the process of leading students to perform different tasks, games, and workouts that improve physical fitness, body control, and health. In the realm of cell and molecular biomechanics, physical education teaching can be regarded as a means to induce specific physiological responses at the microscopic level. The various physical activities in which students partake, like diverse tasks and workouts, exert mechanical forces that permeate throughout the body and impinge upon cells and tissues. During physical exertion, cells within muscles, bones, and connective tissues are subject to biomechanical stress. This stress triggers a cascade of molecular events. Teachers focus on enhancing spatial and manual skills, promoting cooperation, and setting up priorities. In this research, it is proposed to learn about the teaching system of physical education in colleges and universities using artificial intelligence (AI) optimization algorithm. Thus, for predicting the achievements of college students in physical education, we propose the Blue Monkey optimization-driven Weight-Tuned AdaBoost (BM-WTAdaBoost) algorithm. The observations and variables were derived from typical physical education programs of college students during their training sessions. A data pre-processing technique known as min–max normalization is applied to the obtained raw data to enhance its quality. For nonlinear data, Kernel Principal Component Analysis (kernel-PCA) is employed as it helps in extracting the nonlinear information, which in turn helps in making accurate predictions. The following is our proposed model: BM opt with WTAdaBoost to improve selecting features and model accuracy in predicting college students' physical education outcomes. Python program uses our suggested technique. The finding assessment phase assesses the suggested model's prediction efficacy using several measures, including the accuracy ratio (99.8%), F1-score (95.56%), prediction ratio (98.24%), interaction ratio (97.2%), efficiency ratio (98.24%), performance ratio (97.2%), and error rate (5.62%). We also performed a comparative analysis with different traditional approaches to assess the efficacy of the suggested strategy. Comparative analysis with traditional methods shows the superiority of this approach in predicting physical education outcomes considering cell and molecular biomechanics, providing a novel perspective for understanding and optimizing physical education in relation to the microscopic biological world.

Keywords: physical education teaching system; college students; artificial intelligence (AI); blue monkey optimization; wtadaboost algorithm; kernel-PCA; biomechanics

1. Introduction

The importance of physical education in college cannot be overstated. It plays a pivotal role in enhancing intellect, developing talent, and training human resources. In today's world, where the pressures of academic achievement and career readiness are increasingly intense, physical education serves as a vital counterbalance. It is not just about physical fitness; it encompasses a broader spectrum of benefits that contribute to a student’s overall development. Engaging in physical activities helps students cultivate discipline, resilience, and teamwork—skills that are essential both in personal and professional realms. As society advances and places greater emphasis on economic growth and national revitalization, the acquisition of knowledge and strengthening of physical abilities become crucial for every citizen, particularly the youth [1]. The youth represent the future workforce, and their ability to adapt to changing environments is paramount. By integrating physical education into their academic journey, students learn the importance of maintaining a healthy lifestyle, which can lead to improved productivity and creativity. This holistic approach to education helps shape well-rounded individuals who are not only knowledgeable but also physically capable and mentally agile. Lifelong physical education is centered around the idea that engaging in physical activities not only benefits the body but also nurtures the mind, fostering personal growth among students [2]. The connection between physical activity and mental health is profound. Regular exercise has been shown to reduce stress, boost mood, and enhance cognitive function. When students participate in physical education, they are not merely exercising; they are investing in their mental well-being. This investment can lead to improved academic performance, as students who are physically active tend to have better concentration and memory retention.

Colleges and universities are adapting their educational reforms to incorporate robust physical education programs, aiming to enhance program efficiency and effectiveness [3]. This transformation reflects a growing recognition of the need for comprehensive physical education that caters to diverse student populations. Institutions are increasingly offering a variety of activities, from traditional sports to innovative fitness classes, ensuring that there is something for everyone. This diversity allows students to explore different interests and find activities that resonate with them, encouraging lifelong participation in physical fitness. However, recent research highlights several challenges, including the need for diverse teaching approaches, improved remote teaching capabilities, and enhanced technical analysis of physical activities [4]. The rise of online learning and hybrid models has necessitated a shift in how physical education is delivered. Educators must now navigate the complexities of teaching physical activities in a virtual environment, which requires creativity and adaptability. Finding ways to engage students remotely while ensuring they receive the benefits of physical education is a significant challenge that institutions must address.

