



## **A study on the effect of core strength training on footwork flexibility in badminton incorporating deep learning algorithms**

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**SUMMARY:** *Accurately analyzing core strength training postures is the technical cornerstone for improving foot flexibility of badminton players. In this paper, a badminton core strength training posture intelligent analysis system is designed based on deep learning algorithm. Firstly, a human motion data acquisition subsystem was constructed based on IMU sensors to obtain high-precision motion data. Then in order to accurately identify the human motion patterns, a motion recognition model based on symmetric coding, time scale coding and structural coding is constructed, and the model is trained based on a deep learning algorithm (Adam optimizer). Finally, a comparative analysis of the training effect through the compliance and violation indexes of training movements such as pull-ups, sit-ups and push-ups is proposed. The mAP and GFLOPs/V values of the constructed motion recognition model are 93.65% and 25.77, respectively, and the model performance is greater than that of mainstream recognition models. The evaluation effect of the posture intelligent analysis system on the training movement meets the practical use requirements, and the foot flexibility of badminton players is improved after the application of the system, and the p-value is less than 0.05. The deepening application of deep learning technology in the field of sports brings a broader vision for the long-term development of sports.*

**KEYWORDS:** *Deep learning; Motion recognition model; Adam optimizer; Posture intelligent analysis system; Footwork flexibility*

## **1 Introduction**

Badminton, as a fast-moving, explosive and skillful competitive sport, has very high requirements on the physical quality and technical level of athletes [1]. In badminton, every swing and every turn of the players are inseparable from the precise movement of the feet. Footwork is not only a “bridge” connecting each technical action, but also a key factor in determining the rhythm of the game and the victory or defeat [2]. Flexibility, as the core ability to support the smooth execution of footwork, directly affects the efficiency of athletes in high-speed confrontation to complete the change of direction, stop and start [3]. In the training activities of badminton, the traditional training mode tends to focus more on the training of athletes' upper limb strength, lower limb strength and basic techniques, and pays insufficient attention to core strength training. As a link between the upper and lower limbs, strengthening badminton core strength training can strengthen the flexibility of badminton players to ensure that athletes give full play to their role [4, 5]. However, in the core strength training, it is easy to be influenced by the traditional training methods, and thus accustomed to using a single

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method, mechanically organizing some of the exercises such as sit-ups, plate support and other routine aspects of the exercise, which is relatively lacking in the relevance and diversity of training.

With the development of artificial intelligence and its application in the field of sports training, deep learning algorithms have become a key technology to realize the relevance and diversity of sports training [6, 7]. In badminton core strength training, deep learning helps to analyze the athletes' index data, track and study the athletes' demand for foot flexibility training in real time, so that the training program can be adjusted more accurately to better improve the training efficiency [8-10]. In addition, deep learning can also be used to predict athletes' footwork and help athletes make improvements to improve their footwork flexibility [11, 12].

Regarding the application and impact of badminton core strength training, literature [13] explored the impact of core strength training on the dynamic balance, flexibility and footwork skills of badminton players, and through a 12-week controlled experiment, it was found that the experimental group achieved significant improvement in the three indexes, while the control group had no change, which emphasized the effectiveness of the core training to improve the special physical quality. Literature [14] elaborated that badminton footwork mastery and core strength training are closely related, the latter can flexibly drive the body force, improve the flexibility of movement and balance, and with the help of computer technology, the teaching of badminton core strength training to carry out an in-depth exploration and analysis, in order to promote the scientific application of it. Literature [15] emphasized that both core strength and agility are key physical fitness elements in badminton, and analyzed the correlation between core strength and Illinois agility by testing the core strength and agility of 30 athletes and found that core strength and agility were significantly negatively correlated, indicating that core strength enhancement may be accompanied by improvement in agility reaction time. Literature [16] compared the effects of contrast training (combining augmented and isometric training) with core strength training on dynamic balance and agility in 86 college athletes; after 6 weeks of intervention, both groups showed improvement in the parameters, but the contrast training group had a more significant effect, suggesting that it should be used as an adjunct to regular training. Literature [17] analyzed the effects of core strength training on junior badminton players and found that 6 weeks of training significantly improved their dynamic balance and core endurance, but not agility. Literature [18] emphasized the need for good core strength and dynamic balance in badminton, and revealed the positive effects of core training on beginner badminton players through 4 weeks of core strengthening and fitness training for 25 beginners aged 12-19 years, assessed based on the 60-degree curls and modified Sorensen test, and found that core strength was significantly improved after the training, revealing the positive effects of core training on beginner badminton players. Literature [19] emphasized that core strength training is crucial for badminton players to improve the quality of technique and prevent injuries, but the existing studies lacked a systematic analysis of the basic techniques corresponding to the core muscle groups, types of injuries, and their associations. Through literature review and logical analysis, we elaborated on the core muscle groups involved in badminton techniques and the common injuries, explored how the core training can improve the quality of movements, and proposed practical strategies for preventing injuries by strengthening specific It also discusses how core training can improve the quality of movement, and proposes practical strategies to prevent injuries by strengthening specific muscle groups.

The application of deep learning algorithms in badminton training provides technical support to improve the comprehensive performance of athletes. Literature [20] analyzed the association between core strength training and step agility through deep learning algorithms, and constructed a prediction model from core strength to step agility based on the athletic performance, physiology and training data, and experiments showed that the method has higher

prediction accuracy than traditional linear regression, BP neural network, etc., and can effectively deal with high-dimensional data such as video. Experiments show that this method has higher prediction accuracy than traditional linear regression, BP neural network, etc., and can effectively handle high-dimensional data such as video. Literature [21] combines advanced analytics and deep learning to optimize movements through computer vision models to improve hitting speed and agility by 15% and 12% respectively, wearable sensors to predict injury risk to reduce injuries by 25%, and reinforcement learning to improve defense by 20%, confirming that data-driven real-time feedback training is superior. Literature [22] in order to improve the level of badminton training intelligence, proposed a deep learning-based action recognition system, optimized spatio-temporal feature extraction and multimodal fusion, experiments show that its accuracy is up to 0.967, F1 score up to 0.902, the fastest inference time of 10.8 milliseconds, significantly better than the models such as ST-GCN, MM-Net, etc., which is suitable for real-time mobile applications, and provides an effective tool for intelligent training and data analysis provides an effective tool.

