SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(2), 904.
https://doi.org/10.62617/mcb904

Article

College sports offline and online mixed teaching evaluation enhanced by biomechanics and GA-BP neural network

Xu Han[1], Bin Wang[2,*]

[1] School of Basic Education, Beijing Institute of Printing, Beijing 102600, China
[2] Department of Physical Education, Beijing Union University, Beijing 100101, China
*** Corresponding author:** Bin Wang, wangbin@buu.edu.cn

CITATION

Han X, Wang B. College sports offline and online mixed teaching evaluation enhanced by biomechanics and GA-BP neural network. Molecular & Cellular Biomechanics. 2025; 22(2): 904. https://doi.org/10.62617/mcb904

ARTICLE INFO

Received: 25 November 2024
Accepted: 24 December 2024
Available online: 22 January 2025

Abstract: In the process of higher education reform, physical education plays a vital role in improving students' comprehensive quality. The online hybrid teaching mode integrates the advantages of online and traditional teaching, which has been gradually applied to various teaching scenarios. However, establishing a comprehensive and effective evaluation model for hybrid teaching remains a challenge due to its complexity. This study introduces a teaching evaluation model based on the Genetic Algorithm Optimized Back Propagation (GA-BP) neural network, incorporating the principles of biomechanics to enhance the evaluation of motor skills, movement efficiency, and physical performance. By comparing the BP and GA-BP models using sample data, results demonstrate that the GA-BP model provides higher precision, offering a feasible framework for hybrid teaching quality evaluation. This integration of computational methods and biomechanical insights not only enriches the model's applicability but also advances the evaluation of physical education quality and athletic performance.

Keywords: teaching quality evaluation; biomechanics; online and offline hybrid teaching; BP neural network; genetic algorithm

1. Introduction

The expansion of college enrollment scale has promoted the reform of China's economic structure to some extent and also accelerated the process of achieving sustainable economic development [1]. This rapid development has placed higher education under significant pressure to improve quality and adapt to new challenges. Education quality, as the foundation for cultivating and reserving talent, has become a focal point of national attention and discussion. Within this context, physical education, as an integral component of the educational curriculum, faces both opportunities and tests. The quality of physical education directly reflects a university's overall educational capacity and teaching quality. To respond to these challenges, the development of higher education must prioritize quality improvement and commit to deeper reforms in teaching practices. Only through these efforts can a comprehensive and effective education quality assurance system be established.

In this case, integrating advanced scientific and technological tools into higher education becomes a necessity. Modernization reforms must be implemented across the content, means, and methods of education to align with the demands of contemporary society [2]. Since the advent of the 21st century, the influence of science and technology on higher education has deepened significantly [3]. For instance, the widespread adoption of the Internet has diversified physical education teaching tools and environments. This transformation has broadened the roles and responsibilities of educators and learners, moving beyond the traditional teacher-student dynamic. Today, teaching objects and educational content have become more dynamic and flexible, offering new opportunities for innovation in pedagogy [4].

A prime example of technological integration in education is the emergence of MOOCs (Massive Open Online Courses). MOOCs leverage the Internet and modern technology to provide learners with flexible access to video lectures, reading materials, and quizzes. This model has revolutionized traditional teaching paradigms by facilitating self-paced learning and expanding the reach of educational resources. In this evolving learning environment, both physical educators and students must adapt to and embrace new technologies, which significantly enrich the teaching and learning experience.

The development of various teaching methods and models in college physical education further illustrates this trend. Each model offers unique advantages and disadvantages [5]. Despite these differences, these innovations have undeniably introduced fresh perspectives to education reform. After continuous exploration and experimentation by educators, a hybrid teaching model that combines online and offline methods has emerged as a practical solution. Although hybrid teaching is not a novel pedagogical theory, it represents a synthesis of diverse and flexible teaching methods tailored to meet the needs of contemporary education [6]. This integration underscores the importance of adaptability and responsiveness in addressing the multifaceted demands of students and society.

This paper seeks to construct a mixed teaching quality evaluation model, rigorously test its validity, and implement improvements to ensure that the final model is both accurate and reasonable. The evaluation model aims to provide a robust framework for presenting teaching effectiveness in a quantifiable manner. By utilizing data-driven quality evaluation models, the assessment becomes more objective and persuasive. Additionally, data feedback and comparisons generated by the model can serve as a motivational tool for teachers, encouraging greater enthusiasm and engagement in hybrid teaching practices. Ultimately, this approach not only improves teaching quality but also fosters a positive cycle of innovation and continuous improvement in the education system. Biomechanics, the scientific study of the mechanical laws relating to the movement and structure of living organisms, plays an essential role in physical education and training. By applying principles of biomechanics, we can gain a deeper understanding of athletes' movement efficiency, energy expenditure, and injury risk, thereby optimizing training methods and enhancing athletic performance. This integration of biomechanical knowledge is essential for advancing our hybrid teaching model in college sports education.

