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An improved black-winged kite algorithm optimized back-propagation neural network for biceps curl classification

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ABSTRACT

Accurately identifying and classifying biceps curl types is of vital importance for sports training and upper limb joint rehabilitation training. It can improve the effect and reduce the risk of injury caused by incorrect training. In this study, a dataset of biceps curl training was obtained by measuring wearable sensors. After data preprocessing, 340 samples of 35-dimensional feature data were obtained. The classification labels of the dataset were marked as 1-5 according to the five types of biceps curl. This study proposed a black-winged kite algorithm (IBKA) that uses the good point set (GPS) method and the adaptive spiral search rule, a multi-strategy. IBKA optimized the initial weights, biases, and hidden layer numbers and provided them to the back-propagation neural network (BPNN) to establish the IBKA-BPNN model. The constructed IBKA-BPNN model improved the classification accuracy of the training set from 79.83% to 94.54%, and the accuracy of the test set from 69.61% to 88.33%. The IBKA-BPNN model proposed in this study provides a reliable decision-making basis for real-time coaching, athlete performance analysis, and upper limb rehabilitation. Future work will expand the dataset, integrate more bio signals, and explore lightweight deployment on wearable hardware.

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1. INTRODUCTION

Nowadays, people pay more and more attention to physical health and strengthen sports training [1]. Among them, biceps curl is a particularly common training movement. From the perspective of robotics, this sports training is a single-joint elbow flexion exercise, which can make the body more beautiful and can exercise the biceps, brachialis, and brachioradialis [2], [3]. Biceps curl is closely related to professional strength training and daily life, such as weightlifting and carrying goods. It is also one of the regular training items in upper limb rehabilitation training.

It is very important to perform the correct biceps curl type, as incorrect posture during training will not only fail to achieve the desired training effect, but may even cause elbow and shoulder injuries. Especially for professional athletes and upper limb rehabilitation trainers, performing accurate biceps curls is crucial [4]–[6]. During professional sports training, trainees are required to carry out standardized training according to the biceps curl type accurately [7]. In recent years, with the improvement of sensor measurement technology and computer information technology [8], [9], many scholars have integrated computational technology sports training into sports training and achieved many results [10]. Biceps curl type recognition is a supervised learning classification prediction problem. In order to identify the type of biceps curl, wearable sensor devices are often used to collect training process data [11]. Most researchers use advanced Wireless sEMG Sensor BIOM-LE2 and goniometer BIOM-WS150 to detect the electromyography of the biceps and real-time data of elbow joint movement [12].

There are many methods to achieve the multi-category classification problem of biceps curl action recognition. Traditional calculations include logistic regression, Bayesian method, decision tree, random forest, and K-nearest neighbor machine learning method [13]. The mathematical model is simple and fast, but the accuracy is not high for processing multi-dimensional data and nonlinear problems. Support vector machine, radial basis function, and other neural network models are increasingly used in regression and classification applications [14]. Hyperparameter tuning of different algorithms can often seek better accuracy. back-propagation neural network (BPNN) has outstanding advantages in realizing regression prediction and analytical prediction in linear and nonlinear problems through a stacked fully connected structure and gradient descent training [15].

In recent years, swarm intelligence algorithms have been increasingly applied to practical engineering problems and algorithm optimization. These heuristic algorithms are often inspired by the behaviors of animals and plants in nature, such as searching, exploring, capturing, plundering, and evolving. The Black-winged kite algorithm (BKA) [16] is inspired by and simulates the migration and hunting behavior of black-winged kites. It has fast global exploration and local exploitation capabilities and is in the exploratory stage in human motion training applications. Researchers have used many swarm intelligence algorithms to optimize neural network parameters for better accuracy. Particle swarm optimization, gray wolf algorithm, and dung beetle algorithm have been used to adjust neural network weights, architectures, and learning hyperparameters. These algorithms can usually avoid local minima caused by gradient descent methods. This study attempts to improve the BKA algorithm and then tune the BPNN framework to predict five biceps curl postures. The contributions of this study are summarized as follows.