Meeting these challenges is essential as student expectations for comprehensive and engaging physical education continue to rise with societal progress [5]. Today’s students are more health-conscious and aware of the importance of physical fitness than previous generations. They seek programs that are not only effective but also enjoyable and relevant to their lifestyles. This demand for quality physical education emphasizes the need for continuous improvement in teaching methods and curriculum design. Institutions must be proactive in seeking feedback from students and adapting their programs accordingly to meet evolving needs. Effective physical education not only supports overall health and well-being but also addresses specific health concerns such as obesity and related conditions among students [6]. The prevalence of obesity among young adults is a pressing public health issue, and physical education can play a crucial role in combating this trend. By promoting regular exercise and healthy lifestyle choices, physical education programs can help students develop habits that lead to long-term health benefits. Educators have the opportunity to educate students about nutrition, fitness, and the importance of maintaining a balanced lifestyle, which can significantly impact their overall health.

However, concerns about over-exercising and its potential negative impacts on physical health must be addressed to ensure balanced and beneficial physical education experiences. While promoting physical activity is crucial, it is equally important to emphasize moderation and self-awareness. Overtraining can lead to injuries, burnout, and mental health challenges such as anxiety and depression. Physical education programs should focus on teaching students how to listen to their bodies, recognize their limits, and prioritize recovery. By fostering a balanced approach to fitness, educators can help students cultivate a healthy relationship with physical activity that lasts a lifetime. In summary, physical education in college is an essential component of a well-rounded education. It enhances intellect, develops talent, and trains human resources, preparing students for the challenges they will face in the future. As society continues to evolve, the importance of physical education will only grow, making it vital for educational institutions to adapt and innovate. By addressing the challenges of diverse teaching approaches and the integration of technology, colleges and universities can provide engaging and effective physical education experiences that support the overall health and well-being of their students.

The following sections of the paper are organized as follows: Part 2 includes related works. Part 3 goes into extensive detail on the BM-WT AdaBoost. Part 4 discusses the proposed strategy's design of the experiment, findings, and performance evaluation. Part 5 summarizes the findings and recommends areas for future research.

2. Literature review

They demonstrated that the astute progression of college physical education instruction can leverage the benefits of Internet technology and intelligent apparatus to enhance the quality of instruction, and student experience and foster innovation as well as advancement in the field of college physical education [7]. They procedure for evaluating facility associates in academic level body activity programs was created utilizing a fuzzy neural network model for physical education [8]. They determined a technique using information technologies to control the strength and endurance of the students' core muscles that were intended to help them with impairments [9]. Author examined how gender and self-efficacy, two variables that affect students' use of sports wristbands, interact with the Technology Acceptance Model (TAM), which was centered on social cognition theory and gender schema theory [10]. The features of physical education courses; their personal vision research seeks to support university students' competence development while also contributing to the Sustainable Development Goals (SDGs). To advance the SDGs, it was intended to consider how the materials and approaches used in physical education could mobilize critical and systemic thinking [11].

Problem statement

Teaching physical education has several issues. The global crisis's effect on education is one of the main problems and the demand for online solutions to lessen the issue has arisen. The lack of knowledge and readiness among physical education instructors to use Information and Communications Technology (ICT)-related tools and apps in an online environment is another issue. Physical education instructors in distant primary schools also frequently encounter challenges because they work part-time, use antiquated teaching techniques, and have a lot of homework. Other difficulties include poor student interest, inadequate freshman preparedness, and a lack of time for classroom activities while teaching physics to prospective bachelors in technical fields.

3. Methods and materials

This part describes creating an AI-based teaching assessment index system for BM-WTAdaboost. The data was collected from college students' common physical education programs. The Min-max normalization process is conducted to pre-process. The extract of feature using the kernel-PCA approach is accomplished. **Figure 1** shows the proposed architecture.

