TSO Algorithm and DBN-Based Comprehensive Evaluation System for University Physical Education

Yonghua Yang[1]
Hunan Communication Polytechnic, Changsha 410132, Hunan, China[1]

Abstract—With the rise of fitness technologies and the integration of smart applications in education, improving physical education evaluation methods is essential for better assessing student performance inside and outside the classroom. Traditional evaluation methods often lack precision, fairness, and real-time capabilities. This study aims to develop an integrated evaluation method for university physical education using a combination of the Tuna Swarm Optimization (TSO) algorithm and a Deep Belief Network (DBN) to optimize the accuracy and efficiency of evaluating both in-class and extracurricular physical activities. The evaluation system is built using the Campus Running APP, which tracks and analyzes student performance in various physical education aspects, including in-class participation, extracurricular activities, and fitness tests. The TSO algorithm is employed to optimize the DBN, improving its ability to process complex datasets and avoid local optima. The model is trained and tested on a dataset collected from student activity on the Campus Running APP. Experimental results show that the TSO-DBN model outperforms traditional methods, such as DBN, GWO-DBN, and FTTA-DBN, in terms of evaluation accuracy and processing time. The TSO-DBN model achieves a root mean square error (RMSE) of 0.2-0.3, significantly lower than the comparison models. Additionally, it reaches an R^2 value of 0.98, indicating high prediction accuracy, and demonstrates the fastest evaluation time of 0.0025 seconds. These results underscore the model's superior ability to provide accurate, real-time assessments. The integration of the TSO algorithm with the DBN significantly improves the precision, efficiency, and fairness of physical education evaluations. The model offers a comprehensive and objective system for assessing student performance, helping universities better monitor and promote student health and physical activity. This approach paves the way for future research and application of AI-based systems in educational environments.

Keywords—Campus fun run app; integrated evaluation of university sports inside and outside the classroom; tuna swarm optimization algorithm; deep confidence network

I. INTRODUCTION

Robust bodily fitness constitutes the foundational element supporting human existence activities and occupational capabilities, and augmenting physical fitness equates to accumulating "healthful human capital" for national economic endeavors [1]. Pupils, regarded as the nation's pivotal focus for advancement and fostering of aptitude, encounter heightened concern over their corporeal well-being management within tertiary educational settings [2]. Presently, the physical well-being of collegiate scholars appears less than promising [3]. Per the survey documentation, the physical caliber of contemporary collegiate scholars exhibits a sustained downturn trajectory, particularly evident in the realms of endurance caliber, force caliber, and velocity caliber [4]. Experts attribute the causative factors primarily to the inadequate oversight and appraisal of collegiate scholars' engagement in physical exertion, notably extracurricular physical exertion [5].

In tandem with the evolution of computational technology and internet technology, the amalgamation of athletic APPs and physical education has emerged as a focal point for investigation among experts and trainers within the sphere of physical education [6], particularly the inquiry into the harmonization of physical education within and beyond the classroom-oriented towards athletic APPs [7]. The pursuit of an intelligent, systematic, and scientific understanding of the fusion of athletic APPs into and out of physical education sessions not solely invigorates collegiate scholars to proactively engage in physical exertion, but also forges a comprehensive and efficacious conduit for melding physical education sessions, athletic contests, and extracurricular exertion [8]. The investigation into the amalgamation of athletics within and external to the athletic session for athletic APPs encompasses the utilization of athletic APPs in the harmonization of athletics within and external to the athletic session [9], the conceptualization of athletic APPs for the harmonization of athletics within and external to the athletic session [10], and the appraisal of the harmonization of athletics within and external to the athletic session predicated on the athletic APP [11], amongst others.

At present, a voluminous body of literature investigates the orientation of athletic APPs towards amalgamation within and external to physical education sessions, primarily concentrating on the harmonization and implementation of web-based APPs with the orientation towards amalgamation within and external to physical education sessions [12]. Qiu et al. [13] delve into the harmonization of athletics within and external to the classroom towards athletic APPs from three perspectives, such as the appraisal entity, appraisal index framework, appraisal methodology, etc., and provides feedback to collegiate scholars contingent on the appraisal substance and outcomes, thereby enhancing collegiate scholars' self-assurance and impetus to proactively partake in athletics; Liu et al. [14] target the issue of collegiate scholars' lackluster engagement in athletics within and external to the classroom, and via the scrutiny of the athletic appraisal framework and stratagem. It equationtes an integrative appraisal prototype for collegiate scholars within and external to the classroom, and fosters collegiate scholars' athletic prowess in a targeted manner; Liu et al. [15] employ investigative methodologies such as literary technique, questionnaire survey technique, mathematical statistical technique, logical analysis technique, etc., and leverages the collegiate jogging APP as a medium to dissect and probe into the integrative appraisal prototype of collegiate athletics within and external to the classroom. With the progression of artificial intelligence algorithms and big data technology, it has evolved into a trend and feasibility to conjoin intelligent algorithms in investigating the integrative appraisal methodologies within and external to collegiate athletic sessions [16]. From the extant literature concerning the integrative appraisal of university physical education within and external to the session in conjunction with athletic APPs and intelligent algorithms, as well as the research outcomes of preceding investigators on them, albeit there has been an extensive duration and considerable volume of investigations on the application analysis of athletic APPs, there exists a paucity of quantitative analysis of the appraisal methodology for the harmonization of university physical education within and external to the session predicated on athletic APPs, resulting in the harmonization of education within the session being inadequately precise, objective, and systematic [17].

Addressing the issues prevalent in the contemporary integrative appraisal methodology of university athletics within and external to the session predicated on athletic APPs [18], this paper advances an integrative appraisal methodology of university athletics within and external to the session founded on smart optimization algorithm to refine the deep learning network. This paper follows a structured writing process, comprehensively discussing the integrated evaluation system for university physical education from background to conclusion. First, the introduction highlights the current decline in university students' physical fitness and emphasizes the inadequacies of existing evaluation methods, especially in assessing extracurricular activities. In Section II, the analysis of evaluation issues identifies the key problems in current evaluation practices and proposes a solution by combining feature extraction techniques and intelligent algorithms. In Section III, the construction of the integrated evaluation system is based on TSO and DBN to improve fairness, efficiency, and precision. The algorithm principles section explains the mathematical models and optimization process behind TSO and DBN. In Section IV, through experimental comparisons, the paper demonstrates the superiority of the TSO-DBN model in terms of accuracy and processing time, especially compared to other algorithms such as GWO-DBN and FTTA-DBN. Finally, the conclusion summarizes the application prospects of the TSO-DBN model in university physical education evaluation and points out future directions for optimizing the system.