- The BKA algorithm is improved by using multiple strategies, such as the optimal point set and the adaptive t-spiral strategy, to achieve better optimization computing performance.
- The improved BKA (IBKA) algorithm was used to optimize BPNN, and the IBKA-BPNN prediction model is proposed to achieve classification prediction of five types of biceps curls.

The content framework of the subsequent paper is as follows: section 2 details the proposed method, including the dataset source, preprocessing, improved BKA, and BPNN architecture. Section 3 presents the performance test results of the improved BKA and the prediction results of the established IBKA-BPNN model. Section 4 summarizes the findings of the IBKA-BPNN model and discusses the direction of extending this technology to other sports training scenarios.

2. METHOD

This section outlines the overall process of the IBKA-BPNN model for biceps curl classification proposed in this study. First, data collection and data set sources for biceps curl training are introduced. Then, the multi-strategy improvement strategy of the improved IBKA is introduced, focusing on the good point set construction and adaptive spiral search strategy. Finally, the BPNN architecture, parameter selection, and model evaluation criteria are introduced. The overall workflow diagram of the IBKA-BPNN model is shown in Figure 1.

2.1. Measurements and datasets

The experimental data of the biceps curl is measured by referring to the wearable measurement method used in current mainstream research. The data collection samples selected healthy adult volunteers and athletes, and repeated curl measurements were performed. Common dumbbell single-arm biceps curls can be performed in five postures: standard technique, elbow-fling, partial-up, partial-down, and hip-swing. The five types correspond to the five labels 1–5 of the class variable.

The data acquisition scheme is shown in Figure 2. It includes a six-axis inertial measurement unit (IMU), a surface electromyography (EMG) sensor, a flexible fabric strain sensor cuff, and a two-axis electronic goniometer. All data can be transferred to a computer via a USB data acquisition (DAQ) card for storage. The six-axis inertial measurement unit (IMU) is used to capture the linear and angular movement of the forearm during each curl. The surface electromyography (EMG) sensor is used to record muscle activation patterns to distinguish between correct posture and momentum-assisted movement. The two-axis electronic goniometer can measure the flexion angle in real time and can accurately distinguish between lifting and lowering.

The collected dataset includes the Euler angle posture of the wrist, forearm, and upper arm measured by IMU, and 35-dimensional data such as limb segment rotation speed, axis angular velocity, axis acceleration, and axis magnetic field measured by EMG [17].