In addition, literature [23] examined the teaching application of rhythmic training based on SVM classification algorithm for the problems of easy neglect of footwork and irregular movements in badminton training, and experiments showed that its average recognition rate in different rhythmic movements and a variety of training modes reached 0.91-0.97, which confirmed the good classification and recognition effect of the model in teaching. Literature [24] in order to improve the badminton action evaluation accuracy and real-time, the human body posture estimation and motion capture combination, proposed a lightweight OpenPose improvement model, the use of MobileNet instead of VGG19 and optimization of the convolutional structure, experiments show that the performance of the model to improve the 3 times, the accuracy of the arm joints point recognition increased by 3.57%. Literature [25] aims to use machine learning algorithms to develop an intelligent badminton training robot to prevent athlete injuries, optimizing action recognition through Hidden Markov Model, experiments show that its recognition accuracy at the moment of hitting the ball reaches 96.03%, and the robot recognition rate reaches 94.5%, and it remains stable on 120 sets of training data, which provides a high-precision and stable experimental reference for injury prevention. Literature [26] indicated that in badminton dynamic blocking, the stepping strategy is crucial, for this reason, a new method combining deep learning and binocular localization is proposed to record the athlete's stepping data, and its final localization accuracy reaches 74.7%, which reveals the individual differences between different participants in the moving distance and the jumping height, and provides quantitative bases for the development of personalized stepping training plans, which helps to accurately improve the athletic performance.

This paper incorporates deep learning algorithms to design an intelligent analysis system for badminton core strength training posture, so as to determine whether the trainer's movement standard degree is in a reasonable range. The system identifies the movements on the acquired movement data, constructs the movement recognition model using three different time encoder structures (symmetric encoding, time scale encoding and hierarchical encoding), and improves the model recognition accuracy based on the Adam optimizer. The Posture Intelligence Analysis System realizes the training effect assessment through the compliance and violation indicators of core strength training movements such as pull-ups, sit-ups and push-ups. Based on the evaluation results of the system, the coach can provide guidance on the training movements, thus helping badminton players to improve their footwork flexibility.

## 2 Deep learning based training posture intelligent analysis system

The training posture intelligent analysis system constructed by the research is shown in Fig. 1. The system mainly includes image acquisition module, motion analysis module and visualization module parts.

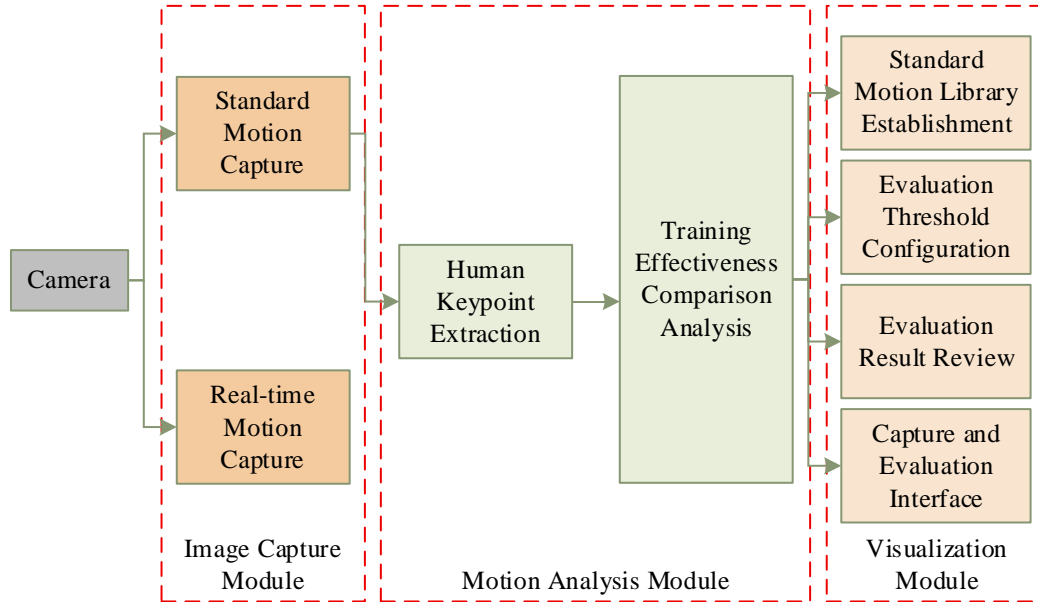


Figure 1: Training posture intelligence analysis system

### 2.1 Motion Data Acquisition

In order to obtain accurate human motion data, this paper designs a human motion data acquisition subsystem based on IMU core sensors and Arduino embedded development board as a data collector. DMP is a unique hardware feature of the IMU device capable of calculating quaternion data from sensor readings. The IMU acquires the data directly from the auxiliary sensors, which allows the embedded processor to process the sensor-fused data without the intervention of the system application processor. In this paper, the MPU6050 IMU monitoring program is developed based on the processing language. The raw data obtained from the accelerometers and gyroscopes are fused through DMP, and the Euler angle information is subsequently extracted from the quaternion representation to compute the yaw, pitch, and roll motions of the IMU. The software first obtains orientation values from XBee Pro and then calculates the relative position of the IMU using the length and orientation values of each part of the human body. The core sensors for measuring the motion status of human joints are two sets of IMU sensors.