II. Physical Education In and Out of the Classroom Analysis of Evaluation Issues

A. Characteristics of Integrated Evaluation In and Out of University Physical Education Classes Extraction

This study focuses on the synthesis of collegiate physical training initiatives, both within the curriculum and as extracurricular activities, as its primary subject for scrutiny. The analysis delves into the extraction of evaluative features pertinent to the amalgamation of these educational and recreational physical activities within the university setting.

1) Feature extraction basis: Campus Trail Le Running APP is a professional online running platform, that is based on GPS and sensor technology, sets the outdoor activity route into several points, randomly designates the activity route before each start of the movement, monitors the movement trajectory through the matching of the movement points, accurately records the movement data such as the movement trajectory, mileage, pace, steps, etc., and automatically counts the pace information of the segmented mileage. This punch card running mode with the help of different collection points to point to the movement fall line, both campus orienteering cross-country style sports fun, but also can promote students' outdoor sports, to achieve the love of campus life running fitness function [15]. This paper combines the portable software of Campus Running APP to carry out the construction of an integrated evaluation system for college physical education inside and outside the classroom, based on the characteristics of Campus Running APP use, extracting features from extracurricular physical exercise, classroom teaching, and participation in the physical health standard test scores and other aspects [19].

2) Principles of feature extraction: To construct an objective and reasonable evaluation feature system for the integration of university physical education inside and outside the classroom, the criteria for feature selection are shown in Fig. 1, and the specific expressions include orientation, accuracy and conciseness, positivity, mutual independence, and cultivation of students' abilities.

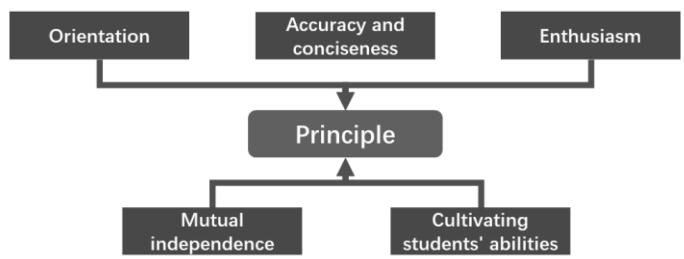

Fig. 1. Feature extraction.

3) Integrated evaluation feature extraction: The holistic assessment facilitated by the Campus Running APP encompasses a methodology that merges the evaluation of student's academic and practical engagement in physical education, both within the confines of the classroom and in extracurricular settings [20]. This approach is designed to gain an in-depth insight into the multifaceted growth of students' competencies and overall quality in physical education, with the ultimate goal of fostering their comprehensive development. The specific dimensions of this integrated evaluation are delineated in Fig. 2 and encompass the following key areas:

a) Extracurricular physical exercise: This domain focuses on the analysis of students' involvement in voluntary physical training outside of formal class hours, including attendance records for extracurricular physical activities (W1), involvement in training sessions for amateur representative teams (W2), and engagement with sports association clubs (W3).

b) Classroom teaching: The classroom teaching component of the evaluation scrutinizes students' in-class performance (T1), their proficiency in sports techniques as assessed through skill evaluations (T2), and their grasp of fundamental theoretical concepts in physical education (T3).

c) In the area of physical fitness testing: In the realm of physical fitness testing, the evaluation looks at the monitoring of students' physical condition (Z1) as part of the integrated assessment.

d) In the area of sports programs: The evaluation of students' involvement in organized sports programs extends to their competitive achievements (X1), technical proficiency as evaluated through ratings (X2), and the tactical understanding demonstrated in analyses (X3).

e) Sports literacy: Lastly, the assessment of sports literacy within the integrated framework includes awareness of sports (S1), consciousness of health (S2), the ability to work effectively in teams (S3), and the capacity for self-management (S4).

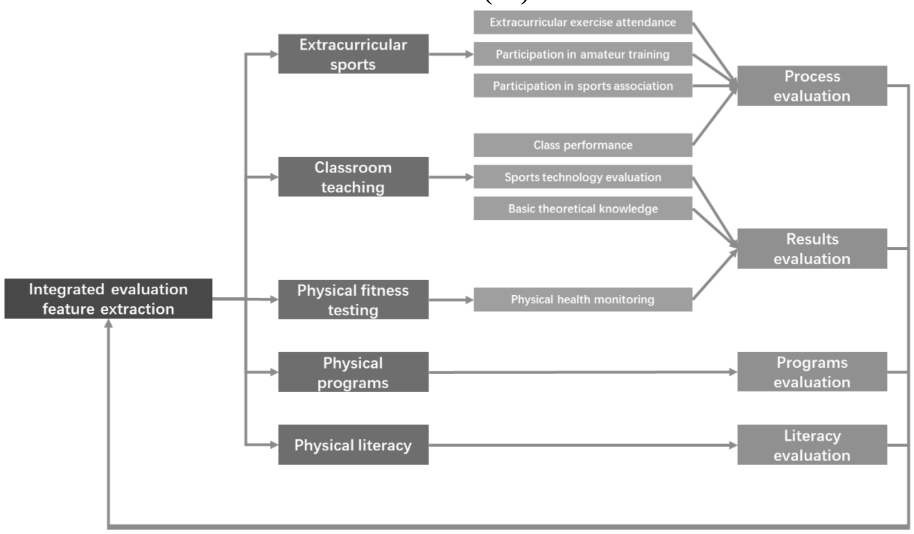

Fig. 2. Feature extraction for integrated evaluation of university physical education.

B. *Construction of Integrated Evaluation System Inside and Outside University Physical Education Classes*

The comprehensive assessment framework for university physical education, spanning both curricular and extracurricular domains, identifies key performance indicators such as out-of-class sports engagement, in-class instruction, physical assessments, competitive sports, and athletic literacy [21]. It utilizes specific metrics like attendance at voluntary sports activities (W1), involvement in amateur team training (W2), membership in sports clubs (W3), in-class deportment (T1), proficiency in sports techniques (T2), foundational knowledge of physical education (T3), surveillance of health and fitness (Z1), outcomes in competitive events (X1), proficiency ratings (X2), strategic evaluations (X3), consciousness of sports (S1), health consciousness (S2), collaborative skills (S3), and self-governance (S4), along with 14 other characteristics as secondary indicators [22]. This framework aims to create a thorough, unbiased, and coherent system for evaluating the integration of physical education experiences within and beyond the academic setting, as illustrated in Fig. 3.

