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Analysis of Technical Details in College Volleyball Training and Athlete Performance Enhancement

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SUMMARY: *The analysis of technical details in the teaching process of college volleyball cannot be separated from the analysis and evaluation of its movements. In this regard, this paper is based on the deep learning algorithm for volleyball basic action recognition, and then construct a training assistance system that can analyze volleyball video action in detail, so as to improve the athletes' athletic ability. The technical action recognition model is a deep learning neural network model containing two layers of one-dimensional convolutional neural network (CNN) and one layer of long- and short-term memory network (LSTM), which can realize the accurate recognition of volleyball actions. The evaluation and recognition accuracy of the four types of movements, namely pad, serve, dunk and block, reached 84.25% after analysis. Based on the algorithm design of this paper, the training assistance system can significantly improve the athletes' athletic ability after application and teaching practice (P>0.05). It shows that the system in this paper can effectively improve the quality and effect of volleyball teaching and promote the modernization of volleyball teaching.*

KEYWORDS: *CNN; LSTM; training assistance system; volleyball professional teaching*

1 Introduction

In contemporary society, after years of development, modern volleyball has become the most ornamental and widely played sport, which has penetrated into every corner of the world with its unique charm and rich and colorful connotation of competitive sports and gradually become the most favorite sports activities in people's life. The Chinese women's volleyball team has always been the only one that has brought us surprises, and is the most praiseworthy one among the three major Chinese teams in terms of the number of matches it has won, and more importantly, its unremitting spirit has deeply influenced several generations of people. However, in recent years, the development of reserve talents of Chinese volleyball makes people not difficult to find that Chinese volleyball players as a whole have problems such as insufficiently refined technology and insufficiently solid basic skills [1-3]. For example, the use of technology and tactics is unreasonable, the technology is rough, the attack is slow, and the strain is poor.

With the continuous development of volleyball, the confrontation in volleyball game is more and more targeted, athletes want to achieve more excellent performance in competitive sports games, it is necessary to further improve their competitive level, which can not be separated from the coaches of the athletes in the daily training of the formulation and control [4, 5]. At present, the data in volleyball training are mostly obtained by manual statistics, and

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the analysis of the data is mainly based on the coach's training experience, based on which the coach can realize the multi-dimensional judgment of the performance of the athletes in training [6]. With the continuous development of science and technology, more and more countries have begun to use a variety of scientific and technological aids to analyze and make decisions about games and training, and the analysis of sports technical details is one of the most widely used technical means in the field of sports analysis because of its strong technical value [7-10].

Volleyball, as a sport with very high skill and physical requirements, is a sport that combines the requirements of teamwork, technology, tactics, physical fitness and other aspects of the group, which puts forward extremely high requirements on athletes' physical fitness and technical ability [11, 12]. As a result, heart rate has also become a major indicator for monitoring the exercise intensity of volleyball players. For example, Ungureanu et al. (2021) investigated heart rate monitoring of athletes during volleyball training and assessed the correlation of age and field position with fatigue according to heart rate-based TRIMP with RPE and mixed-effects modeling, where the magnitude of the training load affects the next day's training status [13]. As for other physical qualities, Miura et al. (2020) used surface electromyography (EMG) to assess the technical details of 11 male volleyball players during dunking in a static standing position, and the backward and sideways shifts of the hitting position of the athletes during dunking may lead to an increase in deltoid muscle activity, which leads to a decrease in centripetal force of the humeral head in the acceleration and deceleration phases, therefore, in the usual training Therefore, focusing on the snapping stroke position and combining it with rotator cuff muscle group plyometric training can reduce the risk of shoulder injury in the use of snapping technique [14].

Volleyball sports technology is divided into five types: padding, blocking, serving, dunking, and passing [15]. For the training and detailed analysis of volleyball techniques, Doroshenko (2013) applied the modeling of technical and tactical movements to the technical training of high-level volleyball players, and the study showed that the proposed modeling technique is able to generate the optimal direction for the training process with the help of a special tool at different stages of the annual training cycle [16]. Ghorbanzadeh et al. (2017) explored the effects of visual feedback, verbal feedback, and verbal-visual feedback on the effectiveness of volleyball serve and pad skills training; the study found that there were significant differences between the groups in the levels of verbal feedback, visual feedback, and verbal-visual feedback on pretest and posttest scores, and all feedback modalities improved participants' skill and technique success rates [17]. Sato et al. (2017) developed a volleyball blocking machine system which consists of a system of three machines used to simulate the movements of a top volleyball blocker, which can be used consistently in real training grounds to improve the offensive training of volleyball players [18]. Cieślicka et al. (2018) proposed a method of initial volleyball technical training based on simulators and interactive technology, which is able to reduce the sensation of pain and fear generated by catching the ball, and it is an effective, convenient, reliable, economical and easy-to-manufacture training tool for volleyball technical movements [19]. Kitamura et al. (2020) explored whether athletes' performance of volleyball skill details (including serving, receiving, blocking, dinking, blocking, and padding) was affected by their improved functional ability, and the study found that increased strength and explosiveness would help athletes perform volleyball skill movements better [20].

