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Evaluation of a Microcontroller-based Smart Wearable Device in College Students' Sports Forging Application

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Abstract

INTRODUCTION: The widespread use of smart wearable devices in various fields, including healthcare and sports, underscores the importance of their application in enhancing physical exercise among college students. Recent advancements in technology have facilitated the development of sophisticated methods to assess and predict physical activity outcomes, making their evaluation increasingly critical.
OBJECTIVES: This study aims to develop a reliable assessment model for smart wearable devices used in college students' sports activities. The objective is to accurately predict and evaluate the effectiveness of these devices in improving students' physical health and promoting lifelong sports habits. Ultimately, the research seeks to integrate advanced computational methods to enhance the accuracy of physical exercise assessments.
METHODS: The research introduces a novel assessment model that combines a zebra behavior-based heuristic optimization algorithm with a convolutional neural network (CNN). By analyzing user behavior data from wearable devices, the model constructs an evaluation index system tailored for college sports activities. The approach optimizes the parameters of the CNN using the zebra optimization algorithm, ensuring enhanced prediction accuracy.
RESULTS: The evaluation model demonstrated high accuracy, with a significant improvement in predicting the outcomes of physical exercises among college students. Comparative analyses with traditional methods revealed that the new model reduced prediction errors and increased real-time performance metrics. Specifically, the model achieved a lower root mean square error (RMSE) in simulation tests, indicating more precise assessments. Figures and statistical data provided in the study illustrate the model's superior performance across various parameters.
CONCLUSION: The developed assessment model significantly advances the application of smart wearable devices in monitoring and enhancing college students' physical activities. By integrating cutting-edge algorithms, the study not only improves the accuracy of exercise assessments but also contributes to the broader understanding of technology's role in health and fitness education. Future research could further refine this model by incorporating additional sensors and data points to expand its applicability and robustness.

Keywords: smart wearable devices; university students' sports forging; application evaluation methods; zebra optimisation algorithm; convolutional neural network

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1. Introduction

With the rapid development of artificial intelligence, the smart wearables industry is gradually expanding into healthcare, sports and fitness, infotainment, and other fields

[1]. According to the latest data from the International Data Corporation, the annual production of smart wearable devices continues to grow [2]. With the increase in the proportion of the number of national participation in physical exercise, the demand for college students to exercise and fitness has also gradually increased, and the content of school physical education teaching is difficult to meet the diversified physical exercise needs of students in colleges and universities [3]. Combined with smart wearable devices based on microcontroller, the study of college students' physical exercise can attract more college students to participate in physical exercise, so that college students can reasonably and effectively use smart wearable devices for physical exercise, cultivate students' lifelong sports awareness, and promote students' physical health [4]. Intelligent wearable devices are defined as a general term for a class of devices that apply wearable technology to the intelligent design and development of products that people wear and carry every day, including smart bracelets, smart watches, smart glasses, ear-wearing devices, smart clothing and smart shoes and socks [5]. Currently, the research on the application assessment of smart wearable devices for college students' physical exercise mainly includes the research on the application of smart wearable devices in college students' physical exercise [6], and the methodology for the application assessment of smart wearable devices [7]. According to the literature [8], smart wearable devices are divided into general class, training class and scientific research class according to the use object and environment in the process of sports training. General class smart wearable devices are oriented to the recovery training of athletes and general fitness needs, and the products tend to be simple and lightweight; training class smart wearable devices are oriented to the monitoring needs of the training class, and the equipment has a strong professional attribute; scientific research class smart wearable devices are oriented to scientific research, and the measurement accuracy of the devices is relatively high. oriented, the equipment measurement accuracy is relatively high, but the operation is relatively complex; literature [9] studied the development strategy of sports class smart wearable devices, and at the same time recognised the value of fitness data of smart wearable devices; literature [10] studied the application of smart wearable devices in sports training to stimulate the enthusiasm for training, adjust the training content in a timely manner, set up a personalised training program and form a scientific evaluation system; literature [11] investigated the main factors of college students feeling too tired of physical exercise; literature [12] studied the strategy of sports APP to improve college students' attitude and behavioural habits of physical exercise. In summary, there are fewer studies on the combination of smart wearable devices and college students' physical exercise, which mainly focus on the basic situation of college students' use of smart wearable devices and the impact of using smart wearable devices on college students' physical exercise attitude, frequency, duration, intensity and other aspects [13]. The current research results on the combination of smart wearable devices and college students' physical exercise are relatively limited and general, and there is a lack of quantitative application assessment and analysis methods [14]. Aiming at the above problems, this paper proposes a method for assessing the application of smart wearable devices in college students' physical exercise based on microcontrollers. This paper mainly takes the application assessment of smart wearable devices as the object of analysis, analyzes the application characteristics of wearable devices for college students' physical exercise, extracts the relevant application assessment feature vectors, optimizes the parameters of the convolutional neural network by combining the animal behaviour heuristic optimization algorithm, and constructs the application assessment model of wearable devices for college students' physical exercise based on the intelligent optimization algorithm and the convolutional neural network. The effectiveness and feasibility of the method proposed in this paper are verified by the user behaviour data of smart wearable devices.

