

Research on Intelligent Analysis Method for the Impact of Running APP Software on Physical Fitness Indicators of College Students

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Abstract

With the development of Internet of Things (IoT) technology, the use of running APP to analyse college students' physical fitness indicators has gradually become a commonly used sports analysis method. Aiming at the problems of insufficient precision of the running APP usage analysis method, easy to fall into the local optimum, and insufficiently comprehensive evaluation effect, this paper proposes a running APP usage analysis method based on deep learning network for some college students' physical fitness indicators. Firstly, feature vectors are taken from the running APP user behaviour data to analyse the values of college students' physical fitness indicators and construct a mapping model of running APP usage analysis for the effects of college students' physical fitness indicators; then, the BiGRU neural network is improved by using the driver-training heuristic optimisation algorithm to construct a running APP usage analysis model for some of the college students' physical fitness indicators; finally, a mapping model is constructed for the effect of running APP usage analysis for some of the college students' physical fitness indicators by using college student-oriented running APP. Finally, the effectiveness and robustness of the DTBO algorithm are compared with the user behaviour dataset of the running APP for college students. Finally, the effectiveness and robustness of the DTBO algorithm are compared using the user behaviour data set of the running app platform for college students.

Keywords: running app software usage analysis, college students' fitness index analysis, two-way gated recurrent unit neural network, driving training heuristic optimisation algorithm

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1 Introduction

The monitoring of college students' physical fitness indicators, as a key part of college students' physical fitness and health management, is a key concern of the government, society and families [1]. With the rapid development of Internet technology and the acceleration of the intelligence of mobile phones, the frequency of people's use of smart

phones has greatly increased, and the use of mobile phone exercise APP to monitor physical health indicators has become a trend in people's health management [2]. The emergence of mobile phone exercise APP brings positive influence to college students, not only can enhance college students to strengthen their physical fitness, but also can guide college students to have a healthy and positive learning and living atmosphere [3]. Running APP, as an important software and function of sports APP, is gradually reflected into the vision of campus college students with the

development of Internet of Things technology, and how to use running APP to influence college students' physical fitness state has also become a favourite hotspot for college physical education researchers and experts [4]. Research on the use of running apps for college students' physical fitness indicators not only encourages and guides students to actively participate in sports activities, but also promotes and develops the improvement of college students' physical fitness [5]. Therefore, it is particularly important to explore the effect of running APP use on some college students' physical fitness in the context of campus physical exercise [6]. Sports running APP refers to the application software that obtains and counts the user's movement track record, movement proximity, movement time, step count and other information by acquiring the user's GPS and through various sensors, and then establishes the user's movement database by counting the step frequency, calorie consumption and other movement information to assist the user in counting the information generated by running [7]. The research on sports running APPs is mainly carried out from two aspects, such as design and application [8]. Literature [9] defined the concept of sports APP and analysed the functional data of sports APP; Literature [10] classified sports APP into fitness and running APP, and analysed the impact of sports APP on the promotion of physical exercise behaviour and the formation of sports habits; Literature [11] studied the main functions of sports APP, including the function of recording sports data, fitness teaching function, information pushing function and social functions, and analysed the functions of the current more popular sports APP; literature [12] investigated the use of college students' fitness APP, and extracted the relevant user behaviour data, analysed the feature vectors, and constructed the APP use evaluation analysis model based on machine learning algorithms. The influence of running APP on college students' physical fitness indicators needs to analyse the running APP user behaviour data, extract the running APP usage effect features, and at the same time, analyse and statistically analyse for different college students' physical fitness indicators, construct the mapping model between the running APP usage effect feature quantity and college students' physical fitness indicators, and analyse the influence effect [13]. Currently, there are fewer running APP usage analysis methods for college students' physical fitness indicators, and the research status is not deep enough, which is reflected in the following aspects: 1) There are more literatures on the assessment of physical fitness indicators, but there is a lack of assessment design and implementation methods combined with sports APPs [14]; 2) Running APP usage analysis models are mainly limited to qualitative analysis only, and there is a lack of quantitative analysis [15]; 3) APP use analysis of behavioural data features extraction dimension is not enough, lack of systematic, targeted and scientific [16].

With the continuous development and improvement of deep learning methods and machine learning algorithms, the running APP usage analysis method based on intelligent algorithms for college students' physical fitness indicators

has gradually entered the vision of research scholars and experts [17]. Literature [18] used shallow neural networks to construct a mapping relationship between behavioural data feature vectors and college students' physical fitness indicators, and proposed a running APP usage analysis model based on artificial intelligence algorithms. Although the simple regression learning algorithm can solve the problem of APP usage effect analysis, it still has the problems of large error and low efficiency of effect analysis [19]. Aiming at the above problems, this paper combines the human behaviour heuristic optimization algorithm with the improved gated recurrent unit network, and proposes a running APP usage effect analysis method based on the improved deep learning algorithm for the influence of college students' physical fitness indicators. The innovation of this paper is that in the running APP usage effect analysis model, the influence of APP user behaviour data feature vectors on various fitness indicators is taken into account, and the running APP usage effect analysis model based on improved gated recurrent unit network is constructed by combining human behaviour heuristic optimization algorithms, and the user behaviour dataset recorded by the APP is used to verify the efficiency and robustness of the proposed method.