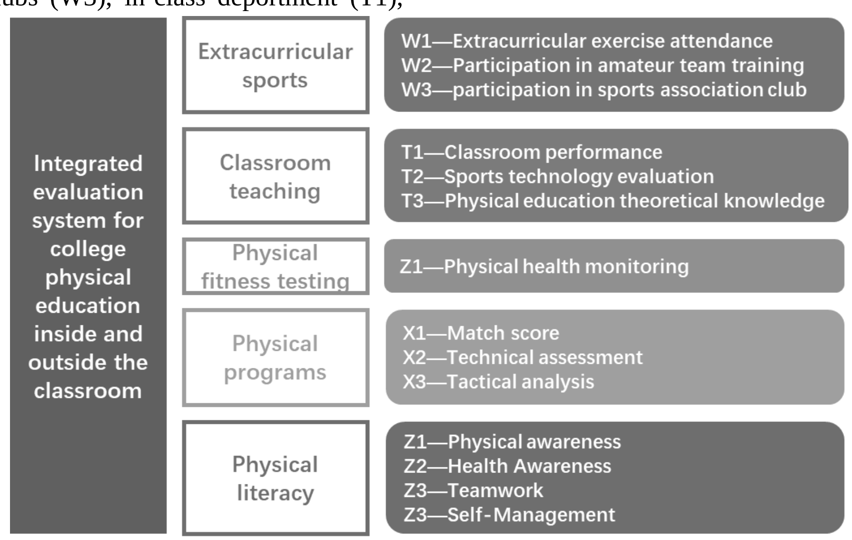

Fig. 3. Integrated evaluation system inside and outside university physical education classes.

III. RELATED WORK

A. Tuna Swarm Optimization Algorithm

The Tuna Swarm Optimization (TSO) methodology, introduced by researchers Xie and colleagues in 2021, represents an innovative approach within the realm of swarm intelligence optimization [23]. This algorithm draws inspiration from the distinct foraging patterns observed in tuna schools, specifically spiral and parabolic strategies, and is distinguished by its streamlined parameter set, robust exploration capabilities, and a keen focus on precision in optimization tasks. In the brief period since its inception, the TSO has been successfully implemented across a variety of sectors, including the optimization of photovoltaic cell parameters, numerical forecasting of wind speeds, classification of wind turbine malfunctions, and image segmentation, yielding commendable outcomes. The detailed strategies for optimization within this algorithm are delineated as follows:

1) Initialisation:

$$X_i^{\text{int}} = rand \times (ub - lu) + lb, i = 1, 2, \cdots, NP \tag{1}$$

From Eq. (1), X_i^{int} denotes the *ith* initialized individual, ub and lu denote the upper and lower bounds of the search space, respectively, NP denotes the number of tuna stocks, and $rand$ denotes a random vector between 0 and 1.

2) Spiral foraging: The other tuna in the group follow the optimal individual in a spiral foraging process, which is modeled mathematically as follows:

$$X_i^{t+1} = \begin{cases} \alpha_1 \times \left(X_{best}^t + \beta \times \left| X_{best}^t - X_i^t \right| \right) + \alpha_2 \times X_i^t & i = 1 \\ \alpha_1 \times \left(X_{best}^t + \beta \times \left| X_{best}^t - X_i^t \right| \right) + \alpha_2 \times X_{i-1}^t & i = 2, 3, \cdots, NP \end{cases} \tag{2}$$

$$\alpha_1 = \alpha + (1 - \alpha) \times \frac{t}{t_{\max}} \tag{3}$$

$$\alpha_2 = (1 - \alpha) - (1 - \alpha) \times \frac{t}{t_{\max}} \tag{4}$$

$$\beta = e^{bl} \times \cos(2\pi b) \tag{5}$$

$$l = e^{3\cos\left(\frac{t_{\max} - t + 1}{t_{\max}} \times \pi \right)} \tag{6}$$

In above equations, X_i^{t+1} signifies the i^{th} entity of the $(t+1)^{\text{th}}$ iteration, X_i^t signifies the i^{th} entity of the t^{th} iteration, X_{i-1}^t represents the i^{th} entity of the t^{th} iteration, X_{best}^t symbolizes the present location of the optimal entity, α_1 and α_2 represents the weighting coefficients regulating the propensity of the entity to migrate towards the optimal entity and the antecedent entity, stands for α constant, symbolizes the current count of iterations, t signifies the utmost count of iterations $t_{\max}$, denotes the arbitrary figure evenly dispersed from 0 to 1, represents a constant, b signifies the separation parameter from the optimal entity or arbitrary entity, denotes the helix line parameter, is the random number. Random figure within 0 and 1, e is a constant, β signifies the separation parameter betwixt an entity and the optimal or arbitrary entity, and l represents the helix parameter.

When the optimal individual fails to find food, continuing to follow the optimal individual is not favorable for foraging, so a coordinate is randomly generated in the search space as a reference point for spiral search. Its position update equation is:

$$X_i^{t+1} = \begin{cases} \alpha_1 \times \left(X_{rand}^t + \beta \times \left| X_{rand}^t - X_i^t \right| \right) + \alpha_2 \times X_i^t & i = 1 \\ \alpha_1 \times \left(X_{rand}^t + \beta \times \left| X_{rand}^t - X_i^t \right| \right) + \alpha_2 \times X_{i-1}^t & i = 2, 3, \cdots, NP \end{cases} \tag{7}$$

In Eq. (7), X_{rand}^t denotes the randomly generated reference point in the search space of the tenth iteration.

```
Algorithm: Pseudocode of TSO
Initialize TSO parameters, including population size, tmax, a, z;
Initialize population;
Evaluate initial population and update best individual with best value;
While t<=tmax do
  for each individual i do
    Update a1, a2, p;
    if rand<z
      Update position at random uniformly;
      if rand>=0.5
        if t/tmax<rand
          Update position using spiral foraging with random reference point;
        else if t/tmax>=rand
          Update position using spiral foraging with best point; end
      else if rand>=0.5
        Update position using parabolic foraging with reference point;
      end
    end
  end
  Evaluate solution and update best solution;
  t = t+1;
end
Output best solution.
```

Fig. 4. Pseudo-code of TSO algorithm.