2. Application of microcontroller-based smart wearable devices in physical exercise for university students

This paper takes smart wearable devices as the object of analysis, and analyses and describes the problem of assessing the application of wearable devices for college students' physical exercise.

2.1. Feature Extraction for Assessment of Physical Exercise Applications of Smart Wearable Devices

In order to construct the evaluation index system of college students' physical exercise wearable device application, according to the application characteristics of smart wearable devices in college students' physical exercise, the evaluation indexes of college students' physical exercise wearable device application are extracted from four advantages, such as monitoring exercise intensity, sports socialisation, sports health management, and exercise motivation stimulation [15], and the specific extracted indexes are shown in **Figure 1**.

Figure 1. Factors influencing the strengths of the assessment of the application of wearable devices for physical activity among students

(1) Monitoring exercise intensity advantages

The monitoring exercise intensity advantage refers to the college students to measure the indicators of exercise time, step count, exercise trajectory, exercise heart rate, etc., and calculate the data of calories burned, mileage, and oxygen saturation, so as to effectively assess whether the exercise load is matched or not and whether the body is fatigued or not [16]. The extracted indicators for monitoring the aspect of exercise intensity include exercise trajectory S1, exercise heart rate S2, exercise steps S3, calories burned S4, and exercise load S5.

(2) Social advantages of sports

Sports social advantage refers to the college students through the circle of friends and all kinds of sports social platform sun ranking, sun mileage, sun sports fitness pictures or videos, to meet the sports social needs of the college student group, and to enhance the recreational nature of physical exercise [17]. The extracted indicators of the social aspect of sports and exercise include exercise comment J1, exercise sending friend circle J2, and exercise liking J3.

(3) Advantages of sports health management

The advantage of sports health management refers to the fact that relying on a powerful data processing system can not only scientifically record the basic health indicators of college students' physical activity population and analyse the wearer's physical condition, but also combine the actual situation of the data with personalized improvement suggestions for the wearer's important physiological activities, such as exercise, diet and sleep, so as to enable college students' physical activity population to always maintain a healthy state of life [18]. The extracted indicators of sports health management aspects include exercise reminder G1, sedentary reminder G2, exercise record G3, sleep quality monitoring G4, and healthy diet reminder G5.

(4) Exercise motivation to stimulate strengths

Exercise motivation stimulation advantage refers to the use of smart wearable devices by college students' physical activity population can be able to detect the indicators that are not easy to be monitored in the process of physical education, and through the data feedback, they can have a better grasp of their own health status and athletic ability, so as to provide the basis for the development of their own personalised physical activity programme [19]. The extracted indicators for the motivational aspects of exercise include health status monitoring F1, athletic ability monitoring F2, and the development of personalised exercise programmes F3.

2.2. Construction of the evaluation system for physical exercise application of smart wearable devices based on microcontroller

The evaluation index system for the application of wearable devices for college students' physical exercise takes the functional aspects of monitoring exercise intensity, sports socialisation, sports health management, and exercise motivation stimulation [20] as the first-level indicators, and takes the exercise trajectory S1, exercise heart rate S2, exercise steps S3, calories burned S4, exercise load S5, exercise comments J1, exercise sending friend circle J2, exercise likes J3, exercise reminder G1, sedentary reminder G2, exercise record G3, sleep quality monitoring G4, healthy diet reminder G5, health status monitoring F1, exercise capacity monitoring F2, development of personalized exercise programme F3 and other 16 characteristic elements as secondary indicators [21], fully embodies the process of assessment of the application of intelligent wearable devices for physical exercise based on microcontrollers, and constructs a comprehensive and effective college students' wearable devices for physical exercise application assessment index system.