The human motion analysis device was developed to analyze the human joint motion, therefore, its accuracy in measuring the human joint motion needed to be tested. The human motion analysis device was worn on the shoulder and the two IMUs were placed on the large and small arms. During the test, subjects were asked to lower their hands and repeatedly bend their elbows seven times. The hand was then straightened to its original position in the plane. While the subject was moving, motion data were collected using human motion analysis equipment, and a high-resolution video with an effective photo resolution of 15M and a pixel and frame rate of 49fps was recorded in the 2D plane using a GoPro Hero 3 device. Finally, the videos were post-processed. Analysis was performed to analyze the elbow motion using the

motion analysis software MaxTRAQ 2D, a video-based motion tracking software that can be used to extract kinematic properties from standard AVI video files. With manual and automatic tracking, users can view angles, distances between points, etc., frame by frame.

## 2.2 Construction and Training of Motion Recognition Models

### 2.2.1 Data processing and representation

The Mocap skeleton in Cartesian space is chosen, i.e., the frame at time  $t$  consists of  $f_t = [x_{i,t}, y_{i,t}, z_{i,t}]_{i=1:N_{joints}}$ , where  $N_{joints}$  is the number of joints.

To standardize the model, the joint angles were converted to Cartesian coordinates of the standardized human model. Joint positions are centered at the origin of the coordinate system, and translations are ignored while preserving the global rotation of the skeleton.

A dataset connected to the matrix  $F_{t:(t+\Delta t-1)} = [f_t f_{t+1} f_{t+2} \dots f_{t+\Delta t-1}]$  can be identified in  $\Delta t$  time windows. The dataset consists of an input frame window  $F_{(t-\Delta t+1):t}$  with an output frame window  $F_{(t+1):(t+\Delta t)}$  for each time step  $t \in [\Delta t, (T - \Delta t - 1)]$ , where  $T$  is the sampling time length.

### 2.2.2 Time encoder

The encoding-decoding framework is used to compute the projection of the high-dimensional input data onto the low-dimensional graph and to predict the output data based on that projection. The high dimensional input data  $x \in R^N$  is given to be optimized by the autoencoder as shown in equation (1):

$$\min_{f,g} \|x - f(g(x))\| \quad (1)$$

In this case, the encoder  $y = g(x)$  maps the input data to the low-dimensional space  $y \in R^M$  with  $N > M$ , while the decoder  $\hat{x} = f(y)$  maps back to the input space  $\hat{x} \in R^N$ , with the functions  $f$  and  $g$  being represented by symmetric multilayered perceptrons.

An alternative approach is used in this system to capture the temporal correlation of human motion data rather than a static representation of human pose. Let  $x \in R^N$  be an observation at time  $t$ , and the optimization function of the time encoder is shown in equation (2):

$$\min_{f,g} \|X_{(t+1):(t+\Delta t)} - f(g(X_{(t-\Delta t+1):t}))\| \quad (2)$$

where the encoder  $y = g(X_{(t-\Delta t+1):t})$  maps the input data into the low-dimensional space  $y \in R^M$  with  $(N \times \Delta t) > M$  and the decoder  $\hat{X}_{(t+1):(t+\Delta t)} = f(y) \in R^{N \times \Delta t}$  is used to map back into data space.

In this application, the input and output matrices have dimensions  $3 \times N_{joints} \times \Delta t$ , and the encoder  $y = g(F_{(t-\Delta t+1):t})$  maps the input data to the low-dimensional space  $y \in R^M$ ,  $(3 \times N_{joints} \times \Delta t) > M$ , the decoder  $\hat{F}_{(t+1):(t+\Delta t)} = f(y) \in R^{3 \times N_{joints} \times \Delta t}$  mapped back into data space.

### 2.2.3 Network structure

Three different temporal encoder structures are used in the paper, and the encoding structures are shown in Fig. 2, with (a) to (c) denoting symmetric encoding, time scale encoding, and hierarchical encoding, respectively. Symmetric encoding follows the autoencoder principle, and since the decoder is a mirrored version of the encoder, the decoder can be regarded as an approximation of the inverse of the encoder, i.e., the symmetric time encoder (S-TE). Time scale coding Since human motion can be described on different time scales, this property can be explicitly introduced into the time encoder. For a given window size  $\Delta t^w$ , the size of the convolution filter is  $3 \times N_{joints} \times \Delta t^w$ , where 3 denotes the 3 dimensions in the Cartesian space  $x$ ,  $y$  and  $z$ . The input data is convolved with filters of different sizes and the outputs of these convolutional layers are cascaded by means of an encoder-decoder using octree structure layers for further processing. The hierarchical coding utilizes the human body represented by a tree structure graph where the nodes consist of individual joints that are connected to the nodes of the corresponding limbs of the human body. The tree structure consists of  $L$  layers, where each layer  $l \in [0, L-1]$  consists of  $N_l$  nodes, and each parent layer  $l \in [1, L-1]$  is connected to its child layer  $k = l-1$ . The link between node  $i$  in layer  $l$  and node  $j$  in layer  $k$  is  $\xi\{(l, i), (k, j)\}$ .