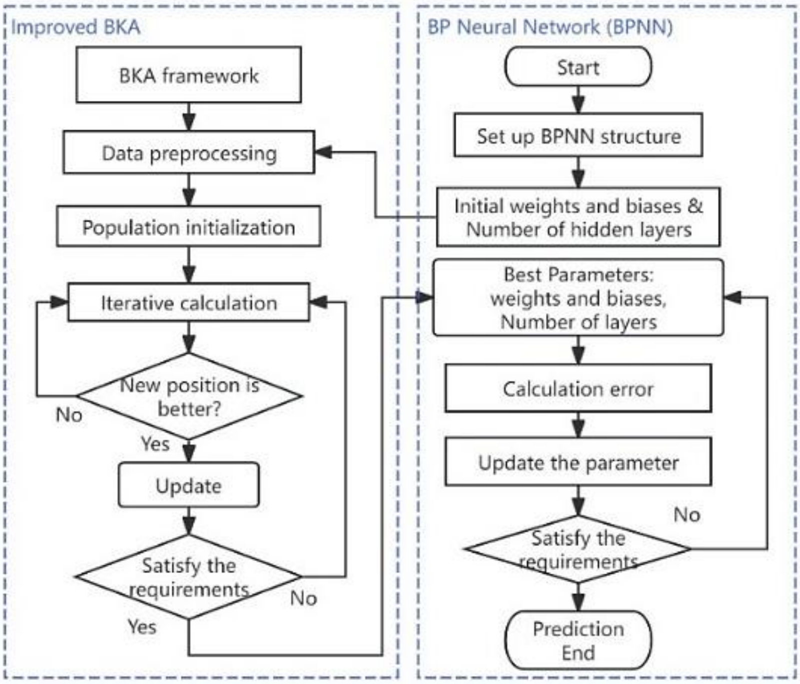


Figure 1. Workflow diagram of the IBKA-BPNN model

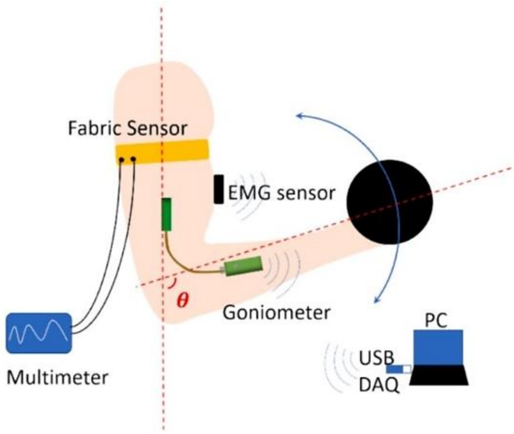


Figure 2. Schematic diagram of data acquisition scheme

The dataset obtained from the preliminary collection was preprocessed to facilitate the subsequent prediction model calculation. Only the data collected during the stable curl training process was retained; all channels of different sensors were time-aligned, and the effective measurement data of the same biceps curl training was converted into a 35-dimensional feature vector. The dataset was labelled 1 to 5 according to the five types of biceps curls. High-frequency electronic noise and low-frequency drift data were eliminated, the distorted fragments collected in the data were deleted, and the 5 types of samples were balanced, resulting in a total of 340 rows and 35 columns of data.

2.2. Improvement of black-winged kite algorithm

The original BKA algorithm is inspired by the attack and migration behaviors of black-winged kites. The prey is equivalent to the global optimal solution of the algorithm. The attack behavior allows the algorithm to find the optimal solution within a specified range, and the migration behavior allows the algorithm to explore new potential solution areas in a larger range to avoid being trapped in the local optimal solution.

The original BKA algorithm uses random population positions for population initialization. To address this instability, this study proposes the good point set (GPS) method [18] to improve the stability of population initialization. For problems with i populations and j dimensions, the method of finding the optimal point set is shown in (1).

$$\begin{cases} r_j^i = mod\left(2\cos\left(\frac{2\pi j}{k}\right)i, 1\right) \\ k = 2j+3 \\ P_j^i = lb_j + r_j^i\left(ub_j - lb_j\right) \end{cases} \tag{1}$$

The results of using GPS population initialization and random population initialization used in the original BKA algorithm are compared, as shown in Figure 3. It can be intuitively seen that GPS population initialization is more uniform and stable than random population initialization.