2 Impact Analysis of College Students' Physical Fitness Indicators Based on Running Apps

2.1 Running App Behavioural Data Feature Extraction

This paper takes running APP as the object of analysis, analyses and describes the basic functions of running APP, and analyses the behavioural data of running APP, and extracts the relevant influence analysis features.

The basic functions of running APP include recording exercise data function, fitness teaching function, information pushing function, and social function [20], and the APP framework functions are shown in Figure 1. The function of recording exercise data mainly records the speed, time, distance, trajectory and calories burned; the fitness teaching function provides professional running teaching courses, which provide users with correct running posture, breathing skills and foot landing in the form of videos, audios and pictures; the information pushing function includes personalised advice, training plans, race notifications and health reminders; the social function It can help users interact with other runners and share their running achievements and experiences.

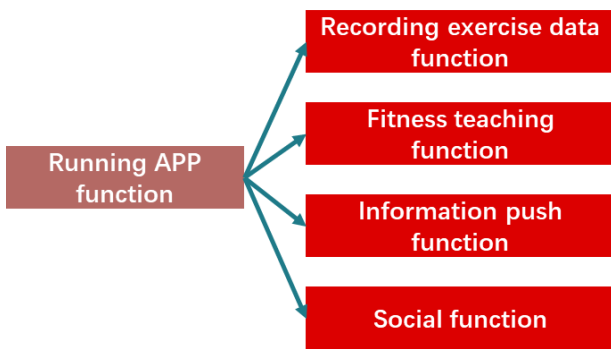


Figure 1 Framework diagram of the basic functions of running APP

For the different functions of running APP, this paper analyses and extracts the features of each function that affect college students' physical fitness indicators [21]. For the function of recording exercise data, the extracted behavioural data feature vectors include user's running speed, time, distance, and calories burned; for the function of fitness teaching, the extracted behavioural data feature vectors include the number of clicks on the running teaching course, the number of comments, and the frequency of viewing; for the function of information pushing, the extracted behavioural data feature vectors include the number of personalised suggestions, the number of training plans, the number of race notifications. In terms of social function, the extracted behavioural data feature vectors include the number of interactions, the number of sharing of running results and experiences.

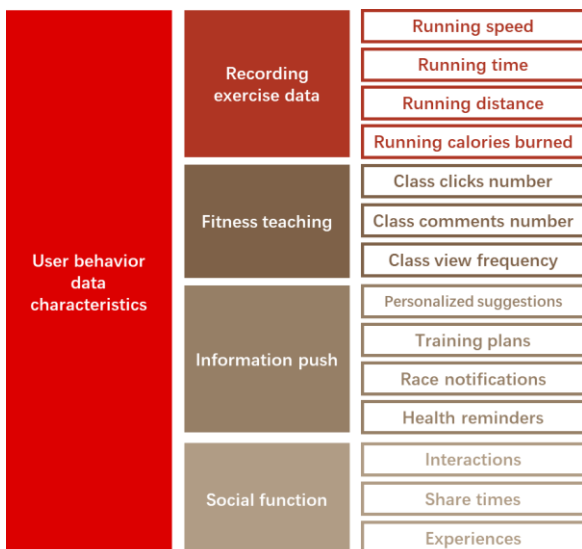


Figure 2 Behavioural Data Characteristics of Running APP

2.2 Analysis of Physical Fitness Indicators for University Students

In order to analyse the Running APP, the Running APP analysis indexes oriented to the impact of college students' physical fitness are mainly analysed in terms of body morphology indexes, body function indexes, and physical fitness indexes, which include the following: 1) selecting height, weight, and BMI as the analysis indexes of the Running APP body morphology; 2) selecting the lung capacity to assess college students' use of the Running APP body function; and 3) selecting the standing long jump, pull-ups, sit-ups, 50 metres, 800 metres, 1000 metres, and seated forward bends to assess the physical fitness of college students using running APP. The structure of running APP analysis indexes for the impact of college students' physical fitness is shown in Figure 3.

Var.	Description
L1	Height
L2	Weight
L3	BMI
M1	Vital capacity
N1	Standing long jump
N2	Pull-ups
N3	Sit-ups
N4	50 meters
N5	800 meters
N6	1000 meters
N7	Sitting forward bends

Figure 3 Running App Analysis Indicators

3 An analytical model of running app usage towards the influence of college students' physical fitness indicators

Aiming at the problem of analysing the effect of the use of running APP software on the influence of some physical fitness indicators of college students, this section specifically analyses the construction of the analysis model of running APP use oriented to the influence of college students' physical fitness indicators. Firstly, the feature dataset is extracted using the running APP user behaviour data, then the values of some college students' physical

fitness indicators are constructed, and finally, the mapping relationship between the feature vectors and the values of

physical fitness indicators is constructed. The mapping relationship of the model is shown in Figure 4.