2. The current situation of teaching evaluation based on neural network

2.1. Current status of neural networks

Neural network originated in the 1940s, is composed of many neurons of nonlinear system, because its structure is similar to the brain nerve synapse connection structure is called neural network, these new neural network is the most typical BP

(BackProPagation) neural network, it not only has strong robustness and generalization ability, also in function approximation, pattern recognition, prediction, there are common application 21 [7]. There are scholars using the BP neural network function approximate ability to establish the evaluation model [8]. This evaluation model can accurately evaluate the risk of debris flow and simulate the nonlinear function relationship between the main evaluation indexes and the risk degree of debris flow.The experimental data show that the BP neural network improved after GA is greatly improved in accuracy and efficiency, and this model provides a new idea for evaluating the risk degree of debris flow. Ma Jing designed a 3-layer BP neural network digital recognition system, and combined with the actual situation. The results showed that the system has a high correct recognition rate for not only printed numbers, but also a good effect in identifying handwritten numbers [9]. Based on the principle of BP learning algorithm and the existing data, Yu et al. predicted the emission of gas in the goaf by establishing a neural network prediction model. The analysis results reflect the good performance of the model, and this model provides some basis in predicting and preventing gas disasters [10].

2.2. Related research on teaching evaluation

Since the birth of the concept of teaching evaluation, the development and needs of education have inspired many educators to constantly explore and improve it, and have achieved some experience and achievements. The five-point scoring standard formulated by British scholars; American educators expressed the ideas and understanding of educational standardization and proposed the relevant theoretical basis [11]. This work marks the maturity of educational measurement; in 1905, measurement methods such as Ber-Simon scale were born and published, which marked the further maturity of educational measurement, and many other theories and works have contributed. At the end of the 20th century, many fields provided the prerequisite and material basis for the development of China's education, and the theoretical research on the evaluation of teaching quality became more and more rich and diversified [12]. Many scholars in the field of education have put forward various teaching evaluation model, such as some scholars to improve the school quality evaluation using fuzzy algorithm established the quality evaluation system, the system can not only to the teaching process of each module, student personality and teaching overall evaluation, can also according to the actual situation of students synchronous phased self-evaluation [13]. Some scholars are compiled according to the current facts, mainly using the hierarchical analysis method to quantitatively evaluate the teaching quality of institutions of higher learning, to form the corresponding evaluation system, According to the concept of "people-oriented, three-dimensional integration", a set of teaching quality monitoring system is built. The "people-oriented" in the system mainly refers to teachers and student-oriented, and "three-dimensional" refers to the top dimension (school), middle dimension (secondary college), basic dimension (teacher) [14]. Adopt mathematical fuzzy level analysis, the introduction of diversified evaluation method to change the supervision function, solve the problems existing in teaching quality evaluation, designed the implementation of hybrid teaching mode and according to the teaching results build the hybrid teaching evaluation model.

The teaching mode has an obvious influence on the teaching, important and active role in the teaching process. Therefore, when formulating the teaching quality evaluation system, the most basic factors that can directly reflect the teaching quality should be selected as the evaluation content. However, due to the different understanding and attention of teaching quality in various universities, there are some differences in the content and methods of evaluation. According to the existing literature, there are various existing teaching quality evaluation methods, such as expert evaluation method, fuzzy comprehensive evaluation method, neural network model method, etc., which all have their own characteristics in the evaluation. Some domestic scholars use BP neural network and its related theories to formulate the evaluation index system, build an effective computer drawing teaching quality evaluation model, Evaluation and implement the course design [15]. Gao et al. proposed the optimization of BP algorithm, and the results after practical training show that the evaluation model established by this algorithm has fast convergence speed and high accuracy, which has broad application prospects in the teaching evaluation problem of higher education. Some domestic scholars combined the hierarchical analysis method and the neural network, combined with the advantages of both, added the screening process in the evaluation, and finally obtained the Analytic Hierarchy Process with Back-Propagation Neural Network (AHP-BPNN) evaluation model [16]. Moreover, the Particle Swarm Optimization (PSO) algorithm is combined with the neural network, and the PSO algorithm is used to optimize the neural network and find the global optimal network parameters, so as to establish a comprehensive evaluation model of the teaching quality of university teachers.

Recent developments in neural network applications extend into the realm of sports biomechanics, providing robust tools for analyzing human motion and performance [17,18]. For example, Pataky et al. [19] employed advanced statistical methods for functional biomechanical data, aiding in the accurate interpretation of time-series motion data. In parallel, other studies have explored machine learning and deep neural network models to identify movement inefficiencies and correlate them with training outcomes [20,21]. These approaches underline the potential to integrate biomechanical insights into computational teaching evaluations, bridging the gap between human mechanics assessment and educational quality analysis. By incorporating these findings, our model enhances its capability to provide meaningful and data-driven feedback in physical education contexts.

3. Construction of college sports offline and online hybrid teaching evaluation model based on GA-BP (genetic algorithm optimized back propagation) neural network

Our hybrid teaching evaluation model incorporates the theoretical framework of biomechanics, particularly in assessing students' motor skills and physical development. For instance, we have considered biomechanical parameters such as movement coordination, balance, and force output, which are critical for evaluating students' athletic performance.