3. Related Technologies

3.1. Zebra optimisation algorithm

The Zebra Optimization Algorithm (ZOA) [22] was proposed by Eva Trojovská et al. in 2022, which simulates the zebra's foraging and defensive behaviour against predator attacks. The Zebra Optimisation Algorithm consists of two stages:

(1) Foraging behaviour

During this phase, population members are updated based on simulations of zebra behaviour when searching for forage. The main diet of zebras is mainly grasses and sedge, but they may also eat buds, fruits, bark, roots and leaves if their preferred food is scarce. Depending on the quality and availability of vegetation, zebras may spend 60-80% of their time eating. Among zebras, there is a species of zebra called the plains zebra, which is a pioneer herbivore that provides for other species that require shorter, more nutritious grasses by devouring the canopy of upper and less nutritious grasses. In ZOA, the best member of the population is considered the pioneer zebra and guides other members of the population towards its position in the search space. Therefore, updating the position of zebra during the foraging phase can be mathematically modelled using the following equation:

$$x_{i,j}^{new,P1} = x_{i,j} + r \cdot \left(PZ_j - I \cdot x_{i,j} \right) \tag{1}$$

$$X_i = \begin{cases} X_i^{new,P1} & F_i^{new,P1} < F_i \\ X_i & else \end{cases} \tag{2}$$

Where, $x_{i,j}^{new,P1}$ denotes the jth dimensional position update information of the ith zebra in the stage, $x_{i,j}$ denotes the jth dimensional position of the ith zebra in the stage, r denotes a random number between 0 and 1, PZ_j denotes the position information of the jth dimension of the pioneer zebra, $I \in \{1,2\}$, $F_i^{new,P1}$ denotes the updated adaptation value of the ith zebra, and F_i denotes the adaptation value of the ith zebra.

(2) Defensive behaviour

In this phase, zebra defence strategies against predator attacks are simulated to update the position of ZOA population members in the search space. The main predator of zebras is the lion; however, they are threatened by cheetahs, leopards, wild dogs, brown hyenas and spotted hyenas. Crocodiles are another predator of zebras when they approach water. Zebra defence strategies vary from predator to predator. The zebra's defence strategy against lion attacks is to flee in a jagged pattern and random sideways turning movements. Zebras are more aggressive against smaller predators such as hyenas and dogs, which confuse and frighten hunters by aggregating. In the ZOA design, it is assumed that one of the following two conditions occurs with equal probability: 1) the lion attacks the zebra and therefore the zebra chooses an escape strategy, and 2) other predators attack the zebra and the zebra chooses an attack strategy.

In strategy 1), when a zebra is attacked by a lion, the zebras flee from the lion near the situation they are in. The specific model is as in the S1 strategy; in strategy 2), when other predators attack one of the zebras, the other zebras in the herd move towards the attacked zebra and try to scare and confuse the predator by creating defence structures. The specific model is as in strategy S2.

$$x_{i,j}^{new,P2} = \begin{cases} S_1 : x_{i,j} + R \cdot (2r-1) \cdot \left(1 - \frac{t}{T}\right) \cdot x_{i,j} & P_S \leq 0.5 \\ S_1 : x_{i,j} + r \cdot \left(AZ_j - I \cdot x_{i,j} \right) & else \end{cases} \tag{3}$$

$$X_i = \begin{cases} X_i^{new,P2} & F_i^{new,P2} < F_i \\ X_i & else \end{cases} \tag{4}$$

Where, $x_{i,j}^{new,P2}$ denotes the location information of the j^{th} dimension of the i^{th} zebra after updating in the second phase, $F_i^{new,P2}$ denotes the value of the adaptation of the ith zebra after updating, R denotes a constant with the value of 0.01, P_S denotes the selection of a random number from 0 to 1, which is mainly used to select the S1 and S2 strategies, and AZ denotes the location information of the attacked zebra.