At this stage, the volleyball training analysis system is still in the more traditional development stage, and has not been able to complete the transformation of the traditional training analysis system to the intelligent analysis system [21]. Behaviorally, the existing volleyball training technology analysis can be divided into two categories: volleyball game-oriented and volleyball training-oriented. Unlike volleyball group training, volleyball solo training focuses more on the individual qualities and skills of volleyball players. Zhou et al.

(2020) explored the effect of visual tracking training on volleyball players' performance and found that the training method can improve volleyball players' ability to dunk the ball in These results suggest that appropriate cognitive training is beneficial in terms of sports skills [22]. Rao (2020) argued that volleyball is a tactically complex, confrontational and comprehensive sport, for this reason, it was proposed to integrate computer technology into the field of volleyball training, aiming to improve the athletes' sports skills and playing ability [23]. Shih et al. (2022) proposed a guided training methodology for team training in combination with the assistance of multiple sensors, and the training of these group training focused on the interaction and cooperation between players in the team [24]. Kioumourtzoglou et al. (2022) explored the effect of a multimedia application on the performance and learning outcomes of basic volleyball skills training, and found that the application contained 3D animations, videos with exercises, and demonstrations of three basic volleyball skills and their rules for teaching and learning [25].

With the rapid development of computer vision technology and artificial intelligence, the application of motion-based target detection and machine learning technology in volleyball and other sports is becoming more and more widespread [26, 27]. In response to the application needs of volleyball technical analysis and guidance, Kovalchuk et al. (2019) proposed that the volleyball technical training method based on special intelligent devices can improve the technical and physical fitness level of female volleyball players, which can develop the amount of distribution of training loads and the intensity structure of the different physical fitness levels of the volleyball players, in order to improve their technical training level in the attack and defense, and this differentiated training method can be used in physical education institutions to increase students' interest in exercise [28]. Jiang et al. (2021) proposed a volleyball technical and tactical diagnostic model based on artificial neural networks, and the average difference between the output assessment scores of the model and the actual experts' scores was less than 1%, which achieved a very high level of accuracy, indicating that the model was technically feasible and the results used for volleyball technical training were relatively reliable [29]. de Leeuw et al. (2022) used wearable sensors to obtain body load data and applied machine learning techniques such as XGBoost, random forest regression, and subgroup discovery to explore the relationship between training load, perceived health, and game performance in professional volleyball players [30]. Astuti et al. (2025) proposed a multi-skill volleyball training model that which consists of skill-based training, a stepwise skill enhancement approach, and a personalized feedback system to improve students' athletic performance in important volleyball skills [31].

This paper proposes a volleyball basic technical action recognition method based on CNN neural network and LSTM recurrent neural network. The model carries out feature extraction on the image data of the movement area through CNN network and controls the state information based on LSTM network in order to complete the classification and recognition work on the basic technical action data set of volleyball video. Relying on the above model, this paper designs a perfect volleyball sports auxiliary training system. The system can not only accurately identify the basic technical movements of volleyball and be used for athletes' training assistance, but also provide services such as standardizing the basic movements of volleyball and formulating the strategies of volleyball matches, which has a better application prospect.

2 Volleyball technical movement recognition based on deep learning

In the teaching process of college volleyball, the analysis of technical details can be realized based on technical action recognition. Through the action recognition algorithm to volleyball training process often occurs in the identification of basic technical movements, the coach can be standardized teaching and personalized guidance to the movement of the athlete, and then effectively improve the athletic ability of the athlete.

2.1 Technical Motion Image Acquisition and Processing

In order to effectively recognize the technical actions of volleyball players, firstly, the motion region of technical actions is extracted by constructing an image acquisition model, and the recognition actions are separated from the background for processing, so as to improve the recognition effect. In this regard, it is necessary to collect images of the technical movements of volleyball players, and obtain the structural data and edge features of the technical movements by synthesizing the movement information database, equipment model and other models. In this regard, the specific workflow of the constructed image acquisition model is shown in Figure 1.

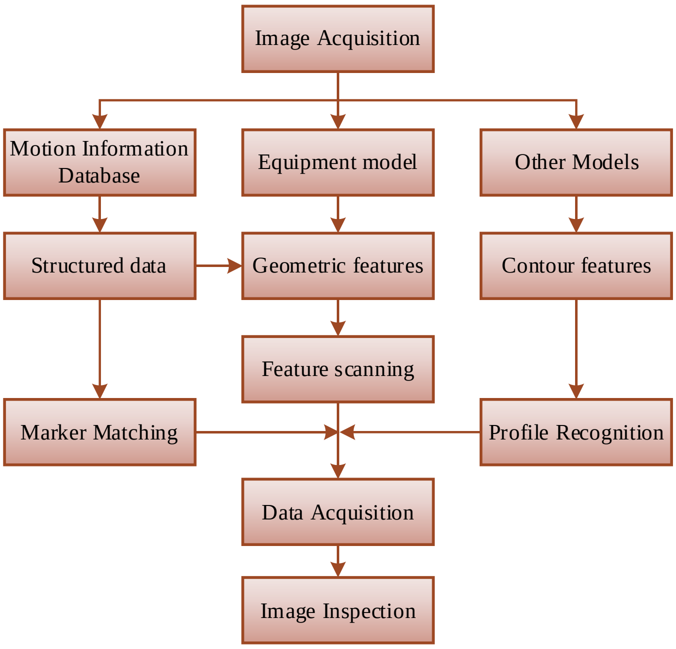


Figure 1: Image acquisition process

As can be seen from the above image acquisition process, the human structure action data is extracted from the action information database and matched with the identification results of the contour recognition of the action of the recognition object. By matching the text logo and the decomposed action contour data of the technical action, the logo matching results are stored as the same set of data, so that the contour matching results can be directly compared with the recognized object when the action is recognized subsequently. In the contour extraction of technical actions, it is necessary to first extract the contour of the recognized object from the image. In order to improve the effect of contour extraction, the image boundary points for the expansion of the operation, after the completion of the expansion of the action video sequence is:

$$u = \frac{z}{\omega b} + v \tag{1}$$

The above operation not only improves the extraction effect of the contour, but also uniformly adjusts the size of the action region, so as to obtain the same size of the motion region image data. Since volleyball players have large movement amplitude when doing technical movements, the movement of each frame image in the motion video is different. Therefore, in order to ensure the extraction effect of the action region, the inter-frame difference method is used to process the images in the sports video:

$$D = \begin{cases} |x_{k+d} - x_k|, |x_{k+d} - x_k| \geq T, \\ 0, |x_{k+d} - x_k| < T. \end{cases} \tag{2}$$

Considering that the action information data contained in each differential image is different, the action region is matched with the image position information by weight assignment. The processing formula is:

$$\begin{aligned} h_t^f &= \tan\left(w_x^f + b_i\right) \\ h_t^b &= \tan\left(w_x^b + b_i\right) \\ u_t &= \varpi\left(h_t^f + h_t^b\right) \end{aligned} \tag{3}$$

where h_t^f and h_t^b represent the forward-propagated and backward-propagated action video sequences, respectively, u_t represents the video sequences after extracting the action region, w_x^f and w_x^b represent the input and output parameters, respectively, b_i represents the action pixel coordinate position information, and ϖ represents the position distribution weights of the differential image data.

2.2 Action Recognition Based on CNN-LSTM Network Models

In this paper, a hybrid neural network model based on CNN feature construction strategy and end-to-end feature construction of LSTM is utilized for the recognition of volleyball technical movements during the teaching process.

2.2.1 CNN-LSTM Neural Network Architecture

(1) Convolutional layer

The sequence image formed after preprocessing the volleyball technical action video data is first processed by CNN and then accessed to the LSTM layer.CNN uses different feature learning methods for different classifiers of the input signal, which is equivalent to the elimination of outliers and the filter for cleaning the data, so that the feature extraction of the image data of the movement region can be effectively realized. The output of each convolutional layer is a set of feature mapping, and the result is activated by adding bias using the ReLU function as shown in the following equation:

$$f(x) = \max(0, x) \tag{4}$$

In this model, a one-dimensional convolution kernel is used to perform the convolution operation on the one-dimensional raw data of the sensor, the input data is accessed continuously to two convolution layers, the size of the convolution kernel is 3, and the feature vectors of the convolution output are pooled.

(2) LSTM layer

The main role of the LSTM is to perform network computation for the network hidden layer for its forward and backward propagation to avoid the gradient explosion problem through the gate control information.The internal structure of the LSTM neuron is shown in Fig. 2.

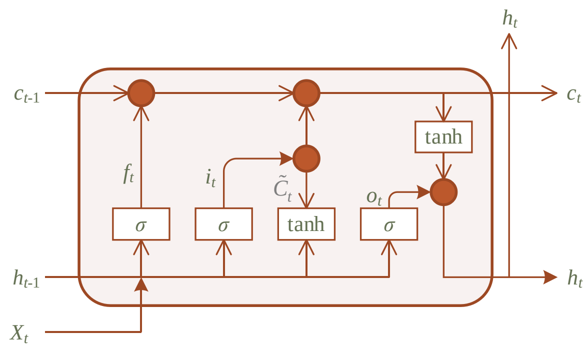


Figure 2: LSTM neuron internal structure

LSTM neurons consist of cell states and “gate” mechanisms (forgetting gate i_t input gate f_t, output gate o). In the figure, c_t denotes the cell state, which represents the long-term memory, and state information is added or deleted on t through the gate structure, which controls the delivery of the modified state information to the next moment, and the activation of each LSTM unit is calculated by the following equations:

$$i_t = \sigma\left(\mathbf{W}_{xi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{x}_{t-1} + \mathbf{b}_i\right) \tag{5}$$

$$f_t = \sigma\left(\mathbf{W}_{xf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{x}_{t-1} + \mathbf{b}_f\right) \tag{6}$$

$$o_t = \sigma\left(\mathbf{W}_{xo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{x}_{t-1} + \mathbf{b}_o\right) \tag{7}$$

$$g_t = \sigma_{\mathrm{h}}\left(\mathbf{W}_{xg}\mathbf{x}_t + \mathbf{W}_{hg}\mathbf{x}_{t-1} + \mathbf{b}_g\right) \tag{8}$$

$$c_t = f_t c_{t-1} + i_t g_t \tag{9}$$

where $\mathbf{W}_x$ is the connection weight matrix of the input vector $\mathbf{x}_t$. $\mathbf{W}_h$ is the connection weights to the short-term state h_{t-1}. $\mathbf{b}$ is the bias term matrix. σ denotes the sigmoid activation function. σ_{h} denotes the $\tanh$ activation function. In the model constructed in this paper, the data processed by the CNN is connected to the LSTM layer with 100 neurons after the Dropout layer.