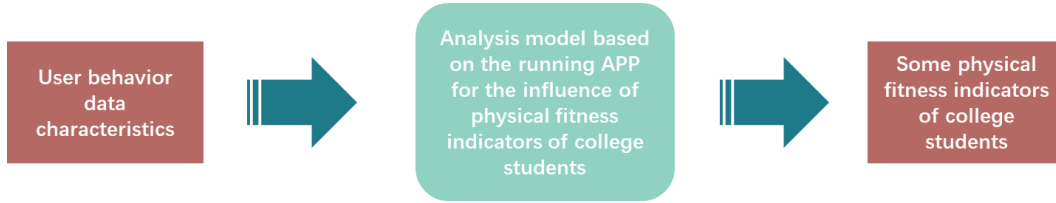


Figure 4 Model mapping relationship diagram

4 Related Technologies

4.1 Neural Networks for Door Control Loop Units

Recurrent Neural Network (RNN) [22] provides an effective solution to the time series prediction problem, but suffers from gradient explosion and gradient vanishing when dealing with long term time series problems. LSTM and GRU, as the advanced version of RNN, effectively solve the gradient problem of RNN. Compared with LSTM, GRU it has a simpler structure, fewer parameters, and introduces the gate structure, which consists of update gates and reset gates [23]. The schematic diagram of GRU network is shown in Fig. 4, and the specific model structure is as follows:

$$r_t = \sigma(W_{hr}h_{t-1} + W_{xr}x_t + b_r) \quad (1)$$

$$\tilde{h}_t = \tanh(W_{rh} \cdot (r_t * h_{t-1}) + W_{xh}x_t + b_h) \quad (2)$$

Where r_t is the reset gate, which determines how much of h_{t-1} 's historical memory is retained. \tilde{h}_t is the latest information of the Candidate hidden layer at the current moment, is the hidden layer information of the cell state at and respectively, , , and are the right to reset. h_{t-1} The information of h_t is the hidden layer information of the cell

state at the moment of $t-1$ and t respectively, W_{rh} , W_{xh} , W_{xr} , W_{hr} are the weights, b_r , b_h are the biases.

$$z_t = \sigma(W_{hz}h_{t-1} + W_{xz}x_t + b_z) \quad (3)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (4)$$

Where W_{hz} , W_{xz} are weights and b_z is bias. z_t is a forgetting gate, which serves to combine the input hidden layer information h_{t-1} at the previous moment with the candidate hidden layer information at the current moment to get the output cellular hidden layer information h_t . When $z_t = 0$, the hidden layer directly outputs the hidden layer information of the previous moment h_{t-1} , and when $z_t = 1$, the candidate hidden layer directly outputs the current hidden layer information h_t .

$$y_t = \sigma(W_{yt}h_t) \quad (5)$$

Where W_{yt} denotes the weights between the current hidden layer output h_t and the final output layer.

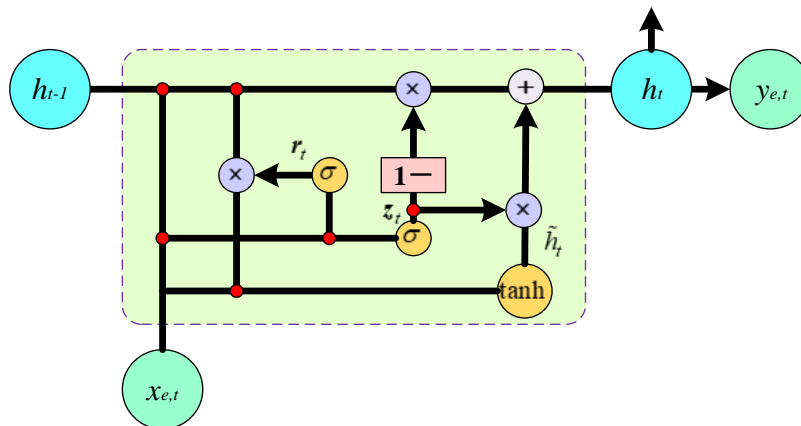


Figure 5 GRU network

4.2 BiGRU Neural Network

BiGRU model two independent GRU blocks [24], by aggregating information from time series data in both forward and reverse directions to obtain timing information, the specific network schematic is shown in Figure 6. From Fig. 6, it can be seen that the current hidden state of BiGRU model neuron is composed of three parts: the current input x_t , the forward hidden state \vec{h}_{t-1} and the reverse hidden state \overleftarrow{h}_{t-1} at the previous moment, and the hidden state update formula of BiGRU model neuron is as follows:

$$\vec{h}_t = GRU(x, \vec{h}_{t-1}) \quad (6)$$

$$\vec{h}_t = GRU(x, \vec{h}_{t-1}) \quad (7)$$

$$h_t = W_t \vec{h}_t + V_t \overleftarrow{h}_t + b_t \quad (8)$$

Where, \vec{h}_t denotes the forward hidden state update formula, \overleftarrow{h}_t denotes the neuron reverse hidden layer state update, W_t denotes the weights of the neuron's forward hidden state \vec{h}_t at moment t, V_t denotes the weights of the neuron's reverse hidden state \overleftarrow{h}_t at moment t, and b_t denotes the bias of the hidden state at moment t.