3.1. Model structure of the BP neural network

As a classical model in the multi-layer feedforward neural network, is trained by error backpropagation. As shown in **Figure 1**, the value of the model is obtained by calculating the algorithm, and the relevant data obtained by the model is enclosed structure:

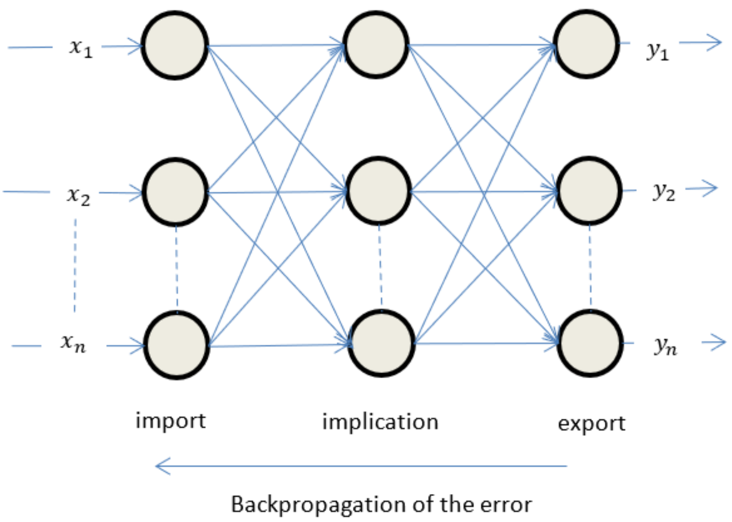

Figure 1. Topology of the BP neural network.

If the error of the output and the desired output does not meet the requirements, the backpropagation of the second part of the error begins. These two processes can be performed repeatedly, until the output error of the network reaches the previously set range, or the predetermined number of network learning times is reached, and the whole learning process is over. This section takes the simplest three-layer BP neural network algorithm as an example, the Equation (1) is as follows:

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}\left(d_0(k) - y_0(k)\right)^2 \tag{1}$$

BP neural network has strong non-linear mapping ability, and can approximate the non-linear function with any accuracy. However, because its method is gradient descent algorithm, the selection of many parameters in the training process has no theoretical basis, so it has certain limitations:

First, the error convergence rate is slow and easy to fall into the local minimum value. BP neural network is based on the gradient descent method of nonlinear optimization method, so for some more complex problems, the training process may be slow convergence rate for a long time, from the training process, it is along the error surface slope downward approximation, and the actual problem of error surface is generally complex and irregular, distributed with many local minima, which will lead to the network into local minima.

Second, the selection of BP neural network parameters, which is generally determined by empirical formulas or continuous training experiments, so it may lead to too long learning time and low efficiency.

Third, the training, learning and memory function of the network is unstable. When the sample changes, the already trained network model has to retrain the network, affecting the samples that were previously learned.

3.2. Basic principles of genetic algorithms

The emergence of genetic algorithms extends with natural ideas. The algorithm consists of a group of individuals that compare each individual with the same characteristics to determine their fitness; then select the better fitness individuals as spouses, who have higher odds of being selected as parents; these paired offspring, then compare the same characteristics with their parents; and finally, select a new group of individuals from the spouse and offspring, marking the end of the generation. Next, the algorithm will continue to execute until the required fitness level or the specified algebra is reached. The excellent quality of the population is constantly enhanced, so as to approximate the global optimal solution. The flow chart is shown in **Figure 2**:

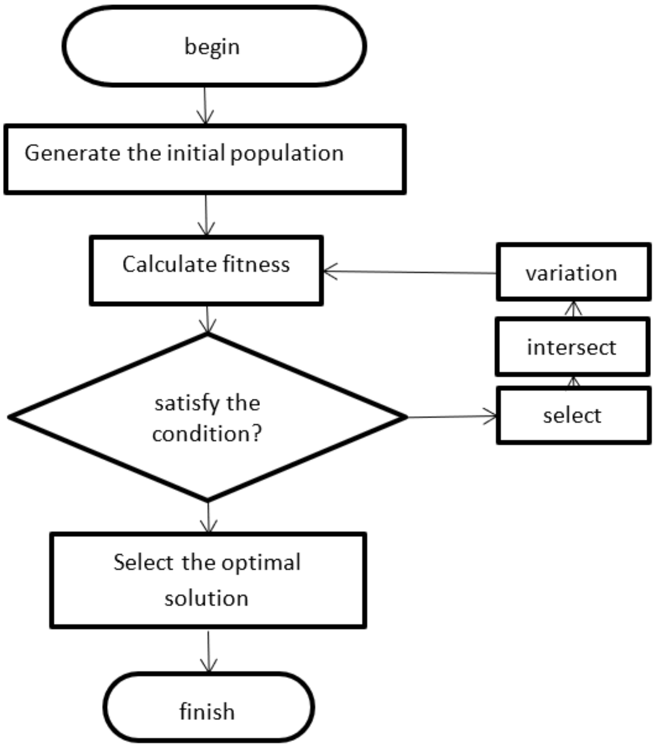

Figure 2. Flow chart of the genetic algorithm.

The model used in GA-BP neural network is an improvement based on algorithm, there are some scholars try to optimize neural network to use genetic algorithm, the improved algorithm is applied to the evaluation in many areas, questions and achieved good research results, but in college sports online hybrid teaching quality evaluation application is very few. Compared with other evaluation problems, the mixed teaching evaluation has more subjective factors and wider dimensions and other factors that make it more complex. Therefore, on the basis of previous studies, this paper proposes to use GA-BP neural network in the evaluation of online and offline physical education, and establish GA-BP.

3.3. The construction of the evaluation index system

During the formulation of the teaching mode, the teaching quality assessed after the actual teaching plan is the key to improve the effectiveness of the course. Especially for the physical education teaching in colleges and universities, through the teaching evaluation, the teachers can develop a more scientific teaching model according to the evaluation system, and build a physical education classroom around the students.