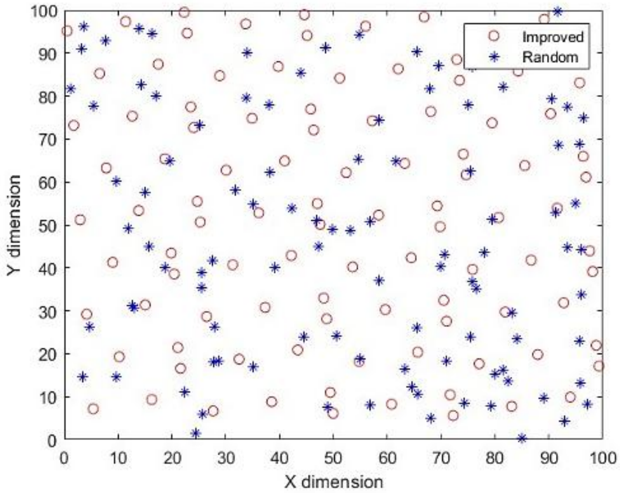


Figure 3. Comparison of population initialization

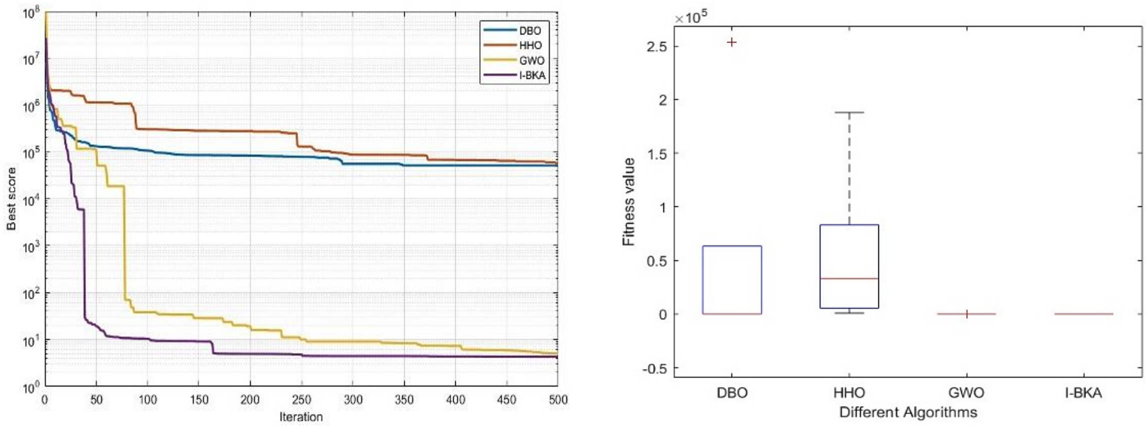
In the attack behavior stage, this study proposes an adaptive T-spiral strategy, as shown in formula (2), which can enhance the algorithm's local exploitation ability to find the optimal solution [19]. It can also expand the neighborhood range to avoid falling into the local optimal solution.

$$\begin{cases} X_{t+1}^{i,j} = X_t^{i,j} + n(1+\sin(r)) \times X_t^{i,j} \times D, \quad p < r \\ X_{t+1}^{i,j} = X_t^{i,j} + n \times (2p-1) \times X_t^{i,j} \times D, \quad other \\ D = x \times y \times z \\ x = p \times \sin(m) \\ x = p \times \cos(m) \\ z = p \times m \\ p = U \times trnd(\frac{vt}{T}) \end{cases} \tag{2}$$

Here, $X_t^{i,j}$, $X_{t+1}^{i,j}$ represent the position of the i-th black-winged kite in the j-dimensional t-th and $(t+1)$-th iteration steps, respectively. r is a random number between 0 and 1. t is the current iteration number, and T is the total number of iterations set. n is the nonlinear factor. m is a random value between $(0,2\pi)$. U is a constant of 2. v is a constant of 5. *trnd* is a variable step length generated using the characteristics of the t distribution.

To verify the superiority of the proposed IBKA algorithm, in addition to the benchmark functions test, a seven-dimensional engineering design task calculation comparison was selected. The IBKA algorithm was compared with the original dung beetle optimizer (DBO) [20], Harris Hawks optimizer (HHO) [21], and grey wolf optimizer (GWO) [22] algorithms. The comparison results are shown in Figure 4.

The algorithms were run 30 times independently, with a population size of 30 and 500 iterations. The convergence curve shown in Figure 4(a) and the box plot shown in Figure 4(b) intuitively express the robustness and superiority of the BKA algorithm improved by good point set initialization and adaptive spiral search.



(a) (b)

Figure 4. Performance comparison of improved BKA algorithm: (a) convergence curves for a 7-dimensional engineering problem and (b) comparison of box plots for optimized calculations

2.3. Back-propagation neural network

BPNN is a feedforward artificial neural network, as shown in Figure 5, which consists of an input layer, multiple hidden layers, and an output layer. The original BPNN network uses the sigmoid nonlinear activation function. Its learning process uses the error back-propagation algorithm [23]–[25].