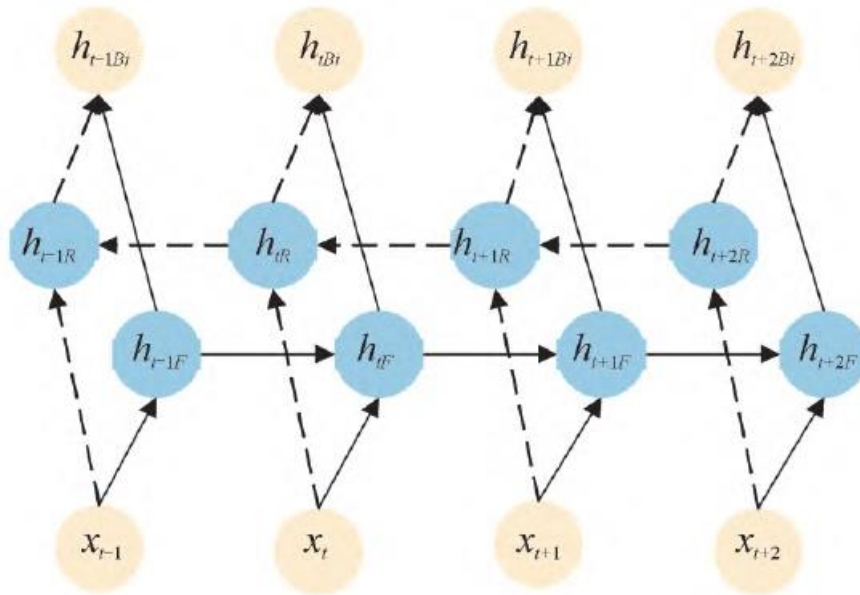


Figure 6 BiGRU network

4.3 Driving training optimisation algorithm

Driving Training-Based Optimization, DTBO [25], is an optimization algorithm based on driving training behaviours proposed in 2022, the algorithm learns driving behaviours through simulation for optimization, with strong optimization ability and fast convergence speed, etc. The specific optimization strategy of DTBO algorithm is as follows:

(1) Initialisation of stocks

Similar to the heuristic algorithm, the DTBO algorithm uses a random initialisation population strategy as follows:

$$x_{i,j} = lb_j + r \cdot (ub_j - lb_j) \quad (9)$$

where $x_{i,j}$ denotes the j th spatial dimension information of

the i th individual, lb_j and ub_j denote the lower and upper boundaries of the j th dimension of the search space, respectively, and r denotes a random number between 0 and 1.

(2) Driving instructor training phase (exploratory phase)

The first phase of the DTBO update was based on the learning driver's selection of a driving instructor, followed by the selected instructor's driver training of the learning driver. A portion of the best members of the DTBO crowd are considered driving instructors and the remaining members are considered learning drivers. Selecting a driving instructor and learning that instructor's skills will result in members of the crowd moving through different areas of the search space. This will improve DTBO's exploration capabilities in terms of searching and discovering the best areas globally. Thus, this phase of the

DTBO update demonstrates the algorithm's exploration capabilities. In each iteration, N members of the DTBO are selected as driving instructors based on the comparison of the objective function values, which are represented as follows:

$$DI = \begin{bmatrix} DI_{11} & DI_{12} & \dots & DI_{1d} \\ DI_{21} & DI_{22} & \dots & DI_{2d} \\ \dots & \dots & \ddots & \dots \\ DI_{N_{DI}1} & DI_{N_{DI}2} & \dots & DI_{N_{DI}d} \end{bmatrix} \quad (10)$$

Where DI denotes the set of coaches, N_{DI} denotes the number of coaches, and the change of N_{DI} decreases with the increase of iterations, which is calculated as follows:

$$N_{DI} = \text{floor}(0.1 * N * (1 - t/T)) \quad (11)$$

Where t and T denote the current iteration number and the maximum iteration number, respectively.