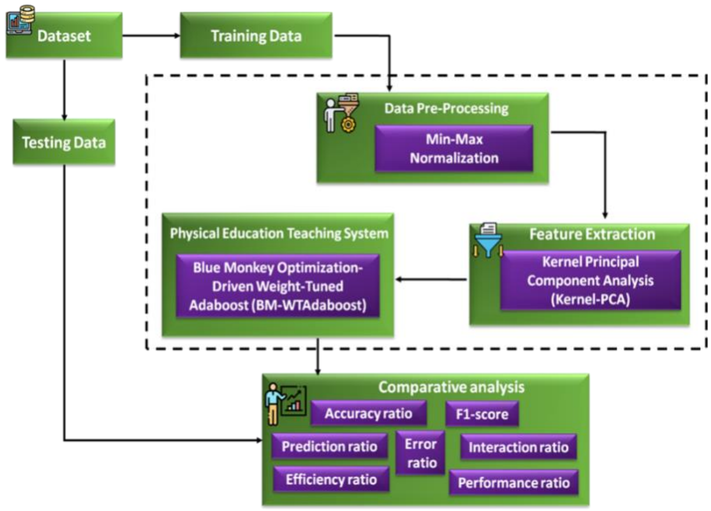


Figure 1. Flow diagram of the proposed approach.

3.1. Data collection

In this paper, we collect data from Kaggle [12] for the Behavioral Risk Factor Surveillance System (BRFSS) dataset is the generalized continuous medical study system globally, conducting over 400,000 senior assessments each year. It offers valuable insights into health behaviors among adults, aiding research and policy initiatives aimed at enhancing public health outcomes across various populations.

3.2. Data pre-processing utilizing min-max normalization

Min-max normalization is a method that implies a linear transition to the initial information range. The process known as min-max Normalization maintains the relationships between the original data. Within a predefined range, the information gets precisely fitted using a simple technique, as following Equation (1),

$$B^{'} = \left(\frac{B - \min\ value\ of\ B}{\max value\ of\ B - \min\ value\ of\ B}\right) \times (E - D) + C \quad (1)$$

where, $B^{'}$-comprises a single set of normalized min-max information. The predefined border$[is\ D, E]$, if the original data's range is$B$.

3.3. Extract the feature using kernel-PCA

Kernel-pca is a kind of PCA that employs kernel functions on nonlinear feature spaces. The technique uses a nonlinear mapping (ϕ) to convert input data (w_j) from space (Q^{NM}) to feature space (E), Equation (2).

$$\varphi: Q^{NM} \to E \quad (2)$$

The kernel function $l(w, w_j)$computes inner products in E E, which are necessary for generating the covariance matrix L. Solve the eigenvalue problem: $QU = \lambda$ U produces eigenvectors U and eigenvalues λ . The main components are data projections onto U.

Polynomial is a popular kernel: $l(x, y) = (y^T x + I)^o$

Gaussian: $l(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$

3.4. Physical education teaching system using blue monkey optimization-driven weight-tuned adaboost (BM-WTAdaboost)

Blue monkey optimization-driven Weight-Tuned Adaboost (BM-WTAdaboost) is an advanced method for physical education teaching systems for college students. This system combines two important elements: Weight-Tuned Adaboost, a machine learning algorithm that modifies the weights of weak learners to enhance overall performance, and Blue Monkey Optimization, a bio-inspired method that optimizes parameters by imitating the behavior of blue monkeys. By utilizing these methods, the system enhances curriculum development, student evaluation, and teaching methodologies in physical education, which in turn helps college students have more individualized and successful learning experiences. Algorithm 1 presents the BM-WT Adaboost algorithm.

Blue monkey optimization (BMO)

Compared to other species, blue monkeys are unique. They usually reside in communities where women make up the majority, (i.e.,) where women remain within their natal groupings. But the moment they become fully grown, the males depart from their groupings. In any group of blue monkeys, there is just one male and several females and young ones. The issue of inbreeding is made worse by this particular instance. When the males reach an older age, they quit the group and join another. The males might at first appear to be alone, although it might take some time for them to join a new group. Blue monkeys are not perfectly intuitive when it comes to social relationships. Playing and grooming others usually results in brief periods of social contact. Babies establish connections with both the mothers and other adults in the group. The mother of those infants stays away from her male counterparts. It's the baby handlers that put forth the most work. The young females carry, nurture, and shield the infants. Babies learn how to respond to this habit, just like all monkeys develop.