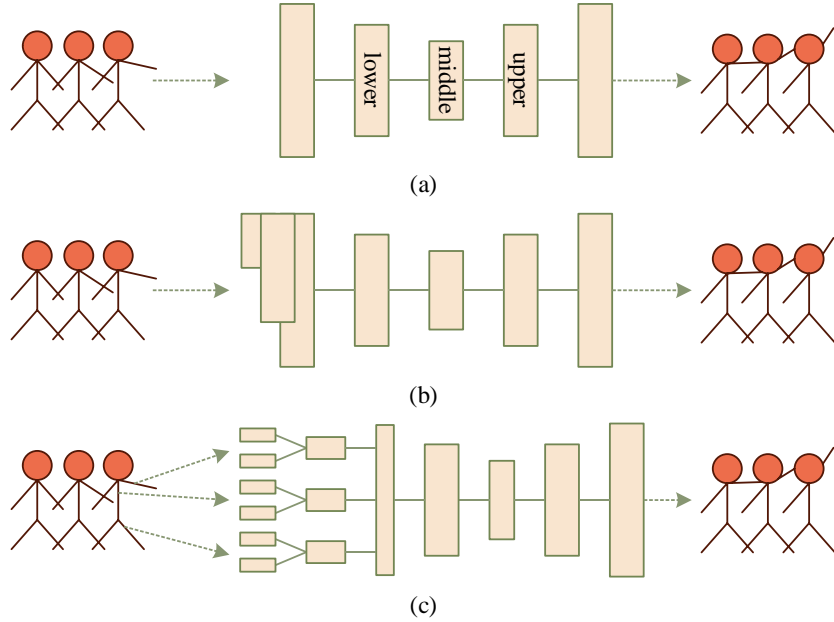


Figure 2: Coding structure

Modeling these nodes as a single feedforward node, each node in the bottom layer receives input from a single joint, i.e.,  $N_0 = N_{joints}$ . Subsequently these nodes are connected by a parent representing the limb, and if joint  $i$  belongs to limb  $j$ , then  $\xi\{(0, i), (1, j)\} = 1$ . Otherwise,  $\xi\{(0, i), (1, j)\} = 0$  until a single node represents the entire body. The single layer is used as input to a temporary encoder which is trained simultaneously with the tree diagram.

### 2.2.4 Model training

The deep learning algorithm, Adam optimizer, is used in the model training stage to adjust the parameters, which can adjust the update step size of each parameter according to its

computational history, which is especially effective when dealing with large-scale datasets. The configuration of the deep learning network realizes an effective combination of feature extraction and sequence analysis, which makes full use of the advantages of convolutional neural network in image processing and the ability of recurrent neural network in time series analysis, so that the model can accurately identify and analyze the continuous motion gestures.

## 2.3 Indicators for assessing the effectiveness of core strength training

Badminton core strength training consists of three exercises: pull-ups, sit-ups and push-ups. In this chapter, the training programs were parametrically represented and training movement analysis indexes were designed to assess the training effects.

### 2.3.1 Core Strength Training Movement Analysis

During the pull-up training process, the initial state of the trainer should be arm hanging, arms straight and grasping the bar. The body rises to the highest point with the lower jaw above the level of the bar. At the same time, in the pull-up process, the use of the body swing to generate the force over the bar movement should be regarded as a violation of the law.

In the push-up training, first of all, the angle between the shoulder joints and the wrist line and the ground is about 90 degrees, and the elbow joints are straight. The elbow joints are kept at the same height as the shoulder joints during the flexion phase, and the body touches the ground only through the palms of the hands and the toes during the whole process, and the torso is kept straight. It is considered a violation when the trainer's shoulder joint point is higher than the elbow joint point during the arm flexion phase, for example.

During sit-ups the hands should be placed in front of the chest, with the wrist joint points coinciding with the shoulder joint points and the ankle joint points fixed and coinciding. The elbows should be in contact with the knees and the joints should be aligned. It is considered a violation of the rules when the sit-up is performed without the hands in front of the chest or without the elbows touching the knees during flexion.

### 2.3.2 Parametric representation of training programs

The qualification index for the pull-up maneuver is primarily based on whether or not the trainer's lower jaw is above the bar; therefore, the camera should be kept as far as possible directly in front of the level of the person being photographed during the acquisition of the trainer's training images. The position of the lower jaw is defined as:

$$H_{chin} = H_{sho} + 0.5(H_{nose} - H_{sho}) \quad (3)$$

where  $H_{sho}$  is the height of the shoulder joint point and  $H_{nose}$  is the height of the nose joint point.

Trainers in the pull-up process due to keep the legs straight, using the knee and hip and ankle joint line formed by the angle of judgment, as shown in formula (4):

$$ang_{knee} = \frac{[x_{knee} - x_{ankle}(x_{hip} - x_{knee}) - y_{knee} - y_{ankle}(y_{hip} - y_{knee})]}{\sqrt{(x_{knee} - x_{ankle})^2 + (y_{knee} - y_{ankle})^2} \sqrt{(x_{hip} - x_{knee})^2 + (y_{hip} - y_{knee})^2}} \quad (4)$$

The  $x_{knee}, y_{knee}$  values represent the horizontal and vertical coordinates of the knee joint points, the  $x_{ankle}, y_{ankle}$  values represent the horizontal and vertical coordinates of the ankle

joint points, and the  $x_{hip}, y_{hip}$  values represent the horizontal and vertical coordinates of the hip joint points.

When the trainer's body descends, according to the elbow and wrist, shoulder line respectively, the angle formed by more than 150 degrees is considered to complete a single pull-up movement, the definition of the angle formed by the formula (5) shown:

$$ang_{elbow} = \frac{[x_{elbow} - x_{sho} (x_{wrist} - x_{elbow}) - y_{elbow} - y_{sho} (y_{wrist} - y_{elbow})]}{\sqrt{(x_{elbow} - x_{sho})^2 + (y_{elbow} - y_{sho})^2} \sqrt{(x_{wrist} - x_{sho})^2 + (y_{wrist} - y_{elbow})^2}} \quad (5)$$

where  $x_{elbow}, y_{elbow}$  represents the elbow joint point horizontal and vertical coordinates,  $x_{sho}, y_{sho}$  represents the shoulder joint point horizontal and vertical coordinates, and  $x_{wrist}, y_{wrist}$  represents the wrist joint point horizontal and vertical coordinates.

Meanwhile, when the trainer performs the pull-up by swinging the body, the violation is judged according to the average height of both knees and the difference of knee and ankle heights, and the height of both knees in the steady state is recorded as  $\overline{H_{knee}}$ , and the average height of both knees in real time is  $\overline{H_{knee}} = \frac{H_{knee1} + H_{knee2}}{2}$ , the height of both knees in steady state was recorded with the real-time average height of both knees  $D_{sr} = |H_{knee} - \overline{H_{knee}}|$ , and the difference between the knee and ankle heights was  $D_{ka} = H_{knee} - H_{ankle}$ , with  $H_{ankle}$  is the ankle height.