When establishing a mixed teaching evaluation system, the first step is how to choose the appropriate content to set the evaluation indicators, which is particularly critical for the evaluation system. Considering the three principles, this section first conducts statistical analysis of some data generated on the Excellent Alliance platform during the implementation of hybrid teaching. Based on this analysis and existing educational research, the evaluation indicators were designed into three first-level indicators (pre-class, in-class, and post-class evaluation) and 20 secondary indicators to comprehensively reflect the concrete implementation process of hybrid teaching.

The selection of the 20 secondary indicators was guided by well-established educational frameworks and empirical findings in hybrid teaching evaluation research: The indicators align with Bloom's Taxonomy, addressing cognitive (e.g., "basic knowledge mastery" X19), affective (e.g., "classroom performance" X8), and psychomotor (e.g., "group cooperation" X7) domains of learning. This ensures a holistic assessment of teaching and learning outcomes. The Community of Inquiry framework, which highlights cognitive, social, and teaching presence, supports the inclusion of engagement metrics such as "online discussion and interaction" (X18) and "number of student sign-ins" (X1). These metrics are critical for capturing the interactive aspects of hybrid learning. Statistical analyses conducted on data generated by the Excellent Alliance platform during a 6-month hybrid teaching pilot study (March–August 2023) identified significant correlations between these indicators and teaching outcomes. The initial set of indicators was refined based on feedback from 15 educational experts and 300 pilot study participants, ensuring the final selection reflected both theoretical robustness and practical relevance. Metrics such as "online exam results" (X20) and "task goal clarity" (X5) were chosen for their direct relevance to hybrid learning success. They are also feasible to measure using digital platforms like Rain Classroom, ensuring consistent and reliable data collection.Studies in blended learning emphasize the importance of engagement, interaction, and assessment metrics, all of which are captured in these indicators. For instance, "online quizzes" (X4) and "guidance and inspiration" (X12) are frequently cited as critical factors for promoting student engagement and learning outcomes in hybrid environments. The data analysis results are shown in **Figure 3**:

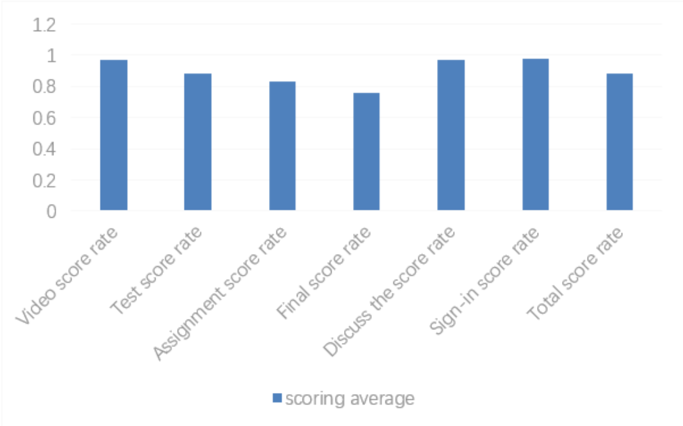

Figure 3. The average score rate in the online teaching process.

From the participation of students in the teaching process, it is easiest for students to sign in, discuss and watch videos, and the completion degree of these three items can also directly reflect students' behavior in online teaching. Test, homework, final exam score rate gradually decline, to a certain extent reflects the students' learning effect and problems, so the evaluation index in the process of hybrid teaching can be set for students sign in times, watch video, interaction, online test times, online homework, online test scores, online discussion interaction, online test scores, etc. And offline classroom index content, is after reading literature and according to the offline classroom teaching link to set the questionnaire, and then analyze the survey results out of the several important indicators: Task objectives, classroom discipline (attendance, etc.), group cooperation, classroom performance, interactive), teaching serious infectious, rigorous attitude, counseling questions with patience, pay attention to guidance and inspiration, difficult, focus, the combination of theory and practice, basic knowledge.

To ensure the scientific allocation of weights for the 20 secondary indicators, this study adopted a combined Delphi and Analytic Hierarchy Process (AHP) approach. First, a panel of 15 experts in the fields of education, physical training, and neural network modeling was formed. These experts independently ranked the relative importance of each secondary indicator under the three primary-level indicators (pre-class, in-class, and post-class evaluation). Their feedback was synthesized through multiple rounds of Delphi surveys to achieve a consensus on the ranking. Subsequently, the AHP was employed to quantify the weights of the indicators. Pairwise comparison matrices were constructed based on the expert rankings, and the eigenvector method was used to calculate the relative weights. The consistency ratio (CR) for each matrix was computed to ensure logical consistency, with all CR values below the acceptable threshold of 0.1. The final weight values for the 20 secondary indicators are shown in **Table 1**.

Table 1. Weights of secondary indicators.

