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Research Article

Research on Aided Judgment of Rural Sports Posture Based on Deep Learning

Hao Guo[1] and Qi Hao[2,3]

[1]*Chongqing College of Humanities, Science & Technology, Chongqing 401524, China*
[2]*Department of Sports and Health, Linyi University, Linyi 276000, China*
[3]*Department of Leisure-Sports, Pai Chai University, Daejeon 35345, Republic of Korea*

Correspondence should be addressed to Qi Hao; haoqi@lyu.edu.cn

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With the rapid development of computer technology, people have begun to combine virtual reality and other technologies to achieve scientific sports auxiliary training, to get rid of the state of traditional sports training purely relying on experience. The article proposes a deep learning BP neural network human body posture recognition algorithm and briefly introduces the human body motion posture. The purpose of this research was to use the powerful data processing, mining, and analysis functions of deep learning to train the massive data generated in competitive sports training and apply it to competitive sports training. It is committed to promoting the accuracy and analysis of competitive sports training. Refinement provides technical guidance for athletes' training, promotes the scientific and informatized development of competitive sports training in China, and provides some reference methods for the research and application of deep learning in competitive sports training. The article's research results show that (1) taking a rural area as an example, we recorded the exercise postures of rural athletes in five different states: static, upstairs, downstairs, walking, and running. Comparing the recognition rate and training time of The BP neural network algorithm, ABC-BP algorithm, AFS-BP algorithm, and ABC-AFS-BP algorithm, it can be found that in terms of recognition rate, ABC-AFS-BP algorithm, AFS-BP algorithm, and ABC-BP algorithm are better than traditional BP algorithm. Among them, the recognition rate of the ABC-AFS-BP algorithm is higher than that of the ABC-BP algorithm, but it takes slightly more time than the ABC-BP algorithm. In terms of training time, the ABC-BP algorithm takes less time, but the accuracy is lower than the ABC-AFS-BP algorithm; the ABC-AFS-BP algorithm has a greater improvement in time consumption than the AFS-BP model and can guarantee the recognition rate and accuracy, and the error rate curves of the four algorithms show that after 500 iterations of the training part, the iteration error value of the ABC-AFS-BP algorithm is the smallest. (2) We evaluated sports postures of athletes from a certain rural team and concluded that bad postures will have a certain impact on the body. Among them, more than 85% of athletes in football and basketball have pelvic rotation. The problem is that football players have reached 90% of the test sample. 60% of football players and basketball players have the problem of collapsed foot. The main problem of aerobic athletes is flat back and collapsed foot. More than 90% of badminton players have high and low shoulder problems, and more than 80% of them have neck problems, which is a very serious body posture problem. (3) Detecting the flexibility experiment of the BP posture detection algorithm, compared with the traditional motion posture recording method, we tested from the three aspects of recording motion accuracy, missed detection rate, and recording time. The result shows BP posture detection. The missing detection rate of the algorithm is low, basically maintained at about 2.0, the accuracy of recording actions is relatively high, generally maintained above 98%, and the highest is 99.15%, and the recording time is short, maintained at 3–4 minutes; comparing traditional posture detection with the BP attitude detection algorithm, the missed detection rate of the algorithm is relatively high, kept at 4–6, the action accuracy is lower than that of the BP attitude detection algorithm, generally kept at about 95%, and the recording time is kept at 5–6 minutes. The posture detection algorithm is more efficient.

1. Introduction

Moving target recognition and analysis is an important research direction in the field of computer vision, which is widely used in our lives, such as intelligent robots, video surveillance, medical education, sports competitions, national defense security, and other fields. Sports applications are also very smart. With the continuous development of computer technology, based on deep learning methods, a sports video key gesture extraction system can be designed to extract the key gestures of athletes in competitive sports training videos to assist athletes and coaches in training reasonably and efficiently and avoid complexity. The interference of the environment on the extraction improves the inaccurate situation of traditional coaches in judging and extracting key gestures based on experience. Target detection and tracking based on deep learning, first, is the problem of target detection, that is, determining the position of the target object in the image or scene, which is generally determined by the bounding box of the object. In response to such problems, the literature [1] proposed that RCNN adopts the method of selecting the domain to obtain the local candidate regions where the detection target may exist in the image, and then, these candidate regions are input into the convolutional neural network to obtain their characteristics, and the classifier is connected to feature map, whether the corresponding area belongs to the target to be detected is judged, and finally, regression is performed on the calibration frame to correct the position of the prediction frame, but RCNN has the problem of repeated calculation. Literature [2] introduced the spatial pyramid pooling layer into CNN and proposed SPP-Net, which reduces the limitation of the CNN network on the size of the input image and improves the accuracy. Literature [3] proposed to use inertial sensors to collect information about human motion and apply the collected information to analyze and recognize human motion. Literature [4] discussed the theoretical framework for studying the coordination strategy of standing posture. The framework consists of a musculoskeletal model of the lower limbs of the human body in the sagittal plane and a technology that geometrically visualizes how the constraints inside and outside the body affect movement. Literature [5] designed an action recognition method based on depth images. The algorithm projects the depth image in three projection planes, extracts the Gabor features from the three projection images, and uses these features to train the extreme learning machine classifier. The calculation efficiency of the algorithm is high, but the performance of recognition of small amplitude actions is not ideal. Literature [6] proposed a time-series deep belief network that can complete online human action recognition. This model solves the problem that the current deep belief network model can only recognize static images, but the training process of this model takes a long time to process, which affects the application performance of the algorithm for large-scale data sets, in addition to the time efficiency issue for large-scale data sets. Literature [7] used asymmetrical system deviation to model human movement information, and the algorithm introduces a posture labeling mechanism to further improve the recognition performance of small movements. To meet the recognition of large-scale data sets and small-scale actions at the same time, a human action recognition algorithm based on multifeature fusion and motion information is designed. Literature [8] learned manual features and deep learning features, and the manual features adopted an improved dense trajectory. Literature [9] used a convolutional neural network based on motion information. High recognition accuracy is achieved for small-range actions, but the amount of features that need to be analyzed is large, and it is difficult to apply to large-scale data sets. Literature [10] used an inverted double pendulum to simulate the human body in an upright posture. The human body posture is a more complicated problem in biomechanics. The model proposed in this article can effectively distinguish the different parameters of the body and effectively control the body's movement posture. Literature [11] analyzed the experimental data, established a human body model, and conducted a simulation experiment on the OSG platform. When a person is exercising, there will be an angle between the limbs and the body. The accelerator is fixed