Group division: Blue Monkey's movements are mimicked by the BMO algorithm. To replicate these encounters, each monkey group had to traverse the search region. It's reported previously that after the monkeys are split up into groups; begin to look for food supplies far away in a region where more robust monkeys are hidden from perspective. The contact between the male and children of Cercopithecusmitis is minimal to nonexistent. In the territorial nature of Cercopithecusmitis, young males ought to go outside as soon as to mature. A rival family's dominating male is going to use them to the test. If manage to get removed from males, to take over the family and they are capable of feeding, clothing and interacting with young males. There is usually just one male blue monkey in each group and an extensive number of females and young ones.

Position update: Within a group, every blue monkey updates to reflect their current location in the best spot. This type of behaviour is described by Equations (3) and (4) such as the ones below:

$$Power_{n+1} = \left(0.7^{\times} Power_n\right) + (X_{lea} - X_n) \times rand \times (Z_{best} - Z_n) \tag{3}$$

$$Z_{n+1} = Z_n + Power_{n+1} \times rand \tag{4}$$

Leader weight is represented by X_{lea}, monkey weight by X_n, leader location is represented by Z best, which might use any value between 0 and 1, monkey power rate by Power, and so on. The progeny of the blue monkey are also updated using the following Equations (5) and (6).

$$Power^D_{n+1} = (0.7 \times Power^D_n) + \left(X^D_{lea} - X^D_n\right) \times rand \times \left(Z^D_{best} - Z^D_n\right) \tag{5}$$

$$Z^D_{n+1} = Z^D_n + Power^D_{n+1} \times rand \tag{6}$$

where Z is the child position, and X^D_n Z^D_{best} is the kid weight, at which all weights are random amounts among 4 and 6. Ratech represents the leader child weight, needs to stand for the kid power rate and rand indicates an arbitrary value between $[0,\ 1]$. The position has to be adjusted after each cycle.

Weight-Tuned AdaBoost: The cconventional AdaBoost method improves the weights of the observations that are incorrectly classified while practicing for every cycle. These samples can be repeatedly inaccurately estimated that could result to a important unitability in the measure allotment of the samples as well as a constant increase in the sample weights. The solution to this issue is to enhance the weight update algorithm. To lessen the imbalance in the sample weight distribution, modify the weight w_t that is produced in the t^{th} itration. This adjustment reduces the difference in sample weights between the $(t-1)^{th}$, and t^{th} iterations. The following is the updated Equation (7):

$$S_t = w_{t-1} + \frac{z.e^{-|z|}}{1 + e^{-|z|}} \tag{7}$$

Here, the altered quantity is denoted by s_t, while the weight that was determined in the previous iteration is represented by $z = w_t - s_{t-1}, w_{t-1}$. The BM-WT Adaboost process is provided in Algorithm 1.

Algorithm 1 The process of BM-WT AdaBoost

Input: D -The collection of information; T-The volume of unsuccessful classification;
Output: H- The successful classification;
Step 1: Initialization sample weights $w_1, s_1 = w_1$; Power ofW, and Blue Monkey and their children population $\mathrm{Bm}(n = 1\ldots., m)$
Step 2: Where (Power ε [0, 1]) (W ε [4, 6])
Step 3:$\mathrm{fort} = 1; t < 1; t + +\mathrm{do}$
Step 4: Training weak classifier h_t using $w_t$andD;
Step 5: Calculating the classification error rate ϵ_t;
Step 6: Calculating the weight α_t of the weak classifierh_t, $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$;
Step 7: Updating weight $w_{t+1}$of D, $x_{s+1} = \frac{x_s}{y_s}\exp$ (-$\propto_s$ $zg_s(w)$) ;
Step 8: Adjusting weight $x_{s+1}, y = x_{s+1} - t_s, t_{s+1} = x_s + \frac{ye^{-|y|}}{1+e^{-|y|}}, x_{s+1} = t_{s+1}$;
Step 9: Forming a new classifier $G_s = G_{s-1} + \alpha_s g_s$;
Step 10:end for
Step 11:$G = \sum_{s=1}^{S} \alpha_s g_s(w)$;
ReturnH.

4. Result

In this research, Python was employed as an examination platform on Windows 10. The experimental data using BM-WT Adaboost classification models is provided, and their efficacy is evaluated using several criteria. BM-WT Adaboost is compared to other techniques, including leisure-time physical activity (LTPA) [13], Human Activity Recognition System (HARS) [13], the Physical Education and Physical Literacy Approach (PEPLA) [13], and Internet of Things-Physical Activities Monitor Systems (IoT-PAMD) [13]. Performance indicators like as accuracy of classification models is evaluated using the following metrics: error rate, F-score, efficiency ratio, performance ratio, prediction ratio, accuracy ratio, and interaction ratio.