The location update model for the training phase of the driving instructor for the DTBO algorithm is calculated as follows:

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + r \cdot (DI_{k_j,j} - I \cdot x_{i,j}) & F_{DI_{k_i}} < F_i \\ x_{i,j} + r \cdot (x_{i,j} - DI_{k_j,j}) & F_{DI_{k_i}} \geq F_i \end{cases} \quad (12)$$

$$X_i = \begin{cases} X_i^{P_1} & F_i^{P_1} < F_i \\ X_i & F_i^{P_1} \geq F_i \end{cases} \quad (13)$$

Where, $x_{i,j}^{P_1}$ denotes the j th dimensional update position of the i th individual, $DI_{k_j,j}$ denotes the j th dimensional information of the k_j coach, I denotes the 1 vs. 2 random choice value, $F_{DI_{k_i}}$ denotes the fitness value of the k_j coach, and F_i denotes the fitness value of the i th individual.

(3) Learning phase for trainees (exploratory phase)

The second phase of the DTBO algorithm update is based on the learning driver imitating the instructor, i.e. the learning driver attempts to simulate and model all the actions and skills of the instructor. This process moves the driver to different locations in the search space, increasing the exploration capability of the DTBO algorithm. In the learner learning phase, new positions are generated based on the linear combination of each member with the coach. The specific position update formula is as follows:

$$x_{i,j}^{P_2} = P \cdot x_{i,j} + (1 - P) \cdot DI_{k_i,j} \quad (13)$$

$$X_i = \begin{cases} X_i^{P_2} & F_i^{P_2} < F_i \\ X_i & F_i^{P_2} \geq F_i \end{cases} \quad (14)$$

$$P = 0.01 + 0.9 \left(1 - \frac{t}{T}\right) \quad (15)$$

(4) Individual practice phase (development phase)

The third phase of the DTBO algorithm update is based on each learner driver's personal practice as a way to improve their individual driving skills. In this phase, each learning driver endeavours to approach his/her best skills. This phase allows each member to discover better locations based on a local search of their current location. This phase demonstrates the ability of the DTBO to utilise local search. The specific location update formula is shown below:

$$x_{i,j}^{P_3} = x_{i,j} + (1 - 2r) \cdot R \cdot \left(1 - \frac{t}{T}\right) \cdot x_{i,j} \quad (16)$$

$$X_i = \begin{cases} X_i^{P_3} & F_i^{P_3} < F_i \\ X_i & F_i^{P_3} \geq F_i \end{cases} \quad (17)$$

Where R denotes a constant with dimension 0.05 and r is a random number between 0 and 1.

(5) DTBO algorithm steps with pseudo-code

According to the optimisation strategy of DTBO algorithm, the flowchart of DTBO algorithm is shown in Figure 7. During each iteration, an initial solution is randomly generated, and the final optimal solution is continuously obtained by evaluation with greedy selection strategy. The optimisation steps of DTBO algorithm are shown below:

Step 1: Initialise the number of DTBO populations with the number of iterations;

Step 2: Initialise the MPA population. Initialise the DTBO population using the random uniform distribution strategy, calculate the fitness value, or obtain the current optimal value and optimal solution;

Step 3: Based on the number of iterations, the search phase is selected. The DTBO algorithm selects the driving instructor training phase, the student learning phase, and the individual practice phase search strategies for updating the population location, respectively;

Step 4: Calculate the fitness value and select and retain the better solution using greedy selection strategy;

Step 5: Determine whether the number of iterations reaches the maximum number of iterations. If it reaches, output the optimal solution and optimal value; otherwise, return to step 3.

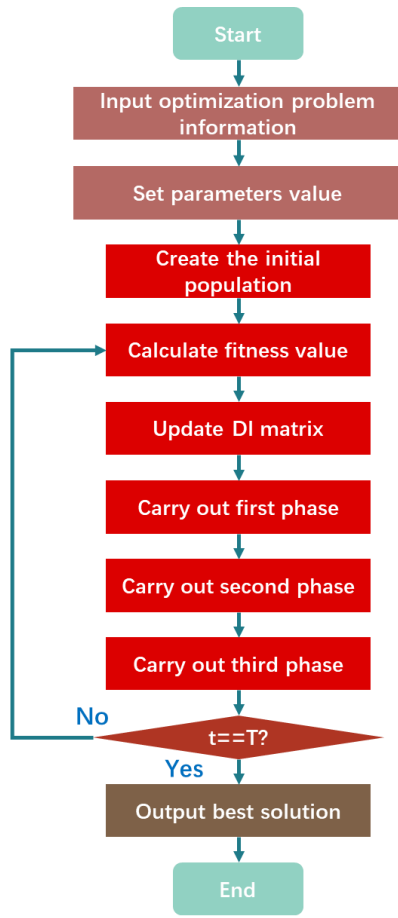


Figure 7 Flowchart of the driving training optimisation algorithm

5 Analysis of running app usage for college students with some fitness indicators based on DTBO algorithm optimised BiGRU network

(1) Decision-making variables

To avoid the optimisation falling into local optimum, which leads to the failure of network training, in this paper, we consider the DTBO algorithm instead of Adma algorithm to obtain the optimal parameters of the network and achieve the training of BiGRU network.