3) Parabolic foraging: Tuna engages in parabolic foraging in addition to spiral foraging. These two foraging methods are used alternately to increase the probability of the tuna catching food, assuming that both methods are chosen randomly with a probability of 50%. The specific updating equation is as follows:

$$X_i^{t+1} = \begin{cases} X_{best}^t + rand \times \left(X_{best}^t - X_i^t \right) + TF \times p^2 \times \left(X_{best}^t - X_i^t \right) & rand < 0.5 \\ TF \times p^2 \times X_i^t & rand \geq 0.5 \end{cases} \tag{8}$$

$$p = \left(1 - \frac{t}{t_{\max}}\right)^{\frac{t}{t_{\max}}} \tag{9}$$

In Eq. (8) and Eq. (9), TF is a random value of -1 or 1, $rand$ denotes a random quantity between 0 and 1, and p is an adaptive change parameter with the number of iterations that determines the magnitude of population exploitation.

4) TSO algorithm pseudo-code: The TSO algorithm's optimization routine initiates by creating a collection of tuna entities at arbitrary positions within the defined search area. As the iterative phase unfolds, each tuna within the population selects at random between two distinct foraging tactics to apply or opts to reposition itself within the search expanse by a fixed probability threshold, denoted by z. The algorithm proceeds to refine the positions of the tuna, iteratively enhancing the solution until the predefined termination criteria are met. Upon completion, it yields the optimal solution entity along with its associated fitness score. A representation of the TSO algorithm's procedural steps is depicted in the form of pseudo-code in Fig. 4.

5) Tuna swarm optimization algorithm steps and processes: In alignment with the optimization strategy of the TSO algorithm, a schematic representation of its flow is presented in Fig. 5. With each cycle of iteration, a preliminary solution is spontaneously generated. Subsequently, through a methodical process of assessment and selection, the algorithm progressively converges towards the ultimate optimal solution. The detailed procedural steps are outlined as follows:

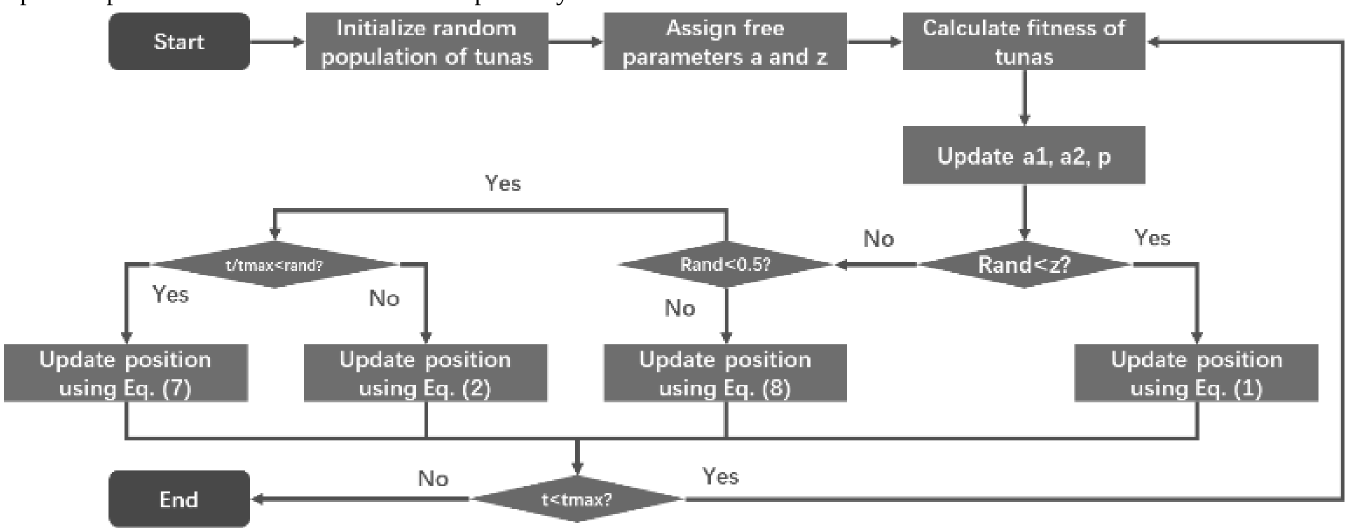

Fig. 5. Flowchart of TSO algorithm.

- Step 1: Initiation involves the configuration of both the demographic parameters and their respective positions within the search space. It is also essential to establish the upper limit for the iteration count and to define additional pertinent parameters for the optimization process;
- Step 2: Calculate the fitness value and record the current optimal individual;
- Step 3: Update the TSO algorithm parameters;
- Step 4: Based on the probability z and the size of the random number, select the appropriate strategy to update the individual location;
- Step 5: Assess the suitability of each candidate solution by computing its fitness value, and document the most advantageous individual identified in the current round;
- Step 6: Evaluate if the ongoing iterations have met the predefined threshold. If the iteration limit has been exceeded, proceed to the conclusion of the algorithm; otherwise, continue with subsequent iterative enhancements. If the maximum number of iterations is reached, carry out the output of the optimal solution and optimal value; otherwise, go to step 3.

B. DBN Network

This paper adopts a deep confidence network to construct an assessment model that integrates the evaluation of college sports activities both in and out of the classroom, tackling the evaluation of behavioral data from sports applications [24].

Deep Belief Networks (DBN) [25] consist of multiple levels of Restricted Boltzmann Machines (RBM), representing the neural network. These networks are structured with an input level and a hidden level, where connects exist with these levels but not among units within the same level. The complex relationships within the input data.

Determine the energy function of the Restricted Boltzmann Machine (RBM). Assuming that $\theta = (\omega, a, b)$ is the DBN network parameter, the energy function of RBM is expressed as:

$$E(v,h|\theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i \omega_{ij} h_j \tag{10}$$

In Eq. (10), (v,h) represents the state values within the Deep Belief Network (DBN), and ω denotes the weights that link the visible and hidden layers of the network a and b are the bias of the visible and hidden layers respectively, and the hidden and visible layer states are binary, i.e. $v \in \{0,1\}$ and $h \in \{0,1\}$.

The method of stochastic gradient descent is employed to estimate the parameters θ of the DBN network. The corresponding parameters θ^* are obtained by solving the maximum of the log-likelihood function:

$$\theta^* = \arg_\theta \max L(\theta) = \arg_\theta \max \sum_{k=1}^{K} \ln p\left(v^k \middle| \theta\right) \tag{11}$$

In Eq. (11), K is the number of training samples.