(3) Algorithm flow

According to the optimisation strategy of ZOA algorithm, the pseudo-code of ZOA algorithm is shown in **Figure 2**. During each iteration, an initial solution is randomly generated, and the final optimal solution is continuously obtained through evaluation and greedy selection strategy.The flowchart of ZOA algorithm is shown in **Figure 3** as follows:

```
Algorithm: ZOA
Set ZOA parameters, including population size, tmax, c1, c2, c3, c4;
Initialize zebras population;
Evaluate initial population and update pioneer zebra (PZ);
While t<=tmax do
    for each zebra i do
        Update pioneer zebra ;
        Calculate new status of the ith zebra using foraging behavior;
        Update the ith zebra;
        if Ps<0.5, Ps=rand
            Calculate new status using strategy 1;
        else
            Calculate new status using strategy 2;
        end if
    end for
    Evaluate object and update pioneer zebra;
    t = t+1;
end
Output best solution.
```

Figure 2. Pseudo-code of ZOA algorithm

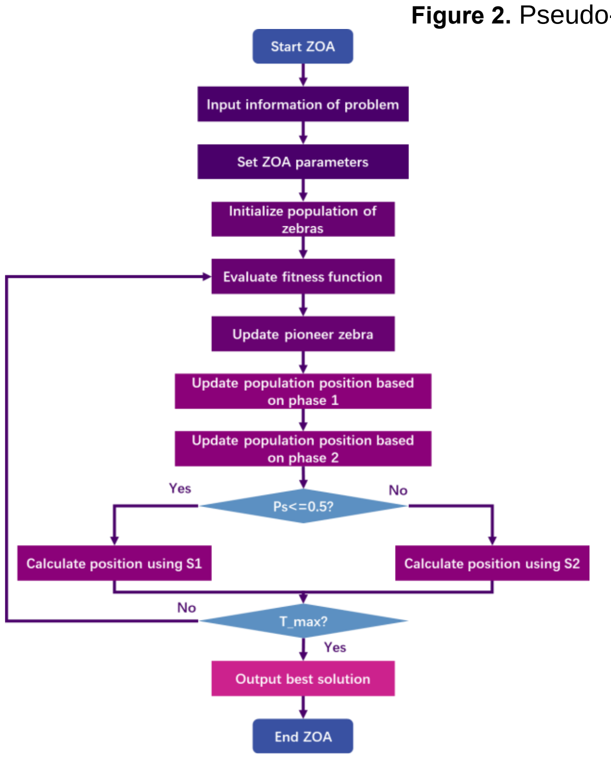

Figure 3. Flowchart of ZOA algorithm

Step 1: Initialise the population parameters as well as the population position, set the maximum number of iterations and other parameters;

Step 2: Calculate the fitness value and record the current pioneer zebra;

Step 3: Update the population individual location information according to the foraging behaviour strategy;

Step 4: Update the population individual location information according to the defence behaviour strategy. If $P_S \leq 0.5$, S1 strategy is used, otherwise, S2 strategy is used;

Step 5: Calculate the fitness value and record the current optimal individual;

Step 6: Determine whether the number of iterations reaches the maximum number of iterations. If the maximum number of iterations is reached, carry out the output of the optimal solution and optimal value; otherwise, go to step 3.

3.2. CNN networks

In order to construct the smart wearable device physical exercise application assessment model, this paper uses convolutional neural network as the application assessment model construction algorithm, which solves the problem of analysing the impact effect of smart wearable devices in physical exercise application [23].

Convolutional neural network (CNN) [24] is a type of artificial neural network that includes one or more convolution layers, i.e., at least one layer that uses convolution operations instead of the usual matrix multiplication operations.The structure of CNN is shown in **Figure 4**. The convolution layer analyses each small piece of the input sample more deeply to obtain features with a higher degree of abstraction; the pooling layer does not change the depth of the output of the previous layer, and can reduce the size of its matrix, thus reducing the number of parameters in the real neural network; the fully connected layer is mainly used to complete the classification task, which is to obtain the scores of each category by weighted summation of the learned feature representations; the last layer of the general classification problem is the Softmax layer, which is used for classification problems. Softmax layer is used to map the scores from the previous layer to the sample labelling space.The features of CNN include sparse connectivity, weight sharing and pooling.

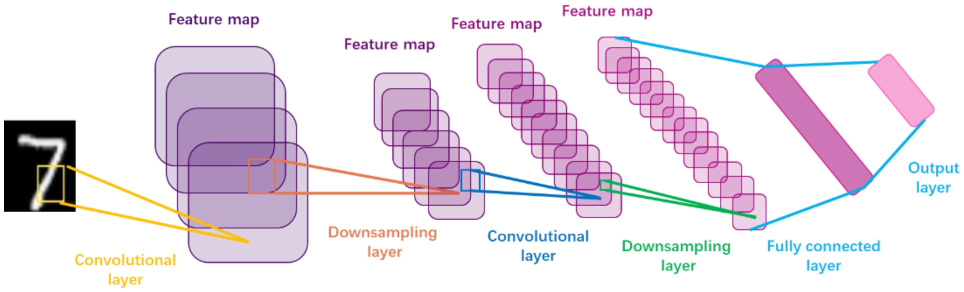

Figure 4. Convolutional neural network

The convolution operation of a convolutional layer is defined as follows:

$$z_j^{(l)} = \sum_{i=1}^{I} w_i^{(l)} a_{i+j-1}^{(l-1)} + b^{(l)} \tag{5}$$

Where i is the index of the convolution kernel, l flag indicates the current convolution layer, $l-1$ indicates the previous layer, I indicates the size of the convolution kernel. $z_j^{(l)}$ denotes the feature value of the convolution layer after the convolution operation, $w_i^{(l)}$ denotes the shared weights, $a_{i+j-1}^{(l-1)}$ is the activation output value of the previous layer, and $b^{(l)}$ is the bias of the convolution layer.

After going through each forward propagation calculation, the gradient of the loss function with respect to the weights and biases needs to be back propagated through the neural network. The optimisation algorithm used in this paper for weights and biases is the Adam optimisation algorithm.

4. Improved Deep Learning Network Based on Zebra Optimisation Algorithm for Smart Wearable Device Application Evaluation Approach

(1) Design of coding method

In order to improve the prediction accuracy of CNN's smart wearable device application evaluation method, the CNN parameters, i.e., network parameter weights and biases, are optimised using the Zebra optimisation algorithm.

(2) Adaptation function design

In order to improve the accuracy of CNN analysis, the root mean square error function is used as the objective function of the ZOA-CNN algorithm, which is calculated as follows:

$$\min RMSE = \sqrt{\left(\sum_{i=1}^{M} (\hat{y}_i - y_i)^2\right) \Big/ M} \tag{6}$$

(3) Steps and Processes

The smart wearable device physical exercise application assessment method based on ZOA algorithm optimised CNN network is mainly to construct the mapping relationship between the analytical features and assessment values by taking the analytical features as inputs and the assessment values as outputs. The flowchart of the smart wearable device physical exercise application assessment method based on ZOA-CNN algorithm is shown in Figure 5. The specific steps are as follows:

Step 1: Construct the index system for assessing and analysing the application of smart wearable devices for physical exercise; divide the data set into training set, validation set and test set;

Step 2: The CNN network parameters are encoded using the ZOA algorithm, and the algorithm parameters such as population parameters and iteration times are initialised; the population is initialised and the objective function value is calculated;

Step 3: Update the population location according to the ZOA algorithm foraging behaviour, defensive behaviour strategy;

Step 4: Calculate the fitness value and update the optimal solution;

Step 5: Determine whether the termination condition is satisfied, if so, exit the iteration, output the CNN network parameters, and execute step 3, otherwise continue to execute step 6;

Step 6: Decode the optimised CNN network parameters based on the ZOA algorithm, obtain the optimal convolutional neural network parameters, and construct a smart wearable device physical exercise application assessment model based on the ZOA-CNN algorithm;

Step 7: Test and analyse the current test set using the trained smart wearable device physical exercise application evaluation model, and output the corresponding test results.