The Accuracy Ratio (AR) in classification models is a concise quantitative indicator of Discriminatory Power. The F1 score is used as a predictor for performance in statistical evaluation of binary grouping and information retrieval systems. The BM-WTAdaboost framework is evaluated against several existing methods, with a visual comparison of its accuracy ratio, F1-score, and error rate, shown in **Figure 2**. Specifically, **Figure 2a** presents the accuracy ratio and F1-score, where the BM-WTAdaboost model demonstrates superior performance compared to other models. The BM-WTAdaboost framework achieves an impressive accuracy ratio of 99.8%, which surpasses the accuracy ratios of other methods, including PEPLA at 64.4%, HARS at 73.1%, LTPA at 82.6%, and IoT-PAMD at 98.3%. This indicates that BM-WTAdaboost has a significantly higher capability of correctly predicting outcomes compared to these models. In addition to accuracy, the F1-score also highlights the BM-WTAdaboost's enhanced predictive performance, achieving a value of 95.56%, while PEPLA, HARS, LTPA, and IoT-PAMD reach F1-scores of 72.2%, 79.9%, 90.1%, and 92.2%, respectively. The F1-score measures the balance between precision and recall, and BM-WTAdaboost's higher score demonstrates that it excels in both aspects, producing fewer false positives and negatives than the comparison methods.

Furthermore, **Figure 2b** illustrates the error rate comparison, providing insights into each model's predictive accuracy relative to the actual results. The BM-WTAdaboost model exhibits a notably lower error rate than the existing methods, with a minimal error rate value compared to PEPLA (74.5), HARS (65.9), LTPA (44.7), and IoT-PAMD (17.5). A lower error rate in BM-WTAdaboost implies it closely aligns with the true model values, indicating superior model robustness and reliability over the alternatives. This reduction in error rate underscores the BM-WTAdaboost framework's effectiveness, making it a preferable option for applications requiring high predictive accuracy.

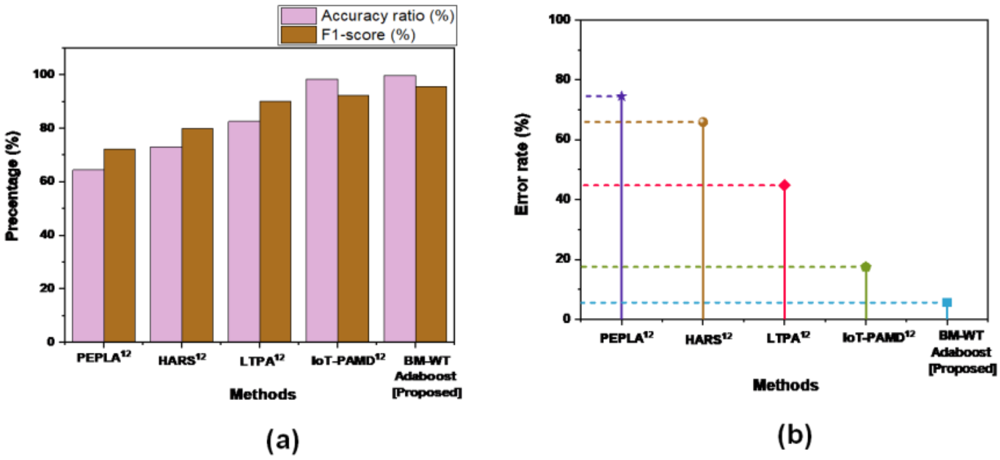
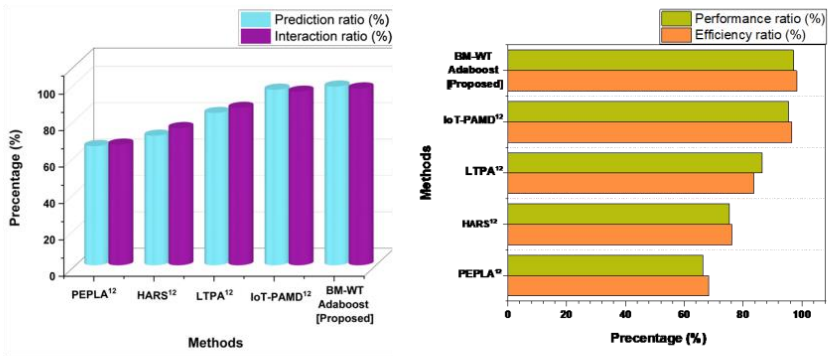


Figure 2. Comparison of the **(a)** accuracy ratio and F-score; **(b)** Error rate.