The energy function serves as the foundation for calculating the joint probability distribution, which is a critical component in understanding the interactions between visible and hidden layers within the network, Eq. (12) and Eq. (13):

$$p(v,h|\theta) = \frac{e^{-E(v,h|\theta)}}{Z(\theta)} \tag{12}$$

$$Z(\theta) = \sum_v \sum_h e^{-E(v,h|\theta)} \tag{13}$$

Establish the condition of the visible layer. The likelihood of the activation for the jth unit within the hidden layer is Eq. (14):

$$p(h_j = 1|v,\theta) = sigmoid\left(b_j + \sum_{i=1}^{n} v_i \omega_{ij}\right) \tag{14}$$

Establish the state of the hidden layer. The likelihood of activation for the ith node in the visible layer of the network is calculated by Eq. (15):

$$p(v_i = 1|h,\theta) = sigmoid\left(a_i + \sum_{i=1}^{n} h_j \omega_{ij}\right) \tag{15}$$

According to Gibbs sampling theorem, the RBM parameter θ is updated with the following Eq. (16) to Eq. (18):

$$\Delta\omega_{ij} = \frac{\partial \log p(v)}{\partial \omega_{ij}} = \varepsilon\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{predict}\right) \tag{16}$$

$$\Delta a_i = \frac{\partial \log p(v)}{\partial a_i} = \varepsilon\left(\langle v_i \rangle_{data} - \langle v_i \rangle_{predict}\right) \tag{17}$$

$$\Delta b_j = \frac{\partial \log p(v)}{\partial b_j} = \varepsilon\left(\langle h_j \rangle_{data} - \langle h_j \rangle_{predict}\right) \tag{18}$$

where ε denotes the learning rate, $\langle \square \rangle_{data}$ is the expectation of training after input data, and $\langle \square \rangle_{predict}$ is the expectation of the model itself.

IV. Result and Discussion

A. Decision-making Variables

The conventional iterative approaches for optimizing the parameters of a Deep Belief Network (DBN) are susceptible to getting trapped at local optima. To counteract these issues, this paper employs the Tuna Swarm Optimization (TSO) algorithm to refine the parameters of the DBN. This includes the weights that connect the visible and hidden layers and the biases associated with these layers. The decision variables for the TSO algorithm's optimization process are represented by the vector $\theta = (\omega, a, b)$.

B. Objective Function

To enhance the precision of DBN training, the TSO-DBN algorithm employs the root-mean-square error (RMSE) as its objective function, which is Eq. (19):

$$\min RMSE = \sqrt{\left(\sum_{i=1}^{M} (\hat{y}_i - y_i)^2\right) \Big/ M} \tag{19}$$

C. Steps and Processes

The assessment technique grounded in the Tuna Swarm Optimized Deep Belief Network (TSO-DBN) for the synthesis of in-class and extracurricular sports education is fundamentally predicated on the correlation between the input features of the evaluation and the output values indicative of the integrated sports classroom performance. It also hinges on the linkage between these features and their respective evaluation outcomes. A visual representation of this integrated assessment methodology based on the TSO-DBN algorithm is depicted in Fig. 6, with the detailed procedural steps outlined below:

- Step 1: Identify and extract the evaluative attributes that are pertinent to the integration of physical education across both classroom and extracurricular domains; subsequently, partition the entire data corpus into three distinct subsets: one for training, another for validation, and the last for testing purposes.
- Step 2: The nascent parameters of the DBN are equationed by leveraging the TSO algorithm, with the initialization of various algorithmic parameters such as the size of the population and the number of iterations. This step also involves the initialization of the population and the computation of the objective function's value.
- Step 3: Position update based on spiral foraging and parabolic foraging optimization strategies.

- Step 4: Calculate the fitness value and update the optimal solution.
- Step 5: Assess if the criteria for ending the iterative process have been met; should this be the case, conclude the iteration, and produce the most favorable set of DBN network parameters, then proceed to Step 3. If not, persist with the process and advance to Step 6.
- Step 6: Translate the refined DBN parameters through the lens of the TSO algorithm, securing the optimal parameters, and subsequently establish the recognition model that is underpinned by the TSO-DBN algorithm.
- Step 7: Utilize the proficiently trained recognition prediction model to conduct an evaluation of the active test dataset, which leads to the generation of the appropriate classification results.

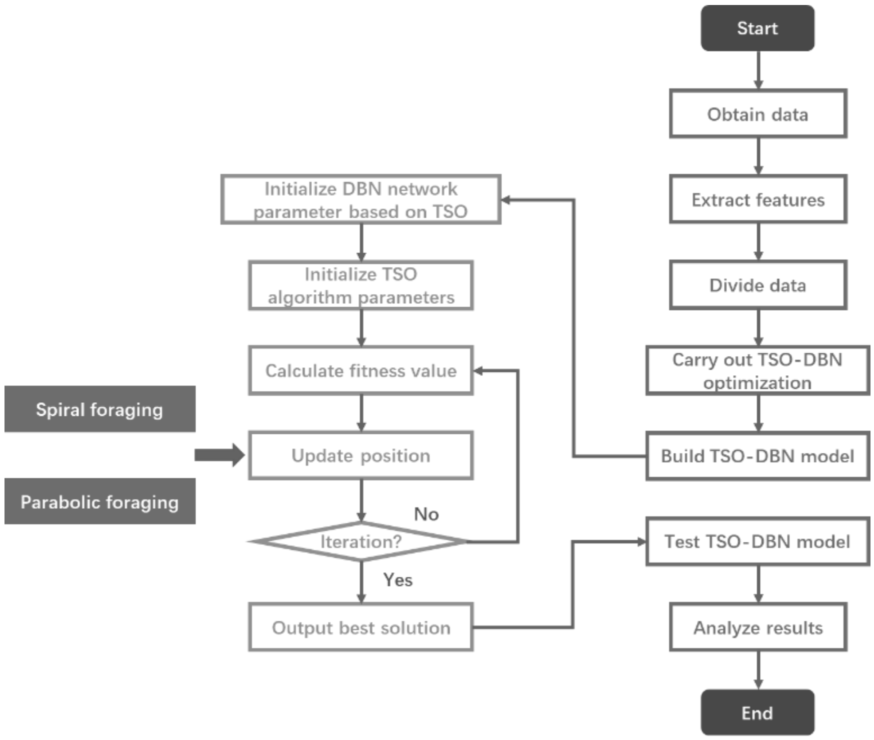

Fig. 6. Flowchart of the integrated evaluation method of university physical education inside and outside the classroom based on the TSO algorithm to improve the DBN network.