(2) Objective function

In order to improve the BiGRU training accuracy, RMSE is used as the objective function of the DTBO algorithm and is calculated as follows:

$$\min fitness = \sqrt{\left(\sum_{i=1}^M (\hat{y}_i - y_i)^2 \right) / M} \quad (18)$$

(3) Steps and Processes

Based on the DTBO algorithm optimization BiGRU network applied to the college students part of the physical fitness indicator APP use analysis method is mainly to run APP user behaviour data feature vector as input, with college students physical fitness indicator value as output, to analyze the mapping relationship between the two. The flowchart of the DTBO-BiGRU algorithm based application for college students' partial physical fitness indicator APP usage analysis method is shown in Figure 8. The specific steps are as follows:

Step 1: Statistics and analysis of running APP software user behaviour data to extract feature vectors;

Step 2: counting and analysing the values of some of the physical fitness indicators of college students using the running APP, corresponding to the characteristic data of Step 1, and constructing a data set for analysing the use of the APP for some of the physical fitness indicators of college students;

Step 3: Divide the data set of the app usage analysis for some physical fitness indicators for college students into a training set, a validation set and a test set;

Step 4: Encode the initial parameters of BiGRU neural network using DTBO algorithm, and also initialise the algorithm parameters such as population parameters, number of iterations, etc.; initialise the population and calculate the objective function value;

Step 5: Sequentially select the driving instructor training phase, the student learning phase and the individual practice phase search strategies to update the location information of the DTBO algorithm population;

Step 6: Calculate the fitness function value and update the global optimal solution;

Step 7: Determine whether the termination condition is satisfied, if so, exit the iteration, output the optimal BiGRU network parameters, and execute step 8, otherwise continue to execute step 5;

Step 8: Decoding the optimised BiGRU parameters based on the DTBO algorithm, obtaining the optimal BiGRU network parameters, and constructing a DTBO-BiGRU based APP usage analysis model for some physical fitness indicators of college students;

Step 9: Use the trained college student oriented partial fitness indicator APP use analysis model to use analysis on the current test set and output the corresponding analysis results.

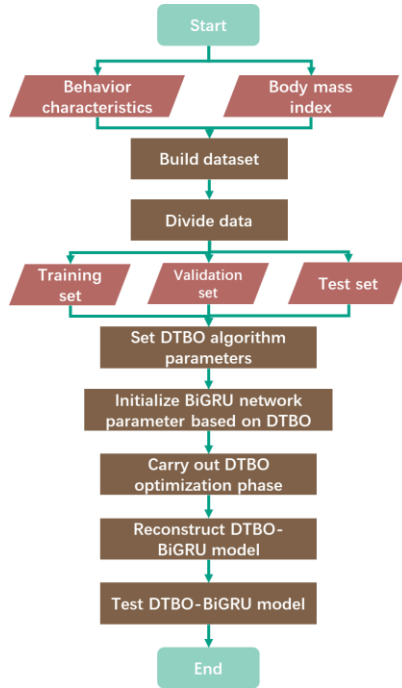


Figure 8 Analysis of the use of applied to college students' physical fitness indicator running APP based on DTBO-BiGRU algorithm

6 Experiments and analysis of results

In order to verify the advantages and disadvantages of the APP application analysis methods proposed in this paper, five analysis methods are selected for comparison, and the specific parameters of each algorithm are set as in Table 1. The experimental simulation environment is Windows 10, CPU is 2.80GHz, 8GB RAM, and the programming language Matlab2019a.

Table 1 Parameter settings of the analysis methods used by APP

arithmetic	parameterisation
LSTM	The number of hidden layer nodes of LSTM network is 100
DTBO-LSTM	The number of nodes in the hidden layer of the LSTM network is 100; the DTBO algorithm population is given by Section 6.3
GRU	The number of nodes in the hidden layer of the GRU network is 100, and the Adam optimisation adjusts the weights
DTBO-GRU	The number of nodes in the hidden layer of the GRU network is 100, and Adam's optimisation adjusts the weights; the DTBO algorithm population is given by Section 6.3
BiGRU	The number of hidden layer nodes of BiGRU network is 100 and Adam optimisation adjusts the weights
DTBO-BiGRU	The number of nodes in the hidden layer of the BiGRU network is 100, and Adam's optimisation adjusts the weights; the DTBO algorithm population is given by Section 6.3

the evaluation index function of APP usage effect , and the specific calculation formula is as follows:

$$MAE = \frac{1}{M} \sum_{i=1}^M |\hat{y}_i - y_i| \quad (18)$$

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

$$MAPE = \frac{100\%}{M} \sum_{i=1}^M \left| \frac{\hat{y}_i - y_i}{y_i} \right| \quad (20)$$

M \hat{y}_i y_i i Where is the number of observed samples, and denote the true and predicted values of the sample respectively.

6.1 Description of the data set

The dataset is mainly derived from running app user behaviour data.