(3) Neural network structure design

The internal structure of the CNN-LSTM model of this design is shown in Fig. 3. It contains input layer, hidden layer, two 1DCNN layers, one LSTM layer, Dropout layer, in addition to pooling layer, fully connected layer and output layer. The details of each layer are as follows:

Input layer: after preprocessing the data in a subsequence of 128 time steps for the CNN model to process, the input is all the motion region image data, the number of features is 20. The CNN input data format is [number of samples, number of time steps, number of input features, here the specific is [4200, 128, 20].

The first CNN layer: feature extraction of the data, the core parameter of the feature map is the number of descriptions of things, and the size of the convolution kernel is the length of time for each processing.

Second CNN layer: the results from the first CNN layer will be fed to the second CNN layer, which performs the same operation on the feature map convolved in the first layer to continue the feature extraction.

Pooling layer: keep the effective features unchanged and reduce the data size and number of parameters as a way to reduce the amount of computation.

LSTM layer: selectively forget the incoming information, the number of neurons inside LSTM is 100. The classification task does not need to output at every time step, the output of the last step is used as the input of the fully connected layer.

Dropout layer: each batch of training randomly discards some inputs of the neural network layer to avoid overfitting, and finally obtains the fused average probability of model prediction.

Fully connected layer: the number of neurons is 100 and Relu activation function is chosen.

Output layer: softmax classifier is used, and the output is the probability value of judging the four types (pad, serve, dunk, and block) of volleyball technical movements. The following formula:

$$\mathrm{softmax}(y_t) = \frac{e^{yt}}{\sum_i e^{yt}} \tag{10}$$

where: i is the category of volleyball technical action, $y_{\wedge} y_i$ is the set of probabilities of volleyball technical action, and the category with the largest probability is selected as the output.

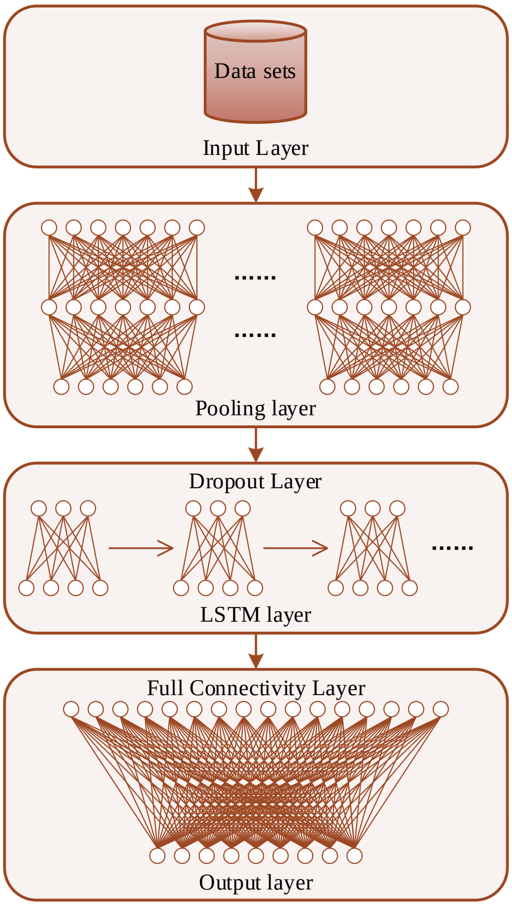


Figure 3: Neural network structure

2.2.2 Model training

The entire data of the motion region image is input into the CNN-LSTM neural network as the features of volleyball technical movements, and the four volleyball technical movement categories of pads, serves, dunks, and blocks are taken as the outputs, and the loss function is used to estimate the deviation of the predicted value from the true value, and the minimization loss function is chosen as the following equation:

$$loss = -\frac{1}{m}\sum_{i=1}^{m}\tilde{y}_i \lg y_i \tag{11}$$

where $\tilde{y}_i$ denotes the i th sample true label and y_i denotes the model predicts the i th sample label. The Adam optimizer is selected and the update step is calculated. The learning rate is set adaptively using the callback function, initialized to 0.002 by default, when the learning rate stops decreasing, indicating that the optimum has been reached.

3 Design of volleyball technical detail analysis system based on action recognition

The system designed in this chapter can be used to identify the four basic technical actions in volleyball including pads, serve, kill shot, and block at the net, analyze the technical classification of athletes in the video of technical actions in volleyball sports by using the CNN-LSTM network model, and make a detailed analytical description accordingly, analyze the acquired dynamic data, and assist in the rehearsal of basic actions. It can also be used for match video analysis to provide support for the comprehensive rationalization of volleyball players' match and training plans and the development of strategies for volleyball matches.

In the overall design phase, various requirements analysis tasks have to be integrated in the software system in order to achieve a common software system design plan. In the overall design of the software system, in order to reduce the logical problems in the development process, the software system will be deployed as a Windows operating system, which defines a unified data and equipment interface standard for the whole system management platform: the application after being added and verified by the background administrators is able to query the training data of volleyball players as well as the analytical reports of the athletes through the interface request. The system mainly realizes four main modules such as data collection and storage, statistical analysis and data display, and system maintenance.