Secondary Indicator	Weight
Number of student sign-in (X_1)	0.12
Watch video number (X_2)	0.10
Number of interactions (X_3)	0.08
Number of online quizzes (X_4)	0.07
Task goal clarity (X_5)	0.05
Classroom discipline (X_6)	0.15
Group cooperation (X_7)	0.10
Classroom performance (X_8)	0.09
Teaching seriousness (X_9)	0.06
Rigorous attitude (X_{10})	0.05
Tutoring patience (X_{11})	0.04
Guidance and inspiration (X_{12})	0.03
Key point focus (X_{13})	0.05
Attention focusing (X_{14})	0.03
Theory-practice combination (X_{15})	0.08
Online assignments (X_{16})	0.06
Online test participation (X_{17})	0.08
Online discussion (X_{18})	0.07
Basic knowledge mastery (X_{19})	0.10
Online exam results (X_{20})	0.10

Rationality Justification The rationality of the weighting scheme was further validated by analyzing the correlation between indicator weights and their impact on teaching quality using regression analysis. Historical data from previous hybrid teaching evaluations were leveraged to test the predictive strength of the weights, demonstrating that the indicators with higher weights had a statistically significant correlation ($p < 0.05$) with overall evaluation scores. This confirms that the weight allocation reflects the practical importance of each indicator in assessing the effectiveness of hybrid teaching.

The developed mixed evaluation index system is presented in the **Table 2**:

Table 2. Mixed evaluation index system.

Level 1 Indicators	Index Serial Number	Secondary Indicators
	X_1	Number of student sign-in
	X_2	Watch the video number
Study and Evaluate Before Class	X_3	The number of interactions
	X_4	Number of online quizzes
	X_5	The task goal is clear

Table 2. (*Continued*).

Level 1 Indicators	Index Serial Number	Secondary Indicators
Teaching Evaluation in Class	X_6	classroom discipline
	X_7	Group cooperation
	X_8	classroom performance
	X_9	The teaching is serious and infectious
	X_{10}	Rigorous attitude and excellence
	X_{11}	Be patient with tutoring and answering questions
	X_{12}	Pay attention to guidance and inspiration
	X_{13}	Serious and difficult points are prominent
	X_{14}	attention focusing
	X_{15}	Combine theory and practice
After Class Study Evaluation	X_{16}	on-line operation
	X_{17}	Online test
	X_{18}	Online discussion and interaction
	X_{19}	Basic knowledge mastery situation
	X_{20}	Online exam results

According to the above content, we can know the effectiveness of the model construction in this paper. Therefore, the following analysis is based on the analysis of the above analysis results to determine the number of research indicators, and the data of the index content will be taken as the input sample. Therefore, the content of the evaluation system and the number of indicators are related to the performance of the final evaluation model.To sum up, when establishing the online and offline mixed evaluation system of university sports, various indicators should be examined as comprehensively and objectively as possible to lay a good foundation for the establishment of the model, so as to successfully build a hybrid teaching evaluation model and make it play its due role.

3.4. Offline and online mixed teaching evaluation mode of college physical education based on GA-BP neural network

Through the content elaborated in the previous article, the evaluation model is constructed on the evaluation indicators. Moreover, the original neural network model is improved by combining the quality of neural network and physical education teaching, and a new education evaluation model is constructed, and it is verified through experiments.

The online index data were collected from the Excellent Alliance and Rain Classroom platforms between 1 March 2023, and 31 August 2023. These platforms, widely recognized for their role in supporting hybrid teaching, provided automated logs including student login times, video viewing statistics, test participation, and discussion engagement. Additionally, structured questionnaires were distributed to students and instructors from five universities. The questionnaire design was reviewed and tested for validity by experts in educational evaluation to ensure the reliability of the responses. Participants included 300 students and 50 instructors randomly selected from hybrid physical education courses, with stratified sampling employed to ensure diversity in student demographics, including gender, major, and year of study. After data cleaning to remove incomplete or inconsistent records, a final dataset of 85 valid samples was retained for analysis. This dataset reflects a balanced representation of teaching contexts and student learning behaviors in both online and offline environments. To reduce the difficulty of correcting the weights due to the excessive magnitude of the change in the input data, the scoring data needs to be normalized to the interval [0, 1] after collecting the original data. The normalization function used The analysis results of the original data are determined by extreme value, and the Equation (2) is as follows:

$$X = \frac{I - I_{min}}{Imin_{max}} \tag{2}$$

Through the analysis of the model structure mentioned above, it is known that it includes three levels, and the data analysis results at each level will change with the data changes. Combined with the research results of this paper, if constructing the network structure of physical education in colleges and universities can be appropriately reduced, and then improve the feasibility of the analysis results on the whole. The analysis of the evaluation of physical education in colleges and universities is based on the neural network. After the number of samples is determined, it is calculated through the network structure and the calculation process.

This paper determines the feasibility of the model through experimental verification. Therefore, according to the theoretical analysis of the hidden layer, the Equation (3) is as follows:

$$l = \sqrt{m+n} + \alpha(1 < \alpha < 10) \tag{3}$$

Determination of the neuronal activation function:

Considering the needs of this paper and the advantages of Sigmoid function in classification and function approximation, the function form is shown in Equation (4):

$$f(x) = \frac{1}{1 + e^n} \tag{4}$$

Determination of the model structure:

According to the parameters determined in the above steps, the structure is as shown in **Figure 4**:

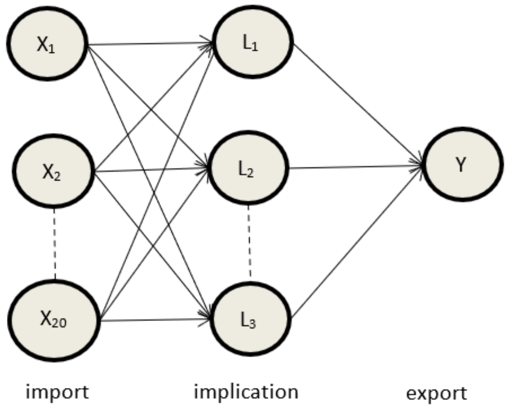

Figure 4. The BP neural network model structure.