This measure assesses the system's ability to predict specific outcomes or actions. Representing the proportion of user actions to page views is the interaction ratio. In **Figure 3a**, the proposed BM-WTAdaboost framework demonstrates a significant improvement in both prediction and interaction ratios compared to existing methods. Specifically, BM-WTAdaboost achieves a prediction ratio of 98.24%, which is markedly higher than other methods, including PEPLA (65.5%), HARS (71.2%), LTPA (83.7%), and IoT-PAMD (96.5%). The interaction ratio of BM-WTAdaboost is also superior, reaching 97.2% compared to PEPLA's 66.3%, HARS's 75.4%, LTPA's 86.5%, and IoT-PAMD's 95.4%. These results indicate that BM-WTAdaboost not only provides enhanced predictive accuracy but also facilitates more effective interactions, setting it apart as a robust alternative to existing schemes. **Figure 3b** provides a comparison of the efficiency and performance ratios, which are essential for assessing resource usage and output reliability over a reporting period. The efficiency ratio evaluates how well the framework utilizes its internal resources and commitments, while the performance ratio represents the model's consistency by comparing measured output to estimated production. **Figure 3a,b** further illustrate BM-WTAdaboost's superiority, highlighting its enhanced efficiency and performance indices relative to competing methods. This visual comparison underscores BM-WTAdaboost's strong performance and practical advantages in terms of both resource efficiency and consistent output. **Table 1** Comparison value of accuracy ratio, F1-score, error rate, prediction ratio, interaction ratio, efficiency ratio, and performance ratio.



(a) (b)

Figure 3. Comparison of **(a)** prediction ratio and interaction ratio; **(b)** efficiency ratio and performance ratio.

Table 1. Comparison value of existing methods with the proposed method.

Methods	Accuracy ratio (%)	F1-score (%)	Error rate (%)	Prediction ratio (%)	Interaction ratio (%)	Efficiency ratio (%)	Performance ratio (%)
PEPLA[13]	64.4	72.2	74.5	65.5	66.3	68.4	66.3
HARS[13]	73.1	79.9	65.9	71.2	75.4	76.3	75.4
LTPA[13]	82.6	90.1	44.7	83.7	86.5	83.7	86.5
IoT-PAMD [13]	98.3	92.2	17.5	96.5	95.4	96.5	95.4
BM-WTAdaboost [Proposed]	99.8	95.56	5.62	98.24	97.2	98.24	97.2

5. Discussion

When used with the Physical Education Teaching System for College Students, current methods such as LTPA, HARS, IoT-PAMD, and PEPLA have their drawbacks. Each of these approaches brings something valuable to the table, but they also come with limitations that can hinder their effectiveness in a college setting. LTPA, or Leisure-Time Physical Activity, is one method that encourages students to engage in physical activities during their free time. While this approach promotes voluntary participation and can lead to increased physical activity levels, it has a significant downside. LTPA could disregard established educational goals in favor of voluntary activities conducted outside of official educational settings [14]. This means that students may prioritize personal interests and leisure activities over structured learning objectives that are crucial for their overall development. As a result, the educational aspect of physical fitness may be overlooked, leading to a gap in knowledge and skills that are essential for a well-rounded education. Similarly, HARS, which stands for Health Activity Recognition Systems, and IoT-PAMD, or Internet of Things-Physical Activity Monitoring and Detection systems, are effective in monitoring and assessing physical activities. These systems utilize advanced technology to track students' movements and engagement in physical activities, providing valuable data for educators. However, their effectiveness in the classroom might be limited by their lack of connection with educational courses [15,16]. If these systems are not integrated into the curriculum, they risk becoming isolated tools that do not contribute to the broader educational experience. Students may receive feedback on their physical activities, but without a clear link to their learning objectives, the data may not be utilized effectively to enhance their education. On the other hand, PEPLA, which stands for Physical Education Personalized Learning Approach, focuses on delivering a comprehensive physical education experience. This method aims to provide students with a holistic understanding of physical fitness, health, and wellness. However, it might not make use of modern technology to provide individualized training and real-time feedback [17,18]. In an era where technology is deeply embedded in education, the absence of personalized, data-driven insights can significantly hinder students' ability to progress and improve. Real-time feedback is crucial for helping students understand their performance and make necessary adjustments. Without it, they may struggle to reach their full potential, missing out on opportunities for growth and development.