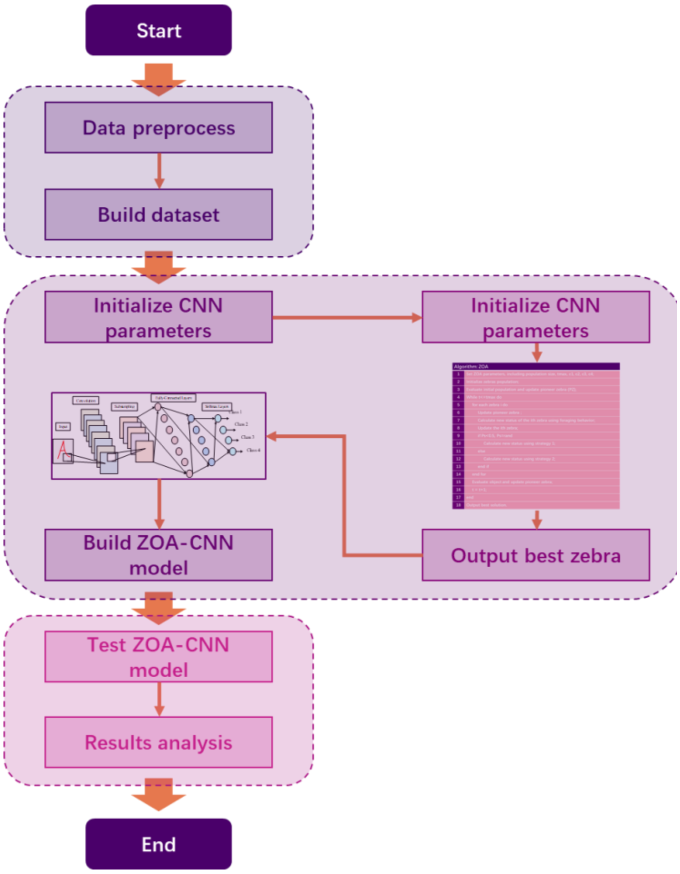

Figure 5. ZOA-CNN-based method for evaluating the physical exercise application of smart wearable devices

5. Experiments and analysis of results

In order to verify the advantages and disadvantages of the smart wearable device physical exercise application assessment method proposed in this paper, five analysis methods were selected for comparison, and the specific parameters of each algorithm were set as in Table 1.The experimental simulation environment was Windows 10, with a CPU of 2.80GHz, 8GB RAM, and the programming language Matlab2021a.

Table 1 Parameter settings of the evaluation method for physical exercise applications of smart wearable devices based on microcontrollers

arithmetic	parameterisation
CNN	The number of nodes in the hidden layer of the CNN network is given by the following analysis, using Adam's technique to optimise network training
TLBO-CNN [25]	The control parameter a of GWO is decreasing from 2 to 0. The number of GWO populations is the same as the CNN network nodes set at BES-CNN
GWO-CNN [26]	The control parameter a of GWO is decreasing from 2 to 0, and the number of GWO populations is the same as the CNN network nodes set in ZOA-CNN
WOA-CNN [27]	FTTA algorithm Pcomm=0.2, Pstudy=0.2, Perror=0.001, number of FTTA populations and CNN network nodes are set at the same level as BES-CNN
MPA-CNN [28]	
ZOA-CNN	BES is a parameter-free optimisation algorithm, and an analysis of the number of BES populations and CNN network nodes yields

(1) Analysis of the effect of population size and the number of CNN hidden layer nodes

In order to analyse the impact of the ZOA algorithm population size and the number of CNN network hidden layer nodes on the smart wearable device physical exercise application assessment method, this paper compares and analyses the performance of the Smart Wearable Device Physical Exercise Application Evaluation method under the conditions of different population sizes and different numbers of CNN hidden layer nodes, and the specific results are shown in **Figure 6** and **7**.

As can be seen from **Figure 6**, with the increase of the number of ZOA populations, the accuracy of the assessment value of the physical exercise application of smart wearable devices also gradually increases; with the increase of the number of CNN nodes, the RMSE of the assessment value of the physical exercise application of smart wearable devices becomes smaller, and the accuracy increases. As can be seen from **Figure 7**, with the increase of the number of ZOA populations, the evaluation time of smart wearable device physical exercise application also gradually increases; with the increase of CNN hidden layer nodes, the evaluation time of smart wearable device physical exercise application increases. In summary, the intelligent optimisation algorithm population size selected in this paper is 80, and the number of CNN hidden layer nodes is 100.

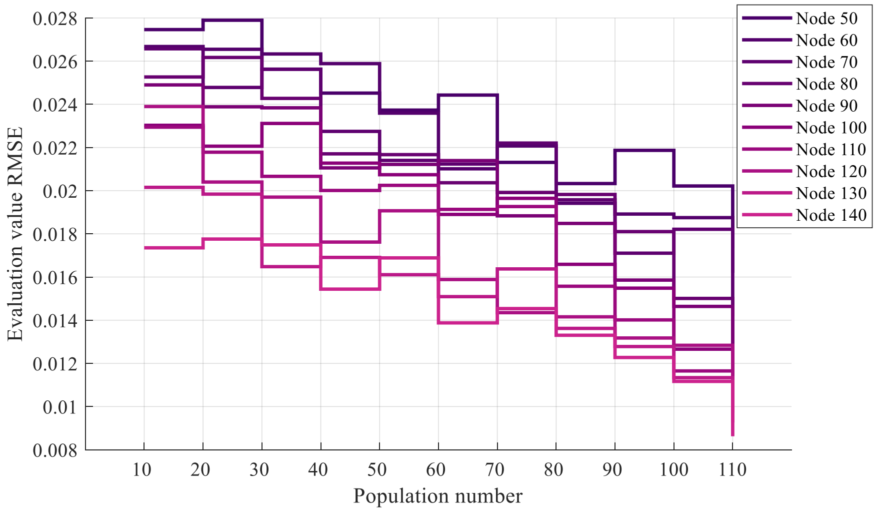

Figure 6. Different population sizes and different number of CNN hidden layer nodes on the prediction accuracy of the applied assessment methods