The action compliance judgment for push-up action is mainly based on the angle between the trainer's body and the ground, and the camera should be set on the side of the person being photographed at an equal height. For the initial position is set to the body and the ground angle less than 15 degrees, in the push-up movement process, the body and the ground angle reaches 5 degrees that the body is considered to have been lowered to the lowest point, rise in the process of the body and the ground angle of more than 13 degrees recorded as a single push-up action, the body and the horizontal angle of the ground by the formula is defined as:

$$ang_{dor} = \cos^{-1} \frac{(x_{neck} - x_{hip})}{\sqrt{(x_{neck} - x_{hip})^2 + (y_{neck} - y_{hip})^2}} \quad (6)$$

In the formula,  $x_{neck}, y_{neck}$  indicates the horizontal and vertical coordinates of the neck joint point. When the trainer's shoulder joint point is higher than the elbow joint point during the sinking process or the degree of arm bending is low, it is judged to be a violation of the rules, i.e.  $H_{sho} > H_{elbow}$  or  $ang_{elbow} > 110^\circ$ .

The normality of the sit-up movement is mainly assessed by the angle between the shoulder joint point and the hip joint point and the ground, and the camera should be placed slightly higher on the side of the person being filmed in order to capture the knees and arms of the person. The initial judgment standard of the sit-ups is set as the angle between the back and the ground is less than 30 degrees, and the angle between the back and the ground is more than 75 degrees and the distance between the head and the knee is less than the threshold value during the flexion movement, which is considered to be qualified, in which the distance adopts the Euclidean distance metrics:

$$l_{kn} = \sqrt{(x_{head} - x_{knee})^2 + (y_{head} - y_{knee})^2} \quad (7)$$

where  $x_{head}, y_{head}$  denotes the horizontal and vertical coordinates of the head, the horizontal and vertical coordinates of the nasal joint points were used instead. The downward movement with the angle of the back ground less than 20 degrees is considered to have completed a single sit-up exercise. When the trainer's arms were not placed in front of the chest, the angle formed by connecting the elbows with the shoulders and wrists was used to judge, and it was judged to be a violation of the rules when the fixed value was exceeded.

### 2.3.3 Analysis of training effectiveness indicators

According to the above analysis and definition, this subsection analyzes and designs the training indexes according to the relevant norms of core strength training for trainers as well as part of the reference knowledge, and designs the compliance indexes and violation indexes from different perspectives, so as to ensure the effective identification of non-standard movements and to realize the multi-faceted assessment of the effectiveness of generic core strength training for trainers, and the designed training movement analysis indexes are shown below.

(1) The indexes of pull-up movement were analyzed as shown in Table 1.

Table 1: Analysis of the upward action index of the lead

Keyframe	Parameter	Compliance index	Violation index
Initial frame	Straight arms	$ang_{elbow} > 150^\circ$	$D_{sr} \approx 0.7(D_{ka})$
	Straight legs	$ang_{knee} > 150^\circ$	
Mandibular bar frame	The lower jaw is more than the bar	$H_{chin} > H_{bar}$	$D_{sr} \approx 0.7(D_{ka})$
	Straight arms	$ang_{elbow} > 150^\circ$	
	Straight legs	$ang_{knee} > 150^\circ$	
End frame	Straight arms	$ang_{elbow} > 150^\circ$	$D_{sr} \approx 0.7(D_{ka})$
	Straight legs	$ang_{knee} > 150^\circ$	

(2) The push-up movement metrics were analyzed as shown in Table 2.

Table 2: Analysis of the action index of push-ups

Keyframe	Parameter	Compliance index	Violation index
Initial frame	Body and ground Angle	$ang_{dor} < 15^\circ$	$H_{sho} > H_{elbow},$ $ang_{elbow} > 110^\circ$
	Straight arms	$ang_{elbow} > 150^\circ$	
	Straight legs	$ang_{knee} > 150^\circ$	
Body sinking frame	Body and ground Angle	$ang_{dor} \approx 5^\circ$	
	Straight legs	$ang_{knee} > 150^\circ$	
End frame	Body and ground Angle	$ang_{dor} > 13^\circ$	
	Straight arms	$ang_{elbow} > 150^\circ$	
	Straight legs	$ang_{knee} > 150^\circ$	

(3) The sit-up movement indexes were analyzed as shown in Table 3.

Table 3: Analysis of the performance indicator of sit-ups

Keyframe	Parameter	Compliance index	Violation index
Initial frame	The arm is placed before the chest	$ang_{dor} < 30^\circ$	$ang_{elbow} > 110^\circ$
	Body and ground Angle		
	Knee bending Angle		
Bending frame	The arm is placed before the chest	$ang_{dor} > 75^\circ$ , $l_{kn} < 15$	$ang_{elbow} > 110^\circ$
	Head and knee distance		
	Knee bending Angle		
End frame	The arm is placed before the chest	$ang_{dor} < 20$	$ang_{elbow} > 110^\circ$
	Knee bending Angle		

### 3 System performance testing and application effect analysis

#### 3.1 Motion Recognition Effect Analysis

##### 3.1.1 Introduction to the data set

In the motion recognition model for action recognition classification experiments, the UFC101 dataset is used as a validation benchmark, which contains 101 action categories covering a wide range of scenarios such as sports and daily activities. Annotation of action types is performed on this dataset, and each video is labeled with a unique action tag.