Therefore, even while these methods provide informative and useful strategies, their exclusive application wouldn't be sufficient to satisfy the complex demands of a contemporary college physical education program. The landscape of education is constantly evolving, and physical education must adapt to meet the needs of today's students. A well-balanced mix of educational pedagogy, technology, and individualized learning methodologies is essential to create a truly effective program that addresses the diverse needs of students. The goal is to study the use of AI optimization algorithms in the teaching of physical education to college students. By incorporating artificial intelligence into physical education, educators can leverage data analytics to enhance learning outcomes. AI optimization algorithms can analyze vast amounts of data, identifying patterns and trends that can inform instructional practices. This approach allows for a more personalized learning experience, catering to the unique needs and abilities of each student [19].

One innovative direction in this research is the creation of a novel BM-WTAdaboost algorithm. This algorithm aims to forecast the physical education accomplishments of college students based on a variety of variables. These variables may include students' performance in other subjects, their participation in physical activities, and other performance markers that can provide insight into their overall fitness and health [20,21]. By analyzing these factors, the algorithm can predict how well students are likely to perform in physical education, allowing educators to tailor their teaching strategies accordingly.

Imagine a scenario where a student excels in certain physical activities but struggles with others. The BM-WTAdaboost algorithm can identify these trends, enabling educators to create targeted interventions that focus on improving specific skills. This individualized approach not only enhances student engagement but also fosters a sense of ownership over their learning journey. Students are more likely to stay motivated when they see that their education is tailored to their interests and capabilities. Moreover, integrating AI into physical education can facilitate the development of a feedback loop where students receive continuous updates on their progress. This real-time feedback can empower students to take charge of their physical education, encouraging them to set and achieve personal goals. With the support of technology, students can track their improvements, celebrate milestones, and stay committed to their fitness journeys. In conclusion, while current methods like LTPA, HARS, IoT-PAMD, and PEPLA offer valuable insights and strategies for physical education, they are not without their limitations. To effectively meet the diverse needs of college students, a more integrated approach that combines educational pedagogy, modern technology, and personalized learning is essential. By exploring the potential of AI optimization algorithms, particularly through the development of the BM-WTAdaboost algorithm, educators can create a more dynamic and responsive physical education system. This innovative approach promises to enhance student outcomes, foster engagement, and ultimately contribute to the holistic development of students in college physical education programs.

6. Conclusion

In this research, an efficient BM-WTAdaboost method is proposed for predicting college students' achievements in physical education taking into account several variables, including their performance in other courses and other measures of their general performance. Assessing the quality of instruction is one of the most important things to perform to improve the physical education curriculum. Education is a huge area that affects many civilizations. This study uses a range of ML techniques, keeping in mind the significance of the physical education system, to create an intelligent and high-performing system that will enhance the physical education industry as a whole. The student accomplishment dataset is used to simulate the enhanced BM-WTAdaboost approach that is suggested in this work. The suggested approach outperforms previous innovative predicting college students' achievements in physical education with accuracy ratio (99.8%); f-score (95.56%), prediction ratio (98.24%), interaction ratio (97.2%), efficiency ratio (98.24%), performance ratio (97.2%) and error rate (5.62%).

Limitation and future scope

The study's limitations were the process of curriculum modification and the identification of unique elements impacting learner success. Future study intends to evaluate teaching quality in college physical education by using survey data to identify characteristics influencing instruction standards and proposing empirical changes. It also intends to use optimization and machine learning to improve physical education systems and increase student accomplishment accuracy.

Author contributions: Writing—original draft preparation, ZG, HG and ZT; writing—review and editing, ZG, HG and ZT. 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.