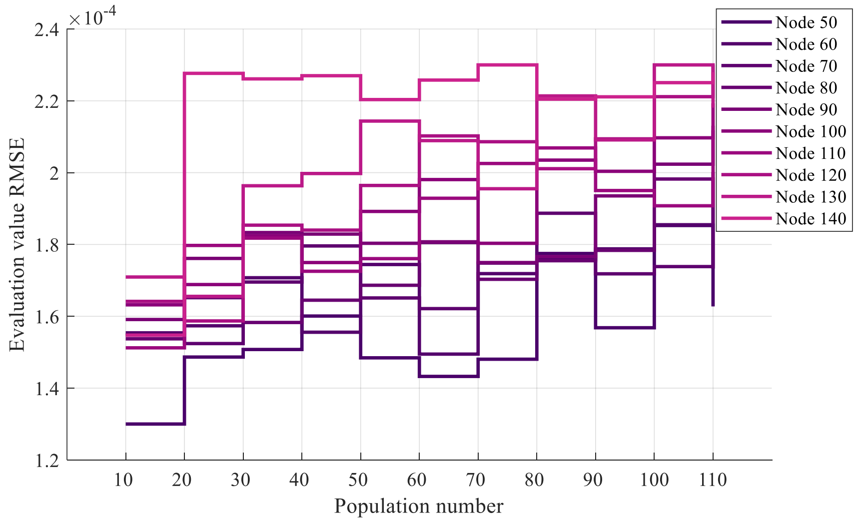

Figure 7. Different population sizes and different number of CNN hidden layer nodes on the prediction time of the applied evaluation methods

(2) Comparison of results of applied assessment methods

In order to verify the effectiveness and superiority of the smart wearable device physical exercise application assessment method based on ZOA-CNN algorithm, the smart wearable device physical exercise application assessment method based on ZOA-CNN algorithm is compared with the smart wearable device physical exercise application assessment methods based on CNN, TLBO-CNN, GWO-CNN, WOA-CNN, MPA-CNN algorithm. methods are compared, and the performance results of each model are shown in **Figures 8, 9, and 10**.

The prediction results of the smart wearable device physical exercise application assessment methods based on each algorithm are given in **Figure 8** respectively. From Figure 8, it can be seen that the predicted value of the smart wearable device physical exercise application assessment method based on the ZOA-CNN algorithm is the closest to the true value; the predicted value of the smart wearable device physical exercise application assessment method based on each of the other algorithms has the same development trend as that of the true value, which indicates the trend of the predicted value of the smart wearable device physical exercise application assessment method based on the machine learning algorithm. In summary, in terms of the prediction accuracy of the analysed values, the prediction accuracy of the smart wearable device physical exercise application assessment method based on the ZOA-CNN algorithm is better than that of the other algorithms.

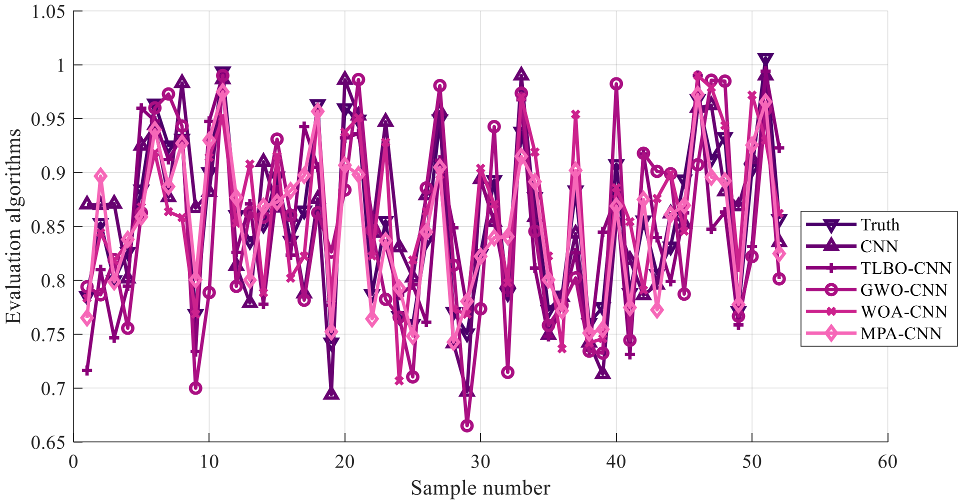

Figure 8. Prediction results of smart wearable device physical exercise application assessment methods based on each algorithm