The function design of each module is as follows:

(1) The player information module mainly realizes the collection of basic information of volleyball players and the analysis of player comparison data.

(2) The training management module mainly analyzes data and extracts skills dynamically from individual training videos and group match videos uploaded by users. When uploading individual practice video, the system will obtain the player's skill dynamic information through the uploaded video, and analyze the longitudinal comparative data, which can be used as the training aid and basis for coaches and players. When uploading the video of team competition, the system will automatically collect and analyze the analysis of the skill movement of each player, so as to judge the situation of the players on the field and the characteristics of the skills they are good at, which will provide assistance for the coach to formulate the teaching strategy. In addition, it can also upload and query each player's body report, including height, arm span, lateral movement rate, muscle content, vertical jump height and other test data.

(3) Data analysis and management module, the module mainly analyzes and manages the statistics of ball players, clubs and other related data, and classifies them by comparing the historical data.

(4) The system maintenance module mainly focuses on the user information management and basic information content of the platform.

4 Empirical analysis

4.1 Model detection

4.1.1 Data set construction

The dataset created in this paper refers to the division characteristics of the UCF-101 dataset, analogous to the form of the UCF-101 dataset for interception and processing, and provides video data including four basic volleyball technical actions: passing, padding, serving, and blocking. The initial creation of the video of the volleyball basic action dataset is realized based on the action image acquisition technology proposed in the previous section. In terms of dataset division criteria, according to the standard training set and test set retrieval documents provided by the UCF official, and according to its prescribed division scheme, all the datasets involved in the arithmetic experiments in this paper are divided using this method.

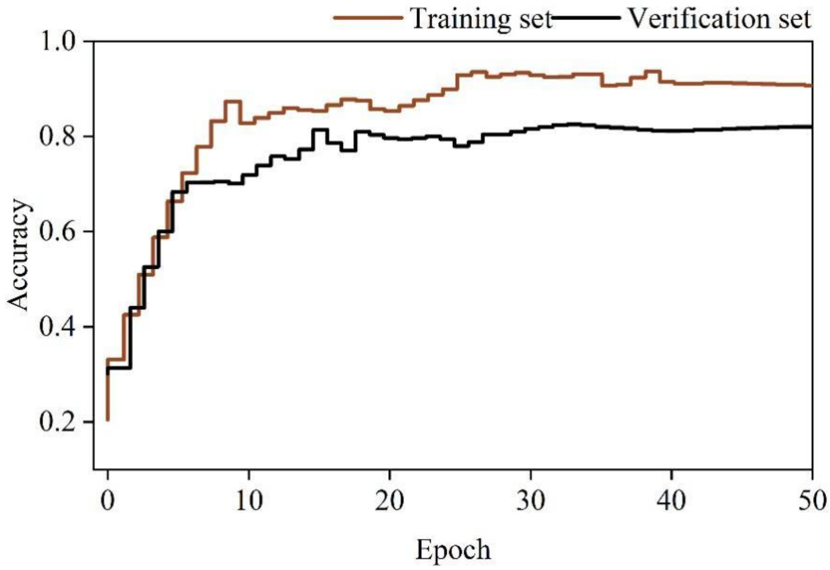
The videos of popular volleyball video self-producers were screened through the major short-video platforms, and the screening objects included professional players' highlights, volleyball netball instructional videos and so on. Any video containing any one of the four types of actions: passing, padding, serving, and blocking, is added to the pre-selected volleyball technical action video set for subsequent processing.

The final processed volleyball video technical action collection is a total of 1600 videos, each type of action 400 paragraphs, duration of 0.6 ~ 1.8 seconds, the lens is not blocked, the background as far as possible without interference with the target.

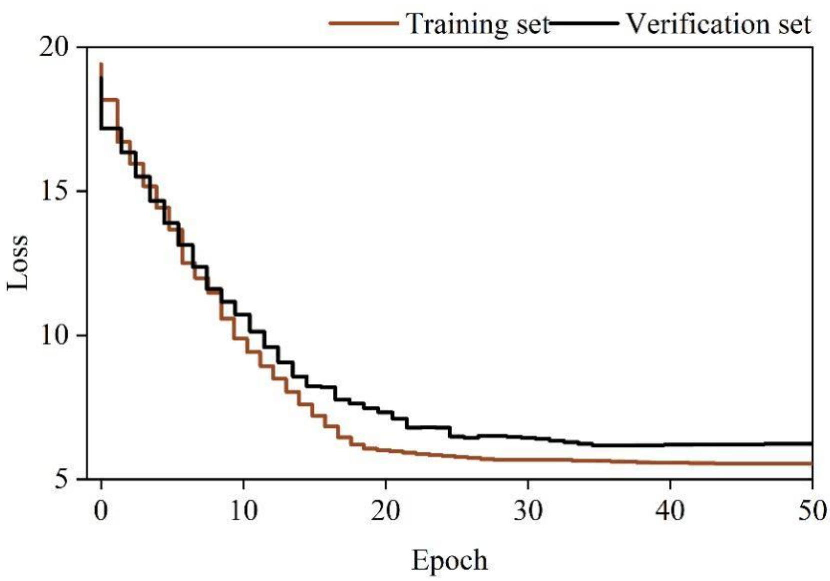
4.1.2 Motion Recognition Experiment

Taking 14 consecutive video image frames as an example, in order to verify the performance of the CNN-LSTM network model for technical action recognition on the volleyball technical action video set, the performance of the commonly used mainstream deep learning models CNN, LSTM, SVM and the CNN-LSTM hybrid model used in this paper are compared on the volleyball technical action video set.