##### 3.1.2 Experimental setup and evaluation indicators

In human action recognition and other fields of research, in order to evaluate the accuracy of the model usually use the class average precision  $mAP$  to measure the accuracy of the model in recognizing multiple action classes. Class-averaged accuracy is obtained by averaging the recognition  $AP$  values of all action classes to obtain  $mAP$  to measure the recognition performance of the model. Accuracy  $AP$  is the ratio of the number of samples correctly predicted by the model to the total number of samples, and the accuracy represents the recognition accuracy of the current class. Equations (8) and (9) are the formulas for  $AP$  and  $mAP$ , respectively:

$$AP = \frac{\sum_{i=1}^n C_{ii}}{\sum_{i=1}^n \sum_{j=1}^n C_{ij}} \quad (8)$$

$$mAP = \frac{\sum_{i=1}^m AP}{m} \quad (9)$$

where  $C_{ij}$  denotes the number of samples with actual category  $C_i$  and predicted category  $C_j$ ,  $n$  denotes the total number of samples, and  $m$  is the number of action categories contained in the samples.

In order to evaluate the recognition efficiency of the motion recognition model, the FLOPs metric is often used in video action recognition, FLOPs refers to the number of floating-point operations, which is one of the important metrics used to measure the computational complexity

of the model and the amount of computation required by the model. GFLOPs is one billion floating-point operations, which is used to measure the amount of computation of the model. Usually, the higher the GFLOPs, the greater the computational complexity of the model and the more computational resources and time are required to complete the reasoning process. Therefore, in applications with limited resources or high real-time requirements, lower GFLOPs values are more desirable, and a more computationally efficient model can be selected. In this paper, the GFLOPs needed to obtain recognition results for action recognition for each video on average is used as a metric GFLOPs/V to evaluate the model's efficiency in recognizing video actions.

### 3.1.3 Analysis of experimental results

In order to verify the superiority of the method proposed in this chapter for action recognition based on symmetric coding, time-scale coding and structural coding, comparisons with four mainstream human action classification methods, namely, ST-GCN, AGCN, PoseC3D, and MS-G3D, were conducted under the same experimental environment, and the classification accuracies as well as the values of the GFLOPs/V metrics were reported in the UFC101 dataset, respectively. The statistics of the experimental results are shown in Fig. 3. Comparing the mainstream similar models on the UFC101 dataset, the class-averaged accuracy mAP value of the motion recognition model constructed in this paper is 93.65%, which is all greater than that of the comparison model, and the GFLOPs/V value is 25.77, which is all smaller than that of the comparison model. It is proved that the method of motion recognition based on symmetric coding, time scale coding and structural coding substantially improves the recognition efficiency while obtaining better recognition accuracy.

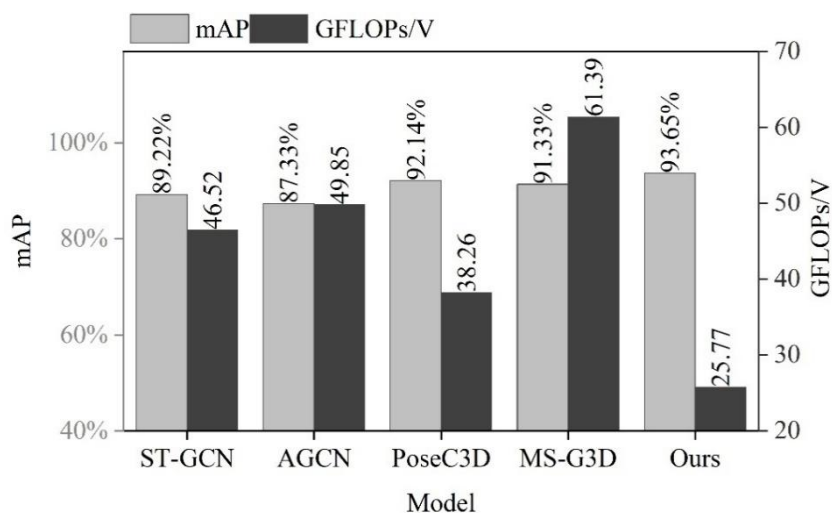


Figure 3: Accuracy of action classification and GFLOPs/V

## 3.2 Athletic Posture Assessment Tests

Badminton core strength training movements (pull-ups, sit-ups and push-ups) were evaluated using the Training Posture Intelligent Analysis System. In order to make the test results more relevant, three testers with different body types were selected for the posture comparison experiment, and the results of the human movement posture assessment are shown in Table 4. The three testers did three groups of different types of exercise movements, and a total of nine movement scores were obtained. The maximum deviation rate was 16.87% for A1 tester's matching test for sit-up movement. Overall the rate of deviation was relatively low for the ratings of the excellent and failing phases and relatively high for the passing phase. The reason

for this phenomenon may lie in the wide range of scores in the passing stage, and the possibility of deviation between the system-calculated scores and human scores is higher. After obtaining the overall similarity score, the tester can extract the key frames of irregular movements from the lower-scoring movements, and improve the accuracy of the movement posture by observing the irregular body movements.

*Table 4: The results of the exercise attitude assessment*

Action category	Tester	Action evaluation	Calculation score	Manual grading	Deviation rate
Lead up	A1	Qualify	82	75	8.54%
	A2	Excellence	92	94	2.17%
	A3	Qualify	85	79	7.06%
Sit-ups	A1	Qualify	83	69	16.87%
	A2	Qualify	81	88	8.64%
	A3	Excellence	94	96	2.13%
Push-ups	A1	Excellence	93	92	1.08%
	A2	Out of line	51	53	3.92%
	A3	Qualify	70	79	12.86%

### 3.3 Effect of system application on foot dexterity

This chapter mainly investigates the effect of core strength training assisted by training posture intelligent analysis system on the foot flexibility of badminton players. The subjects of the study were 40 athletes from the varsity male badminton team of the School of Physical Education of School S. The test persons were randomly divided into the experimental group (N=20) and the control group (N=20), and the basic conditions of the experimental group and the control group are shown in Table 5.  $p \leq 0.05$ , there is a difference in statistics,  $P \leq 0.01$  there is a significant difference, and there is no difference when  $P \geq 0.05$  (the same as below). After independent samples T-test analysis, the P-value of the two groups of testers in the control and experimental groups in terms of age, height, weight, and years of training is greater than 0.05, which indicates that there is no significant difference, and the grouping is scientific and reasonable.