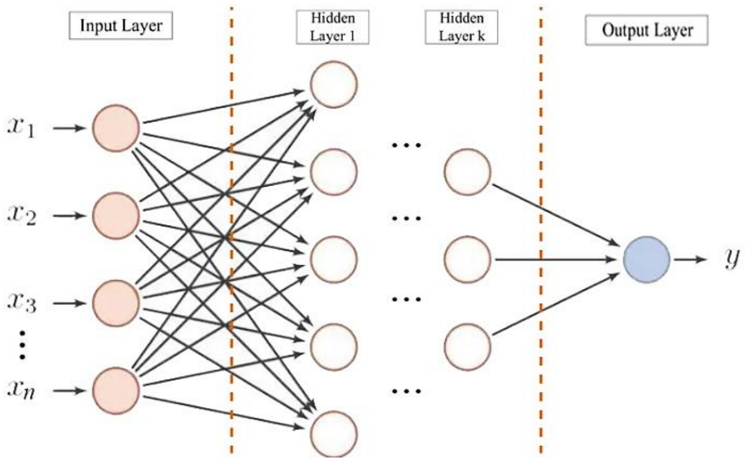


Figure 5. Diagram of BPNN network structure

The neuron's predicted output $\hat{y}_i$ is computed by (3), where w_{ij} and b_{ij} are the synaptic weight and bias, respectively. The network's overall loss is quantified by the sum-of-squared errors in (4), which compares each prediction $\hat{y}_j$ with its ground-truth target y_j. To minimize this loss, the weights are iteratively refined with gradient descent, as shown in (5), where η denotes the learning-rate coefficient that controls the step size of each update.

$$\hat{y}_i = f\left(\sum_{i=1}^{n} w_{ij}x_i - b_{ij}\right) \tag{3}$$

$$E = \sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{4}$$

$$w_{ij} = w_{ij} - \eta\frac{\partial E(w_{ij})}{\partial w_{ij}} \tag{5}$$

The idea of IBKA to optimize BPNN is to use the global optimal solution found by IBKA as the parameters of BPNN. IBKA regards each population as a candidate set of weights, biases, and the number of hidden layers of BPNN. The weights, biases, and number of hidden layers randomly generated by the original BPNN are used as the initial search starting point of the population of IBKA, evaluated on the training set, and iteratively updated. The iterative calculation is stopped until the prediction error of the BPNN network converges below the target threshold. The final BPNN model will be used for the recognition of five types of biceps curls.

3. RESULTS AND DISCUSSION

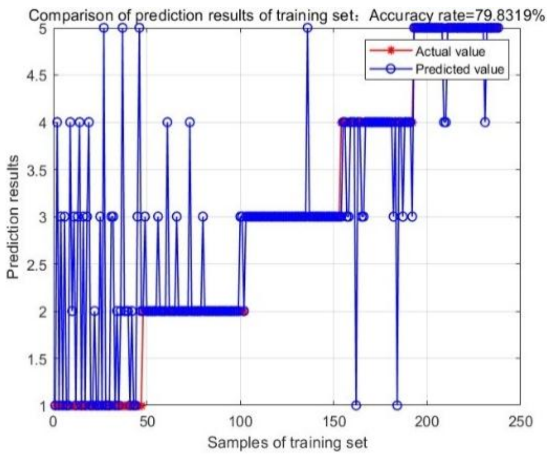
This section outlines the experimental scheme, including data partitioning, evaluation metrics, and computing environment. The classification prediction results obtained using the original BPNN are presented. Subsequently, the proposed IBKA-BPNN model is used for classification prediction. Finally, the practical significance of this study for biceps curl type recognition is discussed.

3.1. Original BPNN prediction

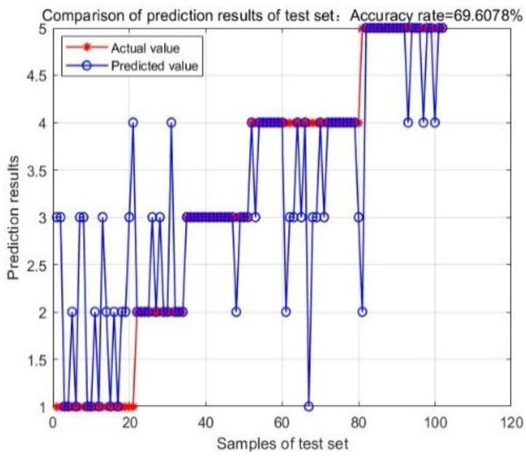
The preprocessed data set contains 340 samples, each with 35 input features. The dataset obtained after preprocessing the data measured in the biceps curl experiment was divided into a training set (70%) and a test set (30%). The robustness was measured by the standard deviation of the average accuracy of the test set over ten runs. The learning rate was set to 0.01, and the number of hidden layers was 6 according to the empirical formula.

To eliminate the contingency caused by random initialization, the complete experiment was repeated 10 times under different random initializations, and the model's robustness was measured by the standard deviation of the average accuracy of the test set. The results of the original BPNN model for biceps curl type classification prediction are shown in Figure 6.