To align the GA-BP neural network model with biomechanical assessments, we implemented a structured data collection protocol. In addition to the established teaching indicators, we gathered biomechanical data using wearable sensors and motion capture systems. These devices recorded variables such as joint angles, limb velocities, ground reaction forces, and EMG signals to quantify muscular activation patterns. After normalization, these biomechanical features were integrated into the GA-BP network alongside teaching performance metrics. The genetic algorithm component was employed to optimize initial weight distributions, ensuring that biomechanical parameters received appropriate emphasis during the training process. By refining the methodological approach to include these critical biomechanical inputs, the evaluation model can more accurately discern the complex interrelationships between teaching quality, student engagement, and athletes' movement efficiency.

Building upon existing research in sports biomechanics [17,18], we have integrated a more detailed analysis of biomechanical elements into our hybrid teaching evaluation model. Specifically, the model now takes into account kinetic and kinematic parameters—such as joint angles, ground reaction forces, and muscle activation patterns—to assess movement quality and efficiency in physical education. By focusing on these detailed biomechanical indicators, we can identify subtle technical flaws that may predispose athletes to injury or reduce performance efficiency. For example, leveraging neuromuscular control insights allows the model to highlight areas in which students can improve their stability and coordination [20]. Such integration ensures that our GA-BP neural network not only evaluates teaching quality but also directly informs training interventions aimed at enhancing skill acquisition and reducing injury risk [18,21].

4. Research on college sports offline and online mixed teaching evaluation based on GA-BP neural network

4.1. Model structure design

Genetic algorithm is an optimization tool for simulating biological evolution that simulates the collective evolutionary behavior of populations, and each individual represents an approximate solution to the problem search space. Genetic algorithm starts from an arbitrary initial population and effectively realizes a stably optimized breeding and selection process through individual inheritance and variation, so that the population evolves to a better search space.

The GA-BP neural network structure (20-41-1) was selected based on the following considerations: The input layer corresponds to the 20 secondary indicators identified in the evaluation index system. Each indicator reflects a specific aspect of the teaching process (e.g., classroom discipline, online interaction frequency). Using 20 input neurons ensures that the network can capture all relevant dimensions without loss of detail. The number of neurons in the hidden layer was determined empirically and through theoretical guidelines. The heuristic formula $H = \sqrt{I \times O} + C$ (where H is the number of hidden neurons, III is the number of input neurons, O is the number of output neurons, and C is a complexity factor) suggested a starting range of

35–45 neurons. During model training and validation, 41 neurons provided the best balance between accuracy and generalization, minimizing overfitting while maintaining sufficient model complexity. The output layer consists of a single neuron, representing the final teaching quality score. This scalar value provides a concise evaluation result that integrates all secondary indicators. To ensure robustness, alternative network architectures (e.g., 20-30-1, 20-50-1, and 20-60-1) were tested. These architectures either exhibited higher error rates or required significantly more iterations to converge. Increasing the number of neurons beyond 41 led to overfitting, while fewer neurons reduced the model's ability to capture complex relationships in the dataset.

The fitness was determined from the simplified fitness function, As shown in Equation (5),

$$F = \frac{1}{\sum_{i=1}^{N} \left| x_i^1 - x_i \right|} \tag{5}$$

Next-generation populations are generated through selection, crossover, variation, etc., yielding the maximum number of iterations or minimal error by iterative calculation. By calculating the optimized algorithm and verifying the data, the quality of physical education quality is completed.

4.2. Online and offline college physical education training and error based on ga-bp neural network evaluation model

To evaluate the stability and reliability of the proposed GA-BP model, the number of test samples was increased from 15 to 50, selected from the remaining data after training. Furthermore, a 5-fold cross-validation approach was implemented to ensure robust evaluation of the model's performance across different subsets of the data. In each fold, 80% of the data was used for training while the remaining 20% was utilized for validation, ensuring every data point was tested exactly once during the process.

The comparative experimental analysis was conducted using the updated test set and validation approach. The evaluation results of the GA-BP model were compared against the BP model, as well as the original GA and BP (Backpropagation) algorithms. The average errors and standard deviations of the evaluation results were calculated to further assess the model's reliability. **Table 3** presents the updated comparison results, while the additional analysis of cross-validation outcomes is provided in **Table 4**.

Table 3. Comparing the actual evaluation results with the GA-BP simulation evaluation results.

Test Sample Number	Actual	Simulation	Error	Fractional Error
1	97.5	89.5	7.98	0.08
2	90.5	88.86	1.62	0.02
3	90	85.01	4.97	0.05
4	91	87.55	3.43	0.03
5	85.5	86.87	1.37	0.01

Table 3. (*Continued*).