*Table 5: The basic situation of the experimental group and the control group*

Categories	Control group	Experimental group	T	P
Age	20.55±1.03	19.65±1.25	1.55	0.15
Height/cm	192.5±9.41	191.4±6.14	0.26	0.54
Weight/kg	90.52±11.41	89.52±11.41	0.27	0.64
Training period	6.6±1.22	6.4±1.74	1.36	0.36

Both the experimental group and the control group underwent a 4-week badminton core strength training, and the experimental group used the training posture intelligent analysis system designed in this paper to guide the practice movements during the training process, while the control group carried out daily training under the guidance of the teacher. Before and after the experiment, 40 badminton players were subjected to hexagonal sensitivity test (T1), left and right back turn test (T2), Illinois sensitivity running test (T3), restricted area sensitivity test (T4), and hexagonal movement test (T5) respectively, which were used to react to the athletes' foot flexibility through these five indexes.

### 3.3.1 Comparison of test metrics before the training experiment

The descriptive statistics of the indicators of the experimental group and the control group before the experiment are shown in Fig. 4, and (a) and (b) represent the statistical results of the experimental group and the control group, respectively. The distribution of the indicators in the figure shows that there is little difference in foot flexibility between the two groups of athletes. The test of difference between the experimental group and the control group for each pre-test index is shown in Table 6. The P-values of the athletes in the experimental and control groups on the hexagonal agility test, right and left backward turn test, Illinois agility running test, restricted area agility test, and hexagonal movement test were 0.21, 0.34, 0.56, 0.41, and 0.16, respectively, and there was no statistically significant difference ( $P > 0.05$ ), which indicated that the athletes in the two groups of the experimental and control groups had no significant difference in the pre-tests of foot dexterity test showed no significant difference and met the basic requirements of the experiment.

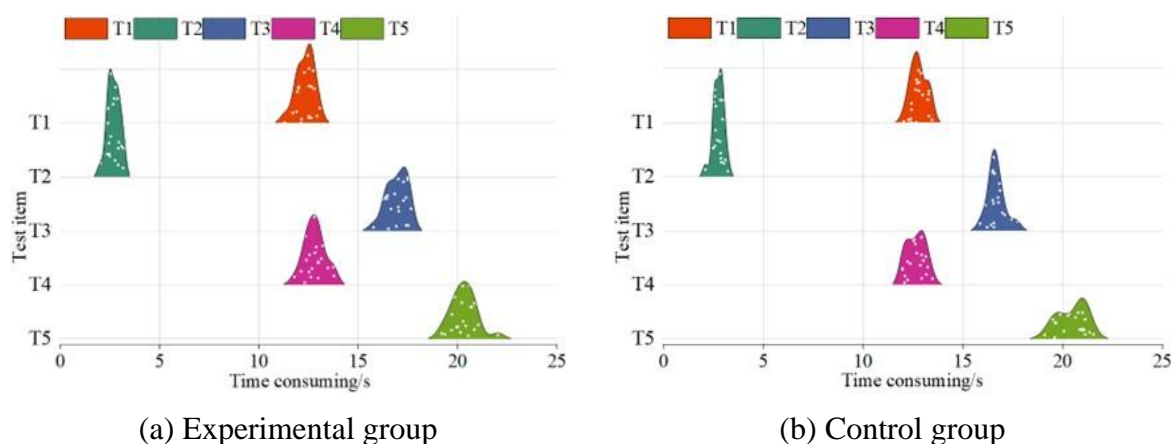


Figure 4: Descriptive statistics of each index in the pretest

Table 6: The difference test of the pretest indexes

Pretest	T1/s	T2/s	T3/s	T4/s	T5/s
Experimental group	12.46±0.44	2.65±0.32	16.88±0.56	12.76±0.43	20.44±0.77
Control group	12.59±0.39	2.81±0.29	16.74±0.41	12.53±0.38	20.16±0.69
P	0.21	0.34	0.56	0.41	0.16

### 3.3.2 Comparison of test metrics after training experiments

The descriptive statistics of the indicators of the experimental group and the control group after the experiment are shown in Fig. 5, (a) and (b) represent the statistical results of the experimental group and the control group, respectively. The distribution of the indicators in the figure shows that there is a large difference in foot flexibility between the two groups of athletes. The test of difference between the experimental group and the control group in the posttest indicators is shown in Table 7. The P-values of the athletes in the experimental and control groups on the five index tests were 0.036, 0.001, 0.022, 0.011, 0.026, respectively, in which there were statistically significant differences between the hexagonal sensitivity test, Illinois sensitivity running test, restriction zone sensitivity test, hexagonal movement ( $P < 0.05$ ), and there were significant differences between left and right post-turn test ( $P < 0.01$ ), indicating that the athletes' foot flexibility was better than that of the control group in the experimental group after applying the training posture intelligent analysis system to assist core strength training.