Figure 6(a) plots the comparison curve between the actual label and the predicted label on the training set. After multiple tests, the average accuracy of the training set is 79.83%. Figure 6(b) plots the comparison curve between the actual label and the predicted label on the test set. The average accuracy of the test set is 69.61%, showing a certain performance fluctuation. The original BPNN model has a small number of high-order category misjudgments, which is related to the overfitting of the model and the initialization setting of the model parameters.



(a)



(b)

Figure 6. The original BPNN classification results: (a) results of training set classification and (b) results of test set classification

3.2. IBPA-BPNN prediction

To solve the problem of insufficient generalization ability and low accuracy rate of the original BPNN on the biceps curl dataset, this study attempts to use the improved BKA algorithm to globally optimize the weights, biases, and number of hidden layers of BPNN. The IBKA algorithm combines the improved strategy of GPS population initialization and adaptive spiral search to accelerate convergence while maintaining population diversity. The population size of IBKA-BPNN is 30, the maximum number of iterations is 30, and the other settings of BPNN are consistent with the original. The convergence curve of the IBKA-BPNN model is shown in Figure 7.

IBKA obtained optimized initial weights and bias values of BPNN, and the optimal number of hidden layers is 10. IBKA optimizes the initial weight, threshold, and hidden layer size of BPNN globally, significantly improving the model's ability to distinguish five biceps curls. Figure 8 shows the confusion matrix of IBKA-BPNN on the training set and test set to verify the classification performance of the model. Figures 8(a) and 8(c) show the classification results in the training phase. The recognition rates of category 4 and category 5 reach 100% and 97.9%, respectively, and the overall training accuracy reaches 94.54%, which is 14.71% higher than that of the original BPNN. Figures 8(b) and 8(d) show the classification prediction results of the test set, and its overall accuracy is improved to 88.33% (the original BPNN is 69.61%).

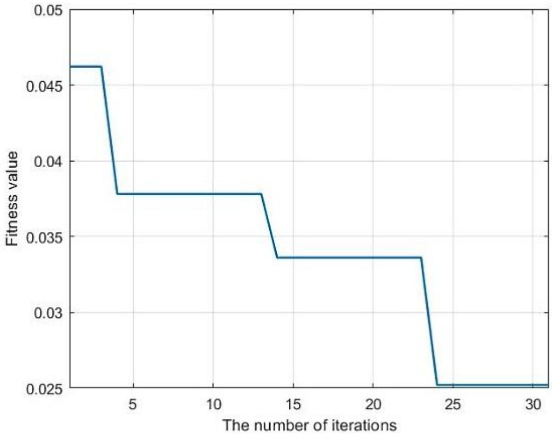
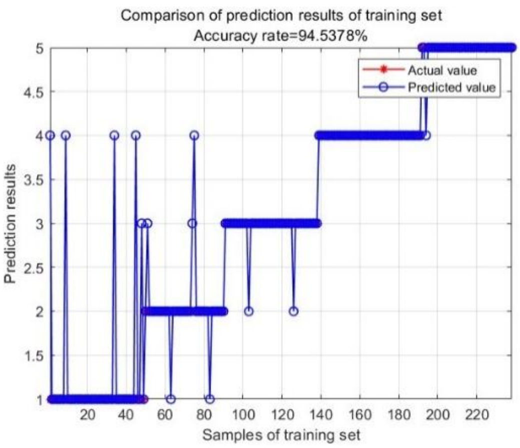
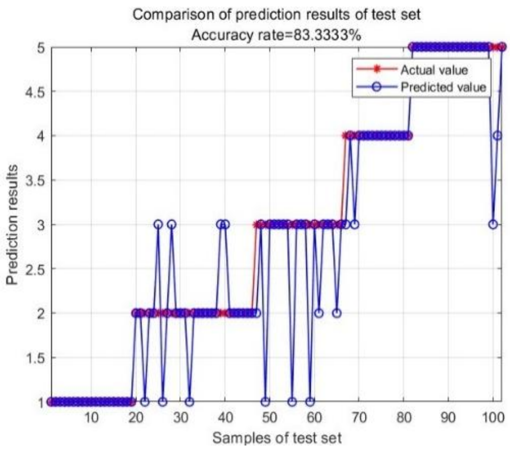