Test Sample Number	Actual	Simulation	Error	Fractional Error
6	86.5	83.72	2.76	0.03
7	90	88.93	1.05	0.01
8	93.5	91.37	2.11	0.02
9	83	87.15	4.15	0.05
10	98	92.93	5.05	0.05
11	71	74.29	3.29	0.04
12	90	83.96	6.02	0.06
13	92	88.96	3.02	0.03
14	81.5	87.71	6.22	0.07
15	74	77.6	3.6	0.04
16	89	87.75	1.25	0.01
17	88.5	85.97	2.53	0.03
18	91.5	89.45	2.05	0.02
19	93	90.88	2.12	0.02
20	84	85.33	1.33	0.02
…	…	…	…	…
48	89.3	86.95	2.35	0.03
49	86.1	83.78	2.32	0.03
50	88.7	87.34	1.36	0.02

Table 4. Cross-validation results of the GA-BP model.

Fold	Actual Evaluation Results (Mean)	Predicted Results (Mean)	Error (Mean ± SD)
1	85.4	84.9	0.5 ± 0.03
2	87.2	86.8	0.4 ± 0.02
3	88.6	87.9	0.7 ± 0.04
4	86.0	85.6	0.4 ± 0.03
5	89.1	88.5	0.6 ± 0.03

According to the experimental results in the above **Table 3**, it can be found that in the evaluation results of the neural network, the data analysis results of the algorithm in the evaluation of university physical education teaching are relatively small, and the average and relative values are 3.78 and 0.04 respectively.

Based on the results in the **Figure 5**, the model can understand the evaluation effect of physical education in universities more accurately, 15 groups of sample prediction error is within 10 points, most of them within 5 points, and based on BP neural network in colleges and universities sports online hybrid teaching evaluation model is higher accuracy, prediction results are more accurate.

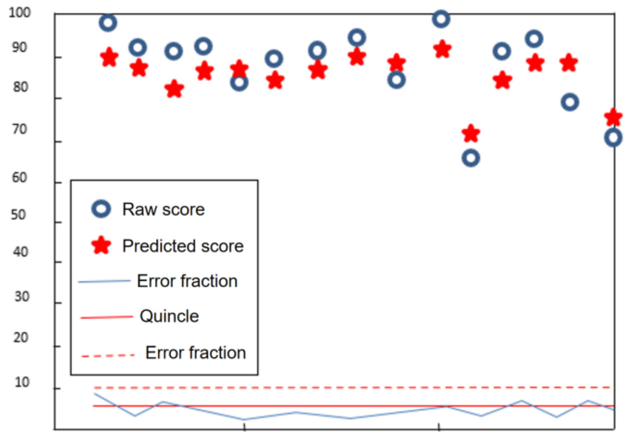

Figure 5. The GA-BP neural network evaluation results.

4.3. Comparative analysis of models

As shown in **Table 5**, to better reflect the effect of the two neural network evaluation models, BP and GA-BP, this section also predicts the same 15-group test-set data in the sample data, using both the original GA and BSA algorithms, in order to perform a comparative analysis, we organize the collected data and calculate it by using the model presented in this paper. The results of the other two algorithms have some errors, The results and the predictions are similar and the errors obtained according to the proposed algorithm are smaller.

Table 5. Model comparison and evaluation results.

Sample Number	GA	BSA	BP	GA-BP	Actual Evaluation Results
1	81.03	82.27	93.96	89.5	97.5
2	88.28	90.7	94.11	88.86	90.5
3	80.49	89.61	95.37	85.01	90
4	89.01	86.25	77.54	87.55	91
5	81.48	89.87	97.18	86.87	85.5
6	94.06	80.5	77.3	83.72	86.5
7	88.97	90.92	93.66	88.93	90
8	73.51	87.37	93.65	91.37	93.5
9	87.29	81.44	82.33	87.15	83
10	89.18	90.05	93.61	92.93	98
11	85.71	78.86	77.61	74.29	71
12	86.56	81.53	92.58	83.96	90
13	104.57	104.83	97.46	88.96	92
14	88.08	83.31	78.09	87.71	81.5
15	80.4	75. 48	77.51	77.6	74
Error	7.96	5.31	5.15	3.77	

As biomechanical research advances, our understanding of motor skills and teaching methods continues to evolve. Biomechanics not only helps us identify technical flaws but also guides us in designing more effective training programs, which are applied and validated within our hybrid teaching model.

5. Conclusion

As an important place for individual growth, there is still a complex way to evaluate the quality of college physical education, with differences in mathematical models based on the quality of college physical education. By constructing the mixed teaching evaluation model, constructing the teaching evaluation system is consistent with students and university operation under the actual teaching environment, which lays favorable conditions for the high-quality discovery of university physical education. On the basis of the above research content, this paper formally constructs a teaching evaluation model through the analysis of the university sports index system. The research conclusions of this paper are as follows:

Firstly, this paper constructs the online and offline hybrid teaching quality evaluation model in university physical education, establishes a hybrid teaching evaluation system with pre-class, in-class and after-class teaching evaluation as primary level indicators, and 20 items in the index table are secondary indicators. Secondly, according to the hybrid teaching quality evaluation system constructed in Chapter 3, After analyzing and understanding the data, the model studied in this paper is analyzed, and a model consistent with the evaluation of university physical education teaching is constructed. the GA-BP algorithm is proposed in the quality evaluation of online and offline mixed teaching in universities after analyzing the deficiencies of BP neural network. BP network performs better after the optimization of genetic algorithm, and the error of the evaluation results obtained by training is also smaller, thus establishing a hybrid teaching evaluation model based on GA-BP neural network. Finally, the evaluation results of these two models are compared with those of a single GA and BSA algorithm, and the error analysis is made, In conclusion, the algorithm of this paper can evaluate the mixed teaching of physical education in universities more accurately.