The experiments in this paper use Python 3.7, and under the optimal performance of the model, the network epoch parameter is set to 55, the batch_size is set to 30, the loss function is the cross-entropy loss function, and the optimizer chooses SGD, which is stochastic gradient descent. For the training set by 14 frames of image data as input, the Accuracy and Loss of the training set and validation set are shown in Fig. 4, and (a) and (b) represent the Accuracy and Loss statistics, respectively. It can be seen that the training results stabilize at the 40th epoch.



(a) Accuracy graph of model training



(b) Loss graph of model training

Figure 4: Model training results

The experimentally derived accuracy rate is used to evaluate the model, and the experimental conclusion of the recognition accuracy rate is shown in Fig. 5, and the gray shaded part indicates the gap between the other models and the CNN-LSTM hybrid model in terms of accuracy rate. The experimental results can be concluded that the performance of the CNN-LSTM hybrid model network in volleyball technical movement recognition is more significantly improved compared to other deep learning network models, with a recognition rate of 92.6%.

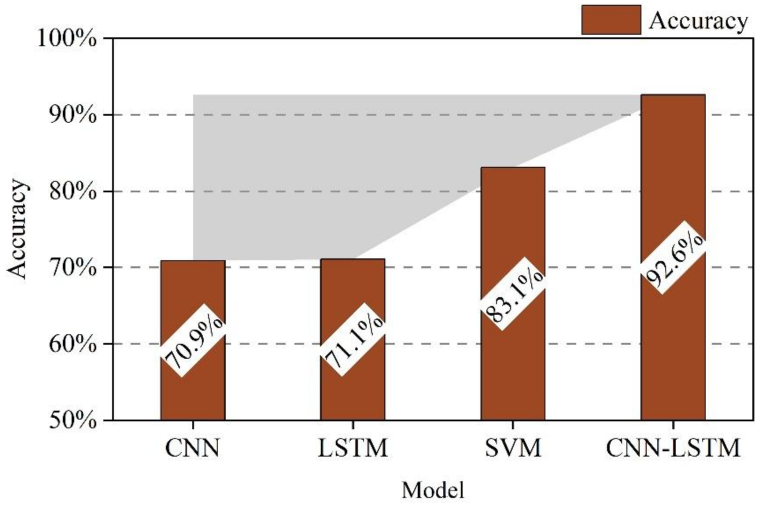


Figure 5: Identification accuracy of various models

The model training confusion matrix is shown in Figure 6, the letters on the matrix represent several different types of volleyball technical movements, A~D represent pad, serve, dunk, and block, respectively. From the results of the confusion matrix, the experiment has a certain chance of misclassification. Some of the data of the serve movements are misclassified into the dunking category, which is mainly due to the fact that these two types of movements involve jumping, arm swinging and hand lifting to catch the ball, which have certain similarities in the extraction of movements, based on which further improvements and adjustments need to be made in the feature extraction and labeling in the future. Despite some misclassification problems, the algorithm still maintains a very good accuracy in recognizing the dunking technical movements in volleyball, with an average recognition rate of 84.25%.

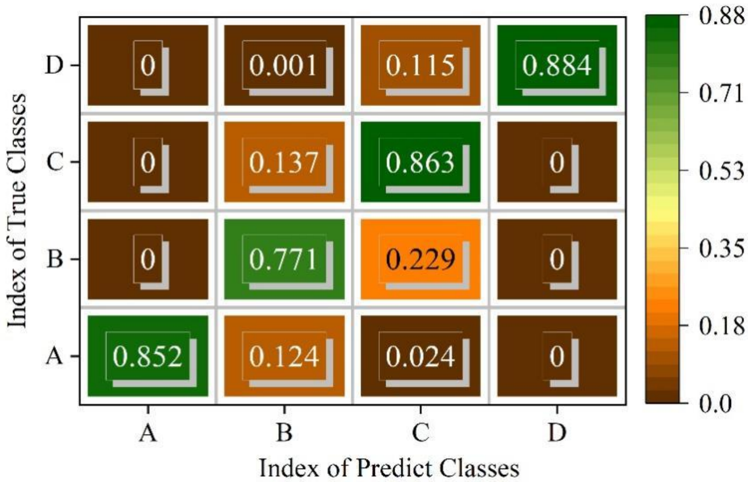


Figure 6: Model training confusion matrix

4.2 Analysis of the effect of improving athletic ability

4.2.1 Experimental design

The study used a group controlled experiment, selected 40 male athletes majoring in volleyball from Nanjing Sports Institute, randomly divided into two groups, experimental and control groups, the specific human parameters of the experimental subjects are shown in Table 1. The basic physical condition and lower limb strength (standing long jump and assisted running touch) of the 40 athletes were statistically analyzed respectively, and there was no statistical difference between the basic conditions of the two groups (P>0.05).