D. *Experiments and Analysis of Results*

To substantiate the strengths and weaknesses of the comprehensive evaluation approach for physical education, both within and beyond the classroom, as introduced in this paper through the Campus Run APP, a comparative analysis was conducted using four distinct analytical methods. Each algorithm's specific parameters were set out in alignment with Table I. The experimental setup was established on a Windows 10 operating system, equipped with a 2.80GHz processor, and 8GB of RAM, and utilizing Matlab2023a as the programming language for the simulation.

TABLE I. PARAMETER SETTINGS OF THE INTEGRATED EVALUATION METHOD FOR PHYSICAL EDUCATION INSIDE AND OUTSIDE THE CLASSROOM BASED ON CAMPUS RUN APP

Arithmetic	Parameterization
DBN	The network architecture consists of three concealed strata, each populated with an identical count of 100 nodes, facilitating complex pattern recognition and data processing
GWO-DBN	The governing parameter a within the Grey Wolf Optimizer (GWO) diminishes from 2 to 0. The count of GWO populations and the DBN network concealed layer node configurations mirror those of the TSO-DBN.
HHO-DBN	DBN network nodes set as in TSO-DBN
FTTA-DBN	FTTA algorithm Pcomm=0.2, Pstudy=0.2, Perror=0.001, FTTA population size and DBN network node settings are the same as TSO-DBN
TSO-DBN	The TSO algorithm is characterized by a set at 0.7, and z at 0.05. The examination of the count of TSO populations in conjunction with the DBN network nodes results in the following observations.

1) Examination of the influence of TSO population count and DBN cryptic node quantity: To scrutinize the effect of the populace magnitude of the TSO algorithm and the quantum of DBN clandestine nodes on the holistic appraisal approach of tertiary physical education sessions both within and beyond the classroom, this paper contrasts and examines the efficacy of the holistic appraisal methodology of physical education sessions within and without grounded upon the Campus Run APP under varying populace magnitudes and differing quantities of DBN clandestine node layers. Fig. 7 and 8 present the diagrams depicting the sway of diverse populace magnitudes and distinct quantities of DBN clandestine nodes on the appraisal precision and duration of the appraisal approach for the synthesis of athletic sessions within and without, respectively.

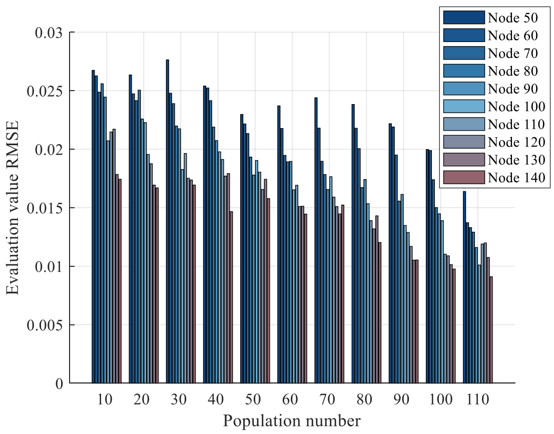

Fig. 7. Effect of different population sizes and different numbers of DBN hidden layer nodes on evaluation accuracy.

From Fig. 7, it is evident that as the optimization escalates, the precision of the appraisal figure of the comprehensive appraisal approach of education sessions based on the Campus Run APP ascends progressively; with the augmentation of the clandestine node count within the DBN tri-layered network, the RMSE value of the comprehensive appraisal figure of the comprehensive appraisal of internal and external physical education sessions based on the Campus Run APP diminishes, resulting in enhanced precision. As discernible from Fig. 8, with the increase of the TSO optimization algorithm population, the appraisal period of the internal and external synthesis of physical education sessions based on the Campus Run APP augments steadily; as the number of DBN network hidden nodes grows rapidly, the appraisal period of the internal and external synthesis of physical education sessions based on the Campus Run APP expands. In summation, by contemplating the equilibrium of precision and temporal performance concurrently, the intelligent optimization algorithm populace magnitude elected in this paper amounts to 80, with the CNN hidden node count standing at 70.

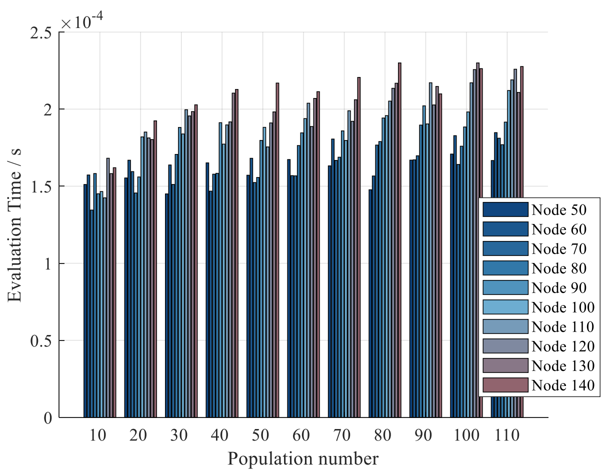

Fig. 8. The impact of varying the size of the population and the count of nodes in the DBN's hidden layers on the duration of the evaluation process.

2) Comparison of evaluation method results: To substantiate the veracity and preeminence of the holistic appraisal approach rooted in the TSO-DBN algorithm for internal and external physical education sessions, the holistic appraisal methodology predicated on the TSO-DBN algorithm for internal and external physical education sessions was contrasted with the holistic appraisal methodology grounded in the DBN, GWO-DBN, HHO-DBN, and FTTA-DBN algorithms. The operational outcomes of each model are exhibited in Fig. 9, 10, 11, 12, and 13.

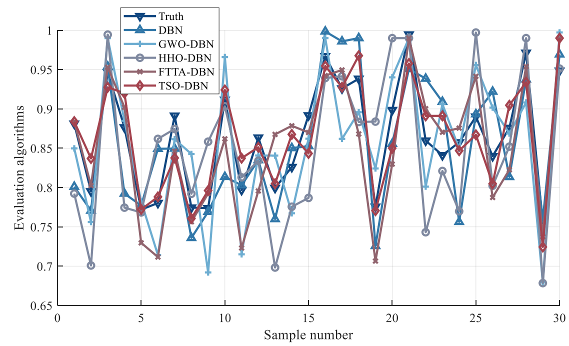

Fig. 9. Predicted results of the integrated evaluation method of physical education inside and outside the classroom based on each algorithm.

Fig. 9 and Fig. 10 depict the forecasted values and relative errors of the holistic appraisal approach of physical education within and without the classroom grounded in each algorithm, respectively. The error of the TSO-DBN algorithm is contained within 0.05, while the residual algorithms' error rankings follow the sequence of FTTA-DBN, GWO-DBN, DBN, and HHO-DBN, with the error scopes restrained within 0.07, 0.08, 0.1, and 0.11, correspondingly. In summation, regarding the forecast precision of the appraisal value, the forecast precision of the integration of internal and external appraisal of physical education sessions based on the TSO-DBN algorithm surpasses that of the other algorithms.