The Smart Sports App uses the Basic Information Management Module to collect data on gymnasiums, physical fitness data tests, PE course results and other physical activity data through the Internet of Things and cloud computing.

6.2 Algorithm Evaluation Indicators

In order to better evaluate the performance of the running APP application analysis method, this paper adopts the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) as

6.3 Parametric impact analysis

(1) Parameter impact analysis

In order to analyse the effect of the population size of DTBO algorithm on the running APP usage analysis method for college students' physical fitness indicators, this paper compares and analyses the performance of the running APP usage analysis method under different population sizes. Figure 9 gives a graph of the effect of different population sizes on the accuracy and time of the running APP usage analysis method.

From Figure 9(a) and (b), it can be seen that as the population size of the DTBO algorithm increases, the analysis accuracy of the analysis method for the college students' physical fitness indicator running APP using the analysis method increases gradually; as the population size of the DTBO algorithm increases, the analysis time of the analysis method for the college students' physical fitness indicator running APP using the analysis method increases gradually; when the number of populations reaches 50, the increase of the analysis accuracy is slow; when the number of populations reaches 70, the analysis time area is stable. In summary, the population size of the intelligent optimisation algorithm chosen in this paper is 50.

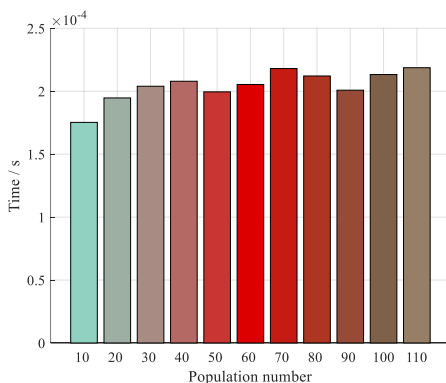
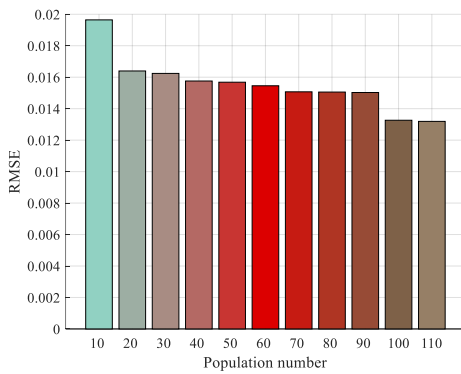


Figure 9 Impact of different population sizes on the performance of analytical methods

6.4 Algorithm Performance Analysis

In order to verify the effectiveness and superiority of the running APP usage analysis method based on DTBO-BiGRU algorithm for college students' physical fitness indicators, the running APP usage analysis method based on DTBO-BiGRU algorithm for college students' physical fitness indicators was compared with the running APP usage analysis method based on LSTM, DTBO-LSTM, GRU, DTBO-GRU, BiGRU for college students' physical fitness indicators. Running APP use analysis methods are compared, and the performance results of each model are shown in Figures 10, 11, 12, and 13.

Running APP usage analysis value for college students' physical fitness indicator is demonstrated by Figure 10. From Figure 10, it can be seen that the analysed value of running APP usage for college students' physical fitness indicators based on DTBO-BiGRU algorithm is the closest to the real value, and other algorithms are different from the real value.

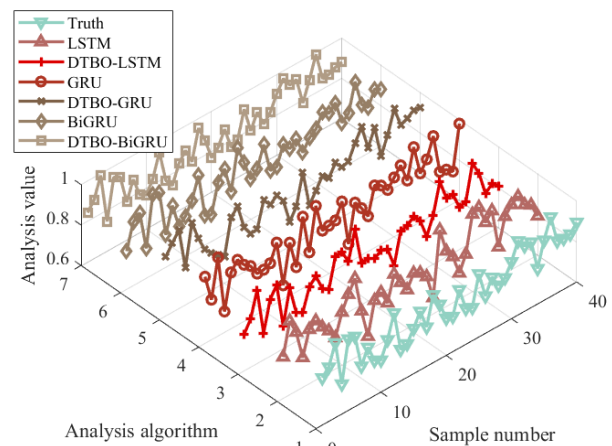


Figure 10 Analysis results of running app usage for college students' physical fitness indicators based on each algorithm

The results of the relative error of the usage analysis of the running APP for college students' physical fitness indicators based on each algorithm are shown in Figure 11. It can be seen from Figure 11 that the relative error between the usage analysis value and the true value of the running APP for college students' physical fitness indicators based on the DTBO-BiGRU algorithm is the smallest, which is controlled in the range of 0.02, and the remaining algorithms ranked by their errors are, in descending order, BiGRU, DTBO-GRU, DTBO-LSTM, LSTM, GRU, and the error range is controlled within 0.045, 0.085, 0.09, 1.20, and 1.25 respectively.