Figure 9 gives the predicted RMSE of the smart wearable device physical exercise application evaluation method based on each algorithm under different working conditions, from **Figure 9**, it can be seen that the ranking of the RMSE of each algorithm under different working conditions is ZOA-CNN, MPA-CNN, WOA-CNN, TLBO-CNN, GWO-CNN, and CNN in the order of ZOA-CNN, MPA-CNN, WOA-CNN, TLBO-CNN, GWO-CNN, and CNN, and the algorithms' performance is relatively stable under different working conditions. The performance of the algorithms under different working conditions is relatively stable, which indicates that the prediction error robustness of the smart wearable device physical exercise application evaluation method of each algorithm is better; Figure 10 gives the prediction time of the smart wearable device physical exercise application evaluation method based on each algorithm under different working conditions. As can be seen from Figure 10, the ranking of the prediction time of each algorithm under different working conditions is MPA-CNN, ZOA-CNN, WOA-CNN, GWO-CNN, TLBO-CNN, and CNN in that order; the prediction time of the algorithms under different working conditions is relatively stable, which suggests that the prediction time of each algorithm's assessment of the physical exercise application of smart wearable devices has better robustness.

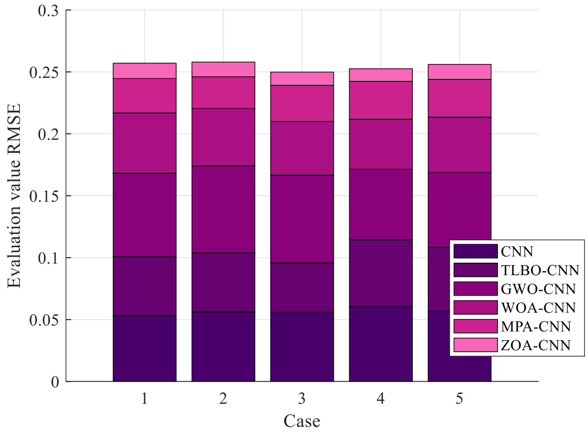

Figure 9. Comparison of RMSE results predicted by smart wearable device physical activity application assessment methods

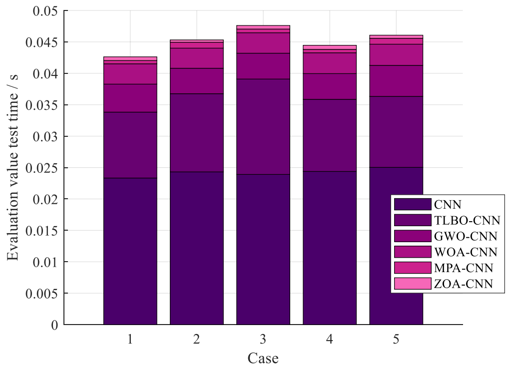

Figure 10. Smart Wearable Device Physical Activity Application Assessment Method Comparison of Prediction Time Results

6. Conclusion

This paper proposes a smart wearable device physical exercise application assessment method based on microcontroller and intelligent optimisation algorithm to improve deep learning network. In the process of constructing the application assessment model of physical exercise for smart wearable devices, the application assessment features are extracted, the application assessment system of physical exercise for smart wearable devices based on microcontroller is established, and the convolutional neural network weights and bias are optimised by combining the zebra-heuristic optimisation algorithm, and the ZOA-CNN application assessment model is constructed.

In order to verify the effectiveness and robustness of the proposed application assessment model, the assessment prediction results were compared using RMSE and elapsed time as the evaluation indexes of prediction accuracy. The results show that the prediction accuracy of the smart wearable device physical exercise application assessment method based on the ZOA-CNN algorithm is better than that of other algorithms; the application assessment prediction time robustness of each algorithm is better.

Future research could consider adding appropriate hardware design elements to the microcontroller-based smart wearable device assessment system for physical activity applications to further illustrate the impact of smart wearable devices on predictive analyses of physical activity assessment.

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