Fig. 11, 12, and 13 exhibit the anticipated RMSE, R2, and duration of the comprehensive physical education in-and-out appraisal methodologies based on each algorithm under variant operational circumstances. As discernible from Fig. 11, 12, and 13, the hierarchy of forecasted RMSE of each algorithm under diverse operational circumstances follows the order of TSO-DBN, FTTA-DBN, GWO-DBN, HHO-DBN, and DBN, and the forecasted RMSE of the comprehensive appraisal approach for internal and external sports sessions based on the TSO-DBN algorithm is the least substantial, with a value spanning from 0.2 to 0.3; the ranking of projected R2 of each algorithm under various operational conditions is TSO-DBN, FTTA-DBN, GWO-DBN, HHO-DBN, and DBN. The anticipated R2 rankings of each algorithm under diverse operational circumstances are TSO-DBN, FTTA-DBN, GWO-DBN, HHO-DBN, DBN, and the comprehensive appraisal methodology based on the TSO-DBN algorithm for internal and external athletic sessions boasts the most extensive projected R2, with a value approximating 0.98; the forecasted duration rankings of each algorithm under varied operational conditions are, sequentially, TSO-DBN, FTTA-DBN, HHO-DBN, GWO-DBN, DBN, and the prediction duration of the comprehensive appraisal methodology of physical education within and without the classroom based on the TSO-DBN algorithm is the briefest, and its value lies within 0.0025. This implies that the comprehensive appraisal approach of physical education within and without the classroom for each algorithm exhibits the optimum performance.

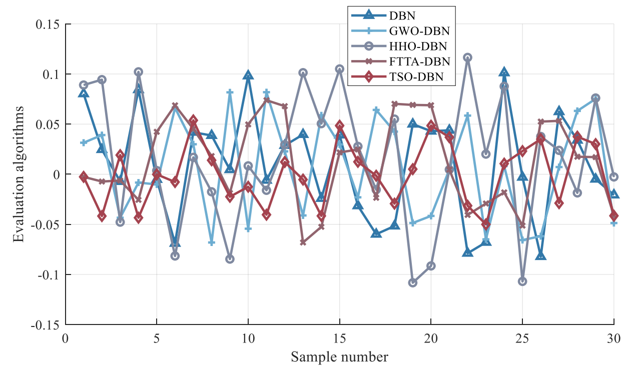

Fig. 10. Results of the relative error between the predicted and true values of the integrated evaluation methods for physical education inside and outside the classroom based on each algorithm.

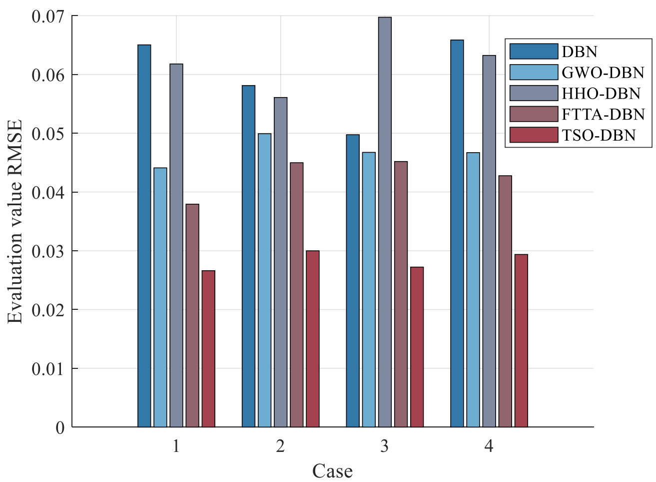

Fig. 11. Predicted RMSE results of the integrated evaluation method of physical education inside and outside the classroom based on the Campus Fun Run App.

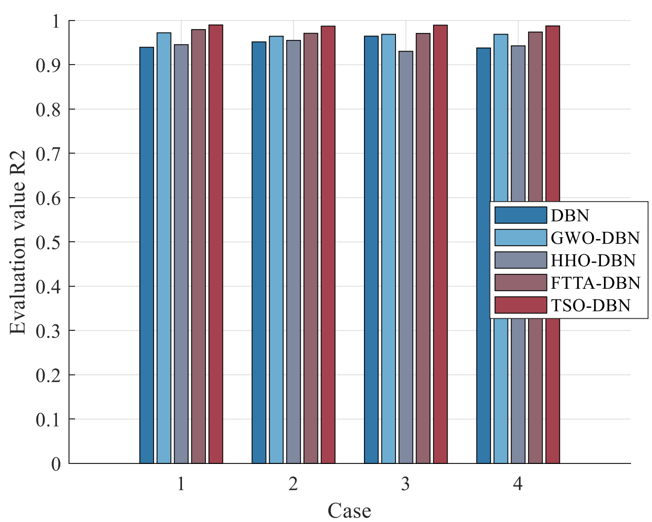

Fig. 12. Predicted R2 results of the integrated evaluation method of physical education inside and outside the classroom based on the Campus Run App.

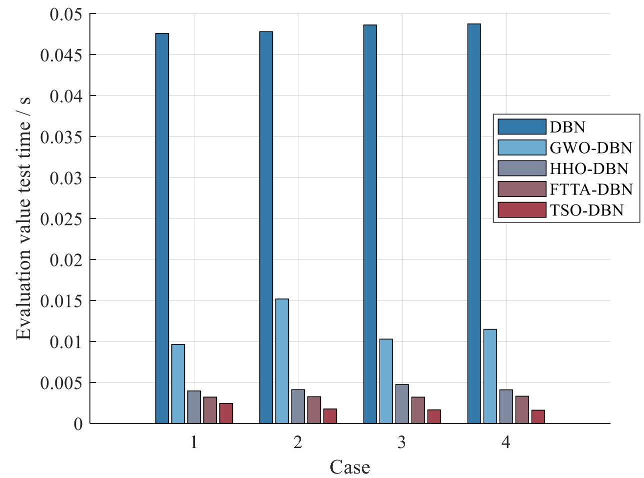

Fig. 13. Predicted time results of the integrated evaluation method for physical education inside and outside the classroom based on the Campus Run APP.