References

1. Li J. Application of mobile information system based on internet in college physical education classroom teaching. Mobile Information Systems 2021; 1-10.
2. Shi Q. Construction of physical education teaching system in colleges and universities based on the concept of lifelong physical education. Journal of Education and Educational Research;2(2):75-78.

3. Li H, Zhang H, Zhao Y. Design of computer-aided teaching network management system for college physical education. Computer-Aided Design and Applications2021; 18:152-162.
4. Ding Y, Li Y, Cheng L. Application of Internet of Things and virtual reality technology in college physical education. IEEE Access 2020; 8:96065-96074.
5. Xing Z, Qi Y. Development of creativity in physical education teachers using interactive technologies: involvement and collaboration. Education and information technologies 2023; 28(5): 5763-5777.
6. Peng C, Zhou X, Liu S. An introduction to artificial intelligence and machine learning for online education. Mobile Networks and Applications 2022;27(3):1147-1150.
7. Zhang X, Ma C. Intelligent Development of College Physical Education Teaching Mode Based on “Internet+”. International Journal of Web-Based Learning and Teaching Technologies (IJWLTT) 2024;19(1): 1-13.
8. Chen R, Wang T, Kim S. Optimizing teaching management in college physical education: A fuzzy neural network approach. Soft Computing 2023; 27(24):19299-19315.
9. Blavt O, Iedynak G, Pereverzieva S, Holub V, Melnyk S. Increasing the Reliability of Test Control Using Information Technologies in Inclusive Physical Education. Physical Education Theory and Methodology 2023; 23(4): 607-613.
10. Zhang X, Wang Y, Leung SO. Technology Acceptance Model (TAM) and sports bracelets usage in physical education for freshmen: the role of gender and self-efficacy. Technology, Pedagogy and Education 2023; 32(1): 45-63.
11. Baena-Morales S, Merma-Molina G, Ferriz-Valero A. Integrating education for sustainable development in physical education: fostering critical and systemic thinking. International Journal of Sustainability in Higher Education 2023; 24(8): 1915-1931.
12. Kaggle. BRFSS Physical Activity 2015-2021. Available online: https://www.kaggle.com/datasets/asasherwyn/brfss-physical-activity-2015-2021 (accessed on 2 June 2024).
13. Li Q, Kumar P. and Alazab M. IoT-assisted physical education training network virtualization and resource management using a deep reinforcement learning system. Complex & Intelligent Systems 2022; 1-14.
14. Guan, J., & Tena, J. D. (2022). Physical activity, leisure-time, cognition and academic grades: Connections and causal effects in Chinese students. Journal of Asian Economics, 78, 101423. https://doi.org/10.1016/j.asieco.2021.101423
15. Shuai Wang, S.W. (2022). Application of Internet of Things Framework in Physical Education System.
16. Wu, D., Guo, Z., Wang, Y. Et al. Auxiliary analysis of digital platform using internet of things technology in physical education teaching. Educ Inf Technol 29, 15855–15874 (2024). https://doi.org/10.1007/s10639-024-12469-6
17. Wyant, J. D., Keath, A., Towner, B., Wayda, V., & Baek, J. H. (2024). Navigating the T.E.C.H.N.O.L.G.Y. Integration Landscape in Physical Education: Principles, Tools, and Solutions for Sustained Use. Journal of Physical Education, Recreation & Dance, 95(9), 29–35. https://doi.org/10.1080/07303084.2024.2396306
18. Li, X., Tan, W.H., Zheng, X. et al. Effects of digital monitoring and immediate feedback on physical activity and fitness in undergraduates. Educ Inf Technol (2024). https://doi.org/10.1007/s10639-024-12990-8
19. Arvidsson, T. S., & Kuhn, D. (2021). Realizing the full potential of individualizing learning. Contemporary Educational Psychology, 65, 101960. https://doi.org/10.1016/j.cedpsych.2021.101960
20. Redondo-Flórez L, Ramos-Campo DJ, Clemente-Suárez VJ. Relationship between Physical Fitness and Academic Performance in University Students. Int J Environ Res Public Health. 2022;19(22):14750. Published 2022 Nov 10. doi:10.3390/ijerph192214750
21. Liu, M., Shi, B. & Gao, X. The way to relieve college students’ academic stress: the influence mechanism of sports interest and sports atmosphere. BMC Psychol 12, 327 (2024). https://doi.org/10.1186/s40359-024-01819-1