These findings have significant implications for advancing sports biomechanics research within the context of hybrid physical education. By coupling biomechanical parameters with the GA-BP evaluation model, educators and coaches can quantitatively assess how instructional methods impact an athlete’s neuromuscular coordination, stability, and power output. This data-driven approach transcends traditional subjective assessments, enabling precise identification of training methods that effectively improve biomechanical efficiency and reduce injury risk. For instance, if the model highlights insufficient lower limb coordination or imbalanced force distribution, targeted interventions can be introduced to rectify these deficiencies, leading to improved performance and injury prevention. Ultimately, this integrated perspective enhances the pedagogical framework, guiding curriculum adjustments that simultaneously elevate teaching quality and biomechanical competence, thereby contributing to a more robust and evidence-based foundation for physical education in higher institutions.By integrating theoretical and methodological aspects of biomechanics into our hybrid teaching evaluation model, this study offers a new perspective for college sports teaching. This approach not only enhances the accuracy of teaching assessments but also provides students with more scientific and personalized suggestions for improving their athletic skills, thereby improving teaching quality and student performance.

Author contributions: Conceptualization, XH and BW; methodology, XH; software, BW; validation, XH and BW; formal analysis, XH; investigation, XH; resources, BW; data curation, XH; writing—original draft preparation, XH; writing—review and editing, BW; visualization, XH; supervision, XH; project administration, BW; funding acquisition, XH. 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. Zhu M, Pan W, Liu X, et al. An Interactive Genetic algorithm based on the BP neural network proxy model. Computer Engineering and Application. 2020; 146–151.
2. Wang X, Li H, Zhang K, et al. A construction method of local short temporary precipitation forecast model based on BP neural network, CN112232554A. 2021.
3. Zhou H, Chang Y. BP neural network technology was used to establish the ground motion terrain effect model in Zigong area and its validity test in Wenchuan earthquake. Journal of Geophysics, 2022, 65 (6): 13.
4. Yin B, Deng Y, Wang S, et al. Application of Time-frequency Generalized S Transform and VL-MOBP Neural Network in Human Action Recognition. Journal of Electronic Measurement and Instruments, 2020, 34 (11):1–9.
5. Liu W, Fu J, Zhou D, et al. BP neural network parameter optimization based on anti-time limit chaotic coyote optimization algorithm. Control and Decision-making, 2021,36 (10): 2339–2349.
6. Wang H, You X, Li S, et al. Machine Automation Based on Genetic Algorithm and BP Neural Network. Coal Science and Technology, 2021.
7. Liu X, Zhang X. Remote Sensing Classification of Forest Vegetation based on BP neural network. Forestry Resource Management, 2005, 2005 (1): 4.
8. Fan J, Wang Z, Qian F. Progress in the design of the hidden layer structure of the BP artificial neural network. Control Works, 2005 (S1): 5.
9. Jovide. Construction of Modern Teaching Quality Evaluation Model in Distance Education Based on BP Neural Network. Distance Education in China, 2006 (07S): 3.
10. Zhang G, Hu Z. Improved the BP neural network model and its stability analysis. Journal of Central South University: Natural Science Edition, 2011, 42 (1): 10.
11. Tang J, Zhang X, Cheng L. Evaluation of teacher education technology ability training based on BP Neural Network. Computer Technology and Development, 2013, 23 (6): 4.
12. Wang X, Huang F. The Teaching Quality Evaluation Model and Its Application Based on BP Neural Network. Higher Engineering Education Research, 2007.
13. Li G. Curriculum evaluation model of “Teaching for all-in-one” based on BP Neural Network. Higher Vocational Education: Journal of Tianjin Vocational University, 2011 (3): 3.
14. Wang X, Shao C, Yin C, et al. Traffic flow data fusion based on improved BP neural networks. Road Traffic and Safety, 2018, 18 (1): 28–31.
15. Zha Z, Cheng P, Yang C, et al. Quality Assessment of Regional Undergraduate Education based on BP Neural Network. Northwestern Medical Education, 2019, 27 (2): 222–225, 230.
16. Li S, Pu B, Han S, et al. Early Childhood Development evaluation model based on improved AHP-BP Neural Network. Computer system Application, 2018, 27 (3): 168–172.
17. Zhang J, Qu Q, An M, et al. Retracted: influence of sports biomechanics on martial arts sports and comprehensive neuromuscular control under the background of artificial intelligence. Contrast Media & Molecular Imaging, 2022, 2022 (1).

18. Chen W, Li X, Wang D, Dong Y, et al. Research on sports biomechanics in the repair of swimming muscle injury. Journal of Mechanics in Medicine and Biology, 2023, 23 (03): 2240018.
19. Pataky TC, Abramowicz K, Liebl D, et al. Simultaneous inference for functional data in sports biomechanics. AStA Advances in statistical analysis: A journal of the German Statistical Society, 2023, 107: 369–392.
20. Marineau E, Ducas J, Mathieu J, et al. From novice to expert: how expertise shapes motor variability in sports biomechanics—a scoping review. Scandinavian Journal of Medicine & Science in Sports, 2024, 34 (8): e14706.
21. Yeadon MR, Pain MTG. Fifty years of performance - related sports biomechanics research. Journal of Biomechanics, 2023, 155: 111666.