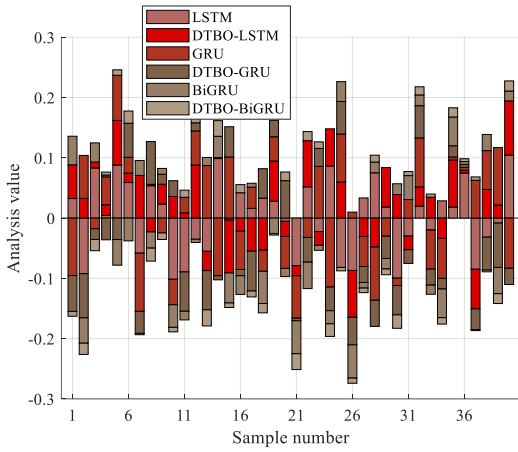


Figure 11 Relative error results between the analysed and true values of running app usage based on each algorithm

The results of the error analysis statistics of running APP usage for college students' physical fitness indicators based on each algorithm are shown in Figure 12. It is not difficult to find out from Figure 12 that in terms of RMSE, the DTBO-BiGRU algorithm has the smallest mean value of RMSE and the smallest standard deviation of RMSE; in terms of MAE, the DTBO-BiGRU algorithm has the smallest mean value of MAE and the smallest standard deviation of MAE; and in terms of MAPE. DTBO-BiGRU algorithm MAPE has the smallest mean value and the smallest MAPE standard deviation.

Algorithm	RMSE_mean	RMSE_std	MAE_mean	MAE_std	MAPE_mean	MAPE_std
LSTM	0.0569	0.0044	0.0490	0.0046	0.0012	0.00056
DTBO-LSTM	0.0482	0.0034	0.0416	0.0039	0.0010	0.00045
GRU	0.0617	0.0048	0.0529	0.0049	0.0013	0.00080
DTBO-GRU	0.0454	0.0041	0.0392	0.0028	0.0010	0.00038
BiGRU	0.0285	0.0040	0.0246	0.0024	0.0006	0.00027
DTBO-BiGRU	0.0119	0.0033	0.0104	0.0010	0.0003	0.00009

Figure 12 Error statistics of running app usage analysis based on each algorithm

As can be seen from Figure 13, the ranking of the mean value of the analysis time of each algorithm is BiGRU, DTBO-BiGRU, DTBO-GRU, GRU, DTBO-LSTM, LSTM, and the ranking of the standard deviation of the analysis time of each algorithm is DTBO-BiGRU, BiGRU, GRU,

DTBO-GRU, DTBO-LSTM, LSTM, which indicates that the The DTBO-BiGRU algorithm has less mean analysis time, is comparable to BiGRU, has the smallest standard deviation, and has the best real-time robustness.

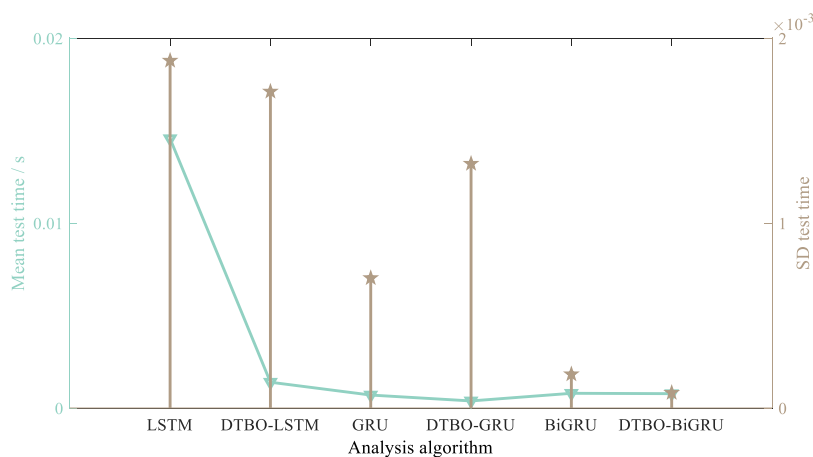


Figure 13 Time results of running app usage analysis based on each algorithm

7 Conclusion

This paper proposes a running APP usage analysis method for some college students' physical fitness indicators. The method extracts feature vectors by analysing the user behaviour data of the running APP, analyses the values of college students' physical fitness indexes, and constructs a running APP usage analysis model for college students' partial physical fitness indexes by improving BiGRU neural network using the driving training heuristic optimisation algorithm. The effectiveness and robustness of the DTBO algorithm are compared and analysed using the user behaviour dataset of the running APP platform for college students. Through simulation analysis, it can be seen that 14-dimensional input features are extracted from the user behaviour data of running APP, and there are 11 physical fitness indexes for college students, and the relative error of the running APP usage analysis method based on DTBO-BiGRU network for college students with some physical fitness indexes is controlled within 0.02, and the analysis time consumed is less than 0.001s, which meets the requirement of real-time performance.

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