V. CONCLUSION

Addressing the prevailing issues of imprecise measurements and a lack of impartiality in the current integrated assessment methods for physical education activities both in and out of the classroom, this paper presents an integrated evaluation model known as TSO-DBN. This model merges the Tuna Swarm Optimization (TSO) algorithm with a deep confidence network to analyze and evaluate the behavioral data collected by the Campus Le Running APP. The methodology involves scrutinizing the existing evaluation challenges, identifying key evaluative features, and developing a cohesive assessment system for university physical education. By integrating TSO with DBN, this paper proposes an enhanced evaluation technique that promises improved predictive performance over existing methods. Comparative analysis demonstrates the superiority of the TSO-DBN model in predictive accuracy for the evaluation of physical education activities. The findings indicate that the TSO-DBN model outperforms alternative algorithms in this context.

For the practical implementation of this project, careful consideration must be given to the process of filtering through the extensive operational data generated by the system. It is essential to identify and select the most indicative feature dimensions and representative samples that will contribute to the dynamic refinement of the network's parameters in real-time scenarios.

ACKNOWLEDGMENT

This work was supported by 2023 Hunan Provincial Department of Education Science Research Project "*Practical Research on New Era Skill Cheerleading in Hunan Vocational Colleges*"(Grant No.:23C0663）

REFERENCES

[1] Lalitha P Y , Sireesha K , Emmanuel N . Evaluation of different integrated pest management modules against Thrips parvispinus Karny in chili [J].Pest Management in Horticulture Ecosystems, 2022(2):28.

[2] Jia B, Wu X, Zhao C.A Novel Training Quantitative Evaluation Method Based on Virtual Reality[J].Journal of Circuits, Systems and Computers, 2023, 32 (04).

[3] Gao Peng. Research on the construction of "inside and outside the classroom integration" teaching mode of public sports in private colleges and universities in Jilin Province[J]. Contemporary sports science and technology, 2022, 12(9):4.

[4] Zulzalil H, Rahmat H, Ghani A A A, Kamaruddin A. Expert Review on Usefulness of an Integrated Checklist-based Mobile Usability Evaluation Framework [J]. Computer Science Research (English), 2023, 5(3):57-73.

[5] Zhu X, Ye Y . Monitoring of clinical signs of intravenous infusion patients with ZigBee wireless technology:[J]. Distributed Sensor Networks, 2022, 18(4):34-40.

[6] Cohen-Azaria Y . Kindergarten teachers' evaluation: perceptions of the new Israeli multiple domains performance tool[J].Quality Assurance in Education, 2022, 30(2):184-198.

[7] Wei W, Qin L, Jiang J . Image analysis and pattern recognition method of three-dimensional process in physical education teaching based on big data[J]...Journal of Electronic Imaging, 2022, 31:061811 - 061811.

[8] Abadi M, Richard B, Shamblen S, Drake C, Schweinhart A, Bokhour B. Achieving Whole Health: a Preliminary Study of TCMLH, a Group-Based Programme Promoting Self-Care and Empowerment Among Veterans:[J].Health Education & Behavior, 2022, 49(2):347-357.

[9] Gou C . An Integrated CoCoSo-CRITIC-Based Decision-Making Framework for Quality Evaluation of Innovation and Entrepreneurship Education in Vocational Colleges with Intuitionistic Fuzzy Information[J].Mathematical Problems in Engineering, 2022.

[10] Wang S . Application of Internet of Things Framework in Physical Education System[J].journal of internet technology, 2022, 23(2):307-320.

[11] Bo S L L . Promoting Effect of School Physical Education on Adolescent Mental Health Education--On the Cultivation of "Masculinity"[J].Psychology Research, 2022, 12(10):795-801.

[12] Taylor J, Avellone L, Brooke V, Wehman P, Inge K, Schall C. The impact of competitive integrated employment on economic, psychological, and physical health outcomes for individuals with intellectual and developmental disabilities[J].Journal of applied research in intellectual disabilities. JARID, 2022, 35(2):448-459.

[13] Qiu C, Xiao H, Wang L, Tian Y. Recent advances in integrated optical directed logic operations for high-performance optical computing: a review[J]. Frontiers in Optoelectronics: English Edition, 2022, 15(1):17.

[14] Liu Y, Sathishkumar V E, Manickam A . Augmented reality technology based on school physical education training[J].Computers and Electrical Engineering, 2022(99-):99.

[15] Liu Yong, Liu Yuanhai, Xiao Jun. Research on the application of Campus Running APP in the integration of university physical education inside and outside the classroom[J]. Education Modernisation, 2020, 7(4): 76-78.

[16] Robin B , Roger M , Lynnae J .Integrated Pest Management Data for Regulation, Research, and Education: Crop Profiles and Pest Management Strategic Plans[J].Journal of Integrated Pest Management, 2022(1):1.

[17] Johnston KC, Marttinen R . Examining evolutions of literacy integration with physical education and health in an after-school program [J].Journal of Adolescent & Adult Literacy, 2023.

[18] Zhu Z, Xu Z, Liu J . Flipped classroom supported by music combined with deep learning applied in physical education[J]. Applied Soft Computing, 2023.

[19] Zhenjun Zhu, Jienna Shang, Ping Wang, Ran Xiang, Dongqing Ye, Jian Zhou, Yan Shi, Zilu Qu. Research on the design and implementation of the teaching mode of "in-class and out-of-class integration" in the course of "University Physical Education" in Guangzhou University[J]. Journal of Guangzhou University (Natural Science Edition), 2022, 21(3): 89-95.

[20] Li Hongbin. The construction of "inside and outside class integration" overall curriculum system of physical education in Qinghai University [J]. Journal of Qinghai University (Natural Science Edition), 2010, 28(1): 92-97.

[21] Duan X X, Wang Y L, Dou W S, Kumar R, Saluja N. An Integrated Remote Control-Based Human-Robot Interface for Education Application[J].International journal of information technology and web engineering, 2022.

[22] Zha S, Jin Y, Wheeler R, Bosarge E. A mixed-method cluster analysis of physical computing and robotics integration in middle-grade math lesson plans [J].Computers & Education, 2022.

[23] Xie L, Han T, Zhou H, Zhang Z R, Han B, Tang A. Tuna Swarm Optimization: a Novel Swarm-Based Metaheuristic Algorithm for Global Optimization[J]. Hindawi Limited, 2021, 2021:1-22.

[24] Umarani O, Jyothi D . Deep Belief Networks Using Convolution Neural Networks Algorithm[J].

[25] Farahat M, Halavati R . Noise Robust Speech Recognition Using Deep Belief Networks[J]. Applications, 2016, 15(01):1650005.