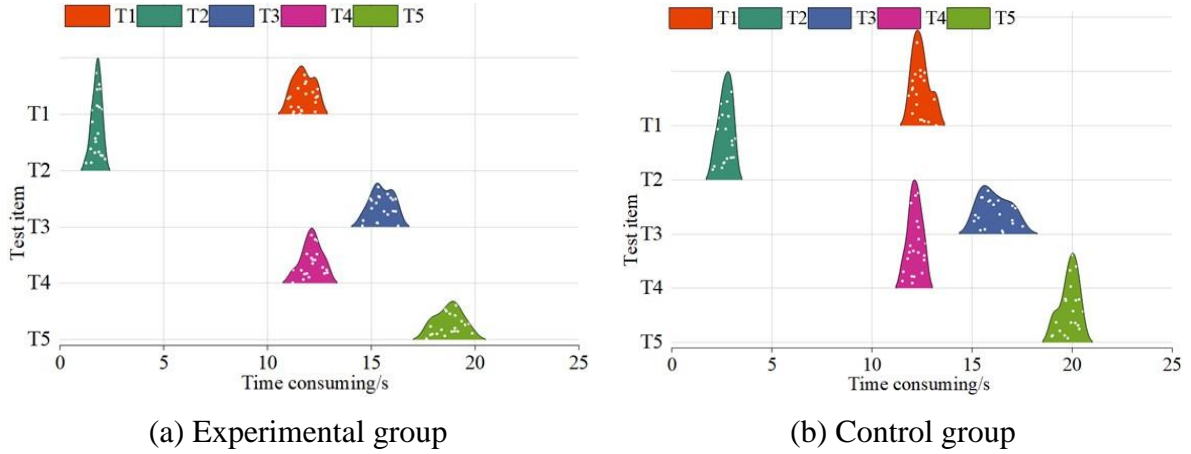


Figure 5: Descriptive statistics of each index in the posttest

Table 7: The difference test of the posttest indexes

Posttest	T1	T2	T3	T4	T5
Experimental group	11.63±0.43	1.74±0.26	15.43±0.54	12.12±0.43	18.55±0.58
Control group	12.41±0.22	2.74±0.22	16.14±0.74	12.26±0.36	19.68±0.57
P	0.036	0.001	0.022	0.011	0.026

### 3.3.3 Comparison of pre- and post-test indicators in experimental and control groups

The difference between the pre- and post-test results of the experimental group and the control group on the five test indexes were tested as follows:

(1) Comparative analysis of the hexagonal sensitivity test indexes is shown in Table 8, the growth rate of the pre- and post-test of the experimental group is 6.67%, which is a significant difference ( $P < 0.05$ ), and the growth rate of the control group is 1.43%, which is not statistically different ( $P > 0.05$ ).

Table 8: Contrast analysis of hexagon sensitive test index

T1	Pretest	Posttest	Difference value	Growth rate	P
Experimental group	12.46±0.44	11.63±0.43	0.83	6.67%	$P < 0.05$
Control group	12.59±0.39	12.41±0.22	0.18	1.43%	$P > 0.05$

(2) Comparative analysis of the left and right post-turn test indexes is shown in Table 9, the growth rate of the experimental group's pre and post-test was 34.34%, with a significant difference ( $P < 0.01$ ), and the growth rate of the control group was 2.49%, with no statistically significant difference ( $P > 0.05$ ).

Table 9: The comparison and analysis of the test index was turned

T2	Pretest	Posttest	Difference value	Growth rate	P
Experimental group	2.65±0.32	1.74±0.26	0.91	34.34%	$P < 0.01$
Control group	2.81±0.29	2.74±0.22	0.07	2.49%	$P > 0.05$

(3) Illinois Sensitive Running Test test index comparison analysis as shown in Table 10, the experimental group before and after the test growth rate of 8.59%, the difference is obvious ( $P < 0.05$ ), the control group growth rate of 3.58%, there is no statistically significant difference ( $P > 0.05$ ).

*Table 10: Analysis of the test index of Illinois sensitive running test*

T3	Pretest	Posttest	Difference value	Growth rate	P
Experimental group	16.88±0.56	15.43±0.54	1.45	8.59%	P<0.05
Control group	16.74±0.41	16.14±0.74	0.6	3.58%	P>0.05

(4) Comparative analysis of restriction zone sensitivity test indexes As shown in Table 11, the growth rate of pre- and post-test in the experimental group was 5.02%, with a significant difference (P<0.05), and the growth rate of the control group was 2.15%, with no statistically significant difference (P>0.05).

*Table 11: Contrast analysis of sensitive test indexes in the restricted area*

T4	Pretest	Posttest	Difference value	Growth rate	P
Experimental group	12.76±0.43	12.12±0.43	0.64	5.02%	P<0.05
Control group	12.53±0.38	12.26±0.36	0.27	2.15%	P>0.05

(5) Comparative analysis of hexagonal movement test indexes As shown in Table 12, the pre- and post-test growth rate of the experimental group was 9.25%, with a significant difference (P<0.05), and the growth rate of the control group was 2.38%, with no statistically significant difference (P>0.05).

*Table 12: Analysis of the correlation of hexagonal mobile test indexes*

T5	Pretest	Posttest	Difference value	Growth rate	P
Experimental group	20.44±0.77	18.55±0.58	1.89	9.25%	P<0.05
Control group	20.16±0.69	19.68±0.57	0.48	2.38%	P>0.05

The test results of the experimental group and the control group on the five test indexes show that the training posture intelligent analysis system designed in this paper can effectively improve the footwork flexibility of badminton players. Under the traditional training method, the control group has some improvement in the test indexes, but there is no significant difference, indicating that the athletes' foot flexibility has not been significantly improved.

## 4 Conclusion

In this paper, deep learning algorithms are integrated to train the motion recognition model in the designed training posture intelligent analysis system, so as to improve the system's recognition effect on badminton core strength training movements. Compared with the mainstream recognition model, the model in this paper has the largest class average accuracy mAP value of 93.65% and the smallest GFLOPs/V value of 25.77, which makes the model performance better. Before and after the application of the system, the growth rates of the athletes on the hexagonal sensitivity test, left and right backward turn test, Illinois sensitivity running test, restricted area sensitivity test and hexagonal movement test were 6.67%, 8.59%, 5.02% and 9.25%, respectively, with statistically significant differences (P<0.05), and the growth rate of the left and right backward turn test was 34.34%, with a significant difference (P<0.01), indicating that badminton core strength training incorporating deep learning algorithms can help improve athletes' footwork flexibility.

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