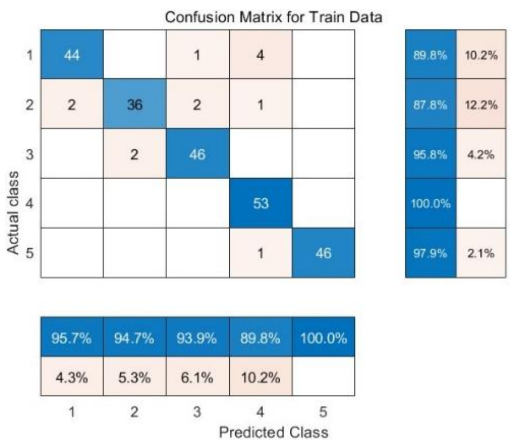
Figure 7. Convergence curve of the IBKA-BPNN model



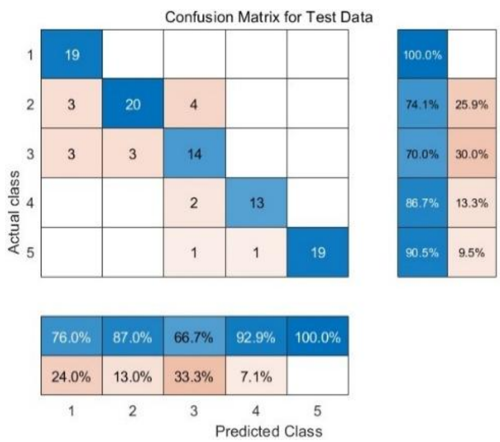
(a)



(b)



(c)



(d)

Figure 8. The IBKA-BPNN classification results: (a) results of training set classification, (b) results of test set classification, (c) confusion matrix for training data, and (d) confusion matrix for test data

IBKA-BPNN shows a comprehensive and significant performance leap compared to the original BPNN in the recognition of five types of biceps curl movements. Based on the same data partitioning and ten independent experiments, the average accuracy of the training set and test set of IBKA-BPNN increased to 94.54% and 83.33%, respectively, which is 14.71 and 13.72 percentage points higher than the 79.83% and 69.61% of the original BPNN model. In terms of comprehensive accuracy, robustness, and other multi-dimensional indicators, IBKA-BPNN is significantly better than the unoptimized BPNN, which proves the effectiveness of the improved BKA algorithm in weight and network structure optimization, and provides a data analysis basis for subsequent classification and training of more complex motion postures.

4. CONCLUSION

This study investigates five common biceps curl classification methods, aiming to maximize the training effect for professional sports training and upper limb rehabilitation training. A wearable sensor dataset was selected in the study, which contains multiple repetitions of the standard technique, elbow-fling, partial-up, partial-down, and hip-swing.

A multi-strategy improved IBKA was proposed. IBKA also surpassed the most advanced optimizers, such as DBO, HHO, and GWO, in an independent seven-dimensional engineering benchmark test, proving the effectiveness of its improved strategy. IBKA was used to optimize the weights, biases, and number of hidden layers of the BPNN, thereby establishing the IBKA-BPNN model. The IBKA-BPNN model improved the accuracy of the training set from 79.83% to 94.54%, and the accuracy of the test set from 69.61% to 88.33%.

These findings indicate that the IBKA-BPNN model provides data support for the classification of biceps curl training and upper limb rehabilitation training patterns, which helps improve the safety and effectiveness of sports training. In the future, the research team will expand the data set to target a wider range of sports training digitization and integrate more biological signals. This research team actively explores the deployment of artificial intelligence technology and develops wearable hardware devices to assist in the sports training process, provide athletes with intuitive feedback on training posture deviations, and accelerate the application of smart sensor-based training systems in sports science and rehabilitation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Kim Geok Soh	✓	✓		✓		✓	✓	✓		✓		✓	✓	
Hazizi Abu Saad	✓			✓		✓	✓			✓				
Haohao Ma		✓	✓	✓	✓				✓		✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author KG upon reasonable request.

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