Table 1: The specific human parameters of the experimental object

Index	N	Height/cm	Weight/kg	BMI	Age	Fixed jump/m	Running high/m
Control group	20	190±2.51	80.62±2.54	22.14±2.1	18.24±0.25	2.96±0.12	3.26±0.14
Experimental group	20	190.1±2.21	80.42±3.25	22.11±2.36	18.11±0.33	2.95±0.11	3.26±0.22
P		0.263	0.221	0.241	0.356	0.248	0.365

The experiment was conducted from April to June 2024 in the gymnasium of Nanjing Sports Institute. The experimental group was taught with the aid of volleyball technical detail analysis system, and the control group was taught with traditional volleyball training methods. The experiment was conducted for a total of 10 weeks, 4 times per week, each time about 45 minutes.

The experimental group analyzed the details of the athletes' volleyball movements based on the Volleyball Technical Details Analysis System. The system identified that most of the athletes were mainly slow in the transition process from judgment to action when performing blocking movements, and their movement speed could not keep up with the fast-paced offense, which led to inappropriate timing of jumps and poor jumping positions. When performing collective blocking, the movement between players is not synchronized and the division of labor is not clear, resulting in missed nets or overlapping. In this case, the system provided a video explanation of standardized blocking movements and formulated a comprehensive and rationalized game strategy to assist the experimental group athletes to improve their training efficiency.

The evaluation of athletic ability was conducted before and after the experiment, and the total score was 100 points from three aspects of physical quality (20 points), special technology (40 points) and practical ability (40 points).

Data processing was analyzed using SPSS22.0 statistical analysis software, in which independent samples t-test was used to compare the physical quality, special techniques and practical ability of the experimental and control groups. The results were expressed as mean ± standard deviation (x ± s), and the level of statistical difference was P<0.05.

4.2.2 Results and analysis

(1) Analysis of the changes in physical fitness before and after the experiments of the two groups

The test of physical quality is mainly assessed in five aspects: running touch, 30-meter run, half “meter” movement, solid ball throw and 1500-meter run. The results of physical quality scores before and after the experiment of the two groups are shown in Figure 7.

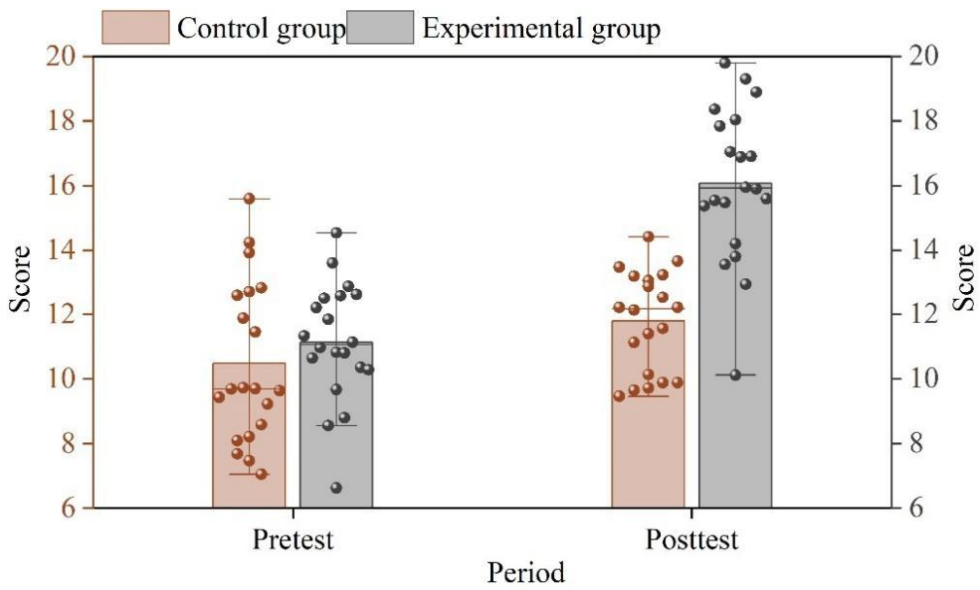


Figure 7: Analysis of physical quality changes

(2) Analysis of changes in special techniques before and after the experiment of the two groups

The test of special techniques mainly evaluates and scores the four techniques of padding, serving, dunking and blocking. The scoring results of the specialized techniques before and after the two groups of experiments are shown in Figure 8.

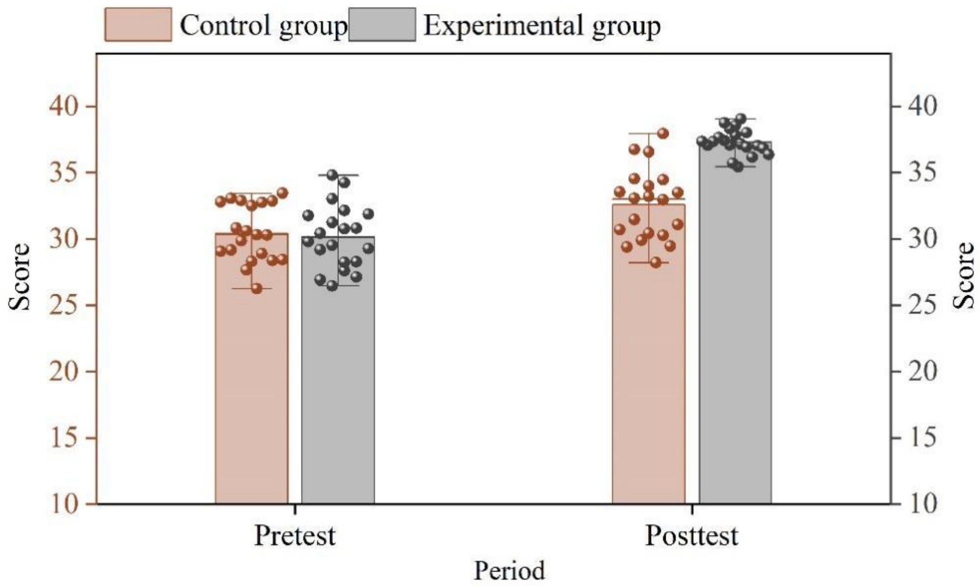


Figure 8: Analysis of special technical changes

(3) Analysis of changes in practical ability before and after the experiment of the two groups

The test of practical ability is mainly assessed from four aspects: the use of technology in the game, tactical awareness, clinical judgment and teamwork ability. The scoring results of practical ability before and after the two groups' experiments are shown in Figure 9.

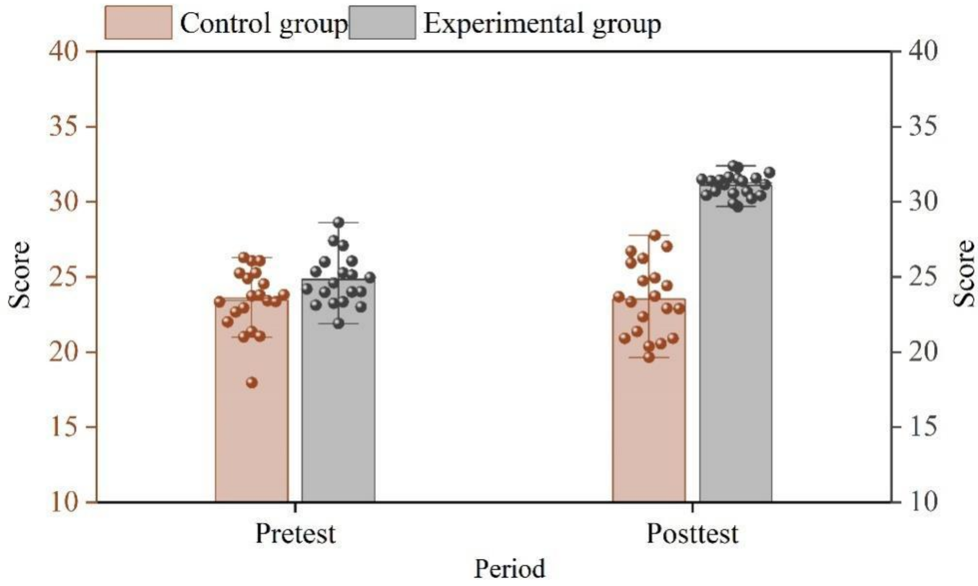


Figure 9: Analysis of combat ability

(4) Analysis of the effect of comprehensive athletic ability improvement

The analysis of the effect of comprehensive motor ability enhancement is shown in Table 2. The mean values of the pre-test and post-test of the control group were 65.6 and 67.64, respectively, and the effect of comprehensive sports ability enhancement was not significant ($P>0.05$), while the mean values of the pre-test and post-test of the experimental group were 65.91 and 85.34, respectively, which was an enhancement of 19.43 points, and $P=0.000$, which indicated that the use of volleyball technical details analysis system based on action recognition could significantly enhance the comprehensive sports ability of athletes.

Table 2: Analysis of the effect of comprehensive motion ability

Group		Physical quality		Special technical		Combat ability		Integrated motor ability	
		x±s	p	x±s	p	x±s	p	x±s	P
Control group	Pretest	11.18±2.05	0.241	31.21±2.12	0.362	23.21±3.01	0.523	65.6±2.01	0.552
	Posttest	11.23±2.06		32.15±0.24		24.26±2.52		67.64±2.63	
Experimental group	Pretest	11.21±2.11	0.001	31.01±0.22	0.003	23.69±2.41	0.000	65.91±2.32	0.000
	Posttest	15.86±2.01		38.42±1.12		31.06±1.52		85.34±1.01	

In summary, the study assesses the effect of athletes' athletic ability improvement from physical quality, special technology and practical ability, and the results show that after the use of volleyball technical details analysis system based on action recognition, the athletes' athletic ability is improved to different degrees compared with the athletes who are trained according to the traditional method of volleyball training.

5 Conclusion

The study designed a technical detail analysis system that can provide athletes with volleyball training assistance, and the system is mainly realized based on the motion recognition model. Based on the self-made volleyball video technical action dataset in this paper, the experimental results: the motion recognition model designed in this paper has a more obvious improvement

in recognition accuracy compared with the mainstream recognition model. The average recognition rate of the four basic volleyball technical movements of pads, serve, dunk and block can reach 84.25%. After using the system of this paper for volleyball training, the athletic ability of the athletes increased from 65.91 to 85.34 points. The athletes' physical quality, specialized techniques and practical ability were significantly improved (P>0.05).
In the future, the volleyball teaching mode will also continue to be optimized and improved, injecting new vitality into the vigorous development of volleyball and promoting the wider popularization and deeper development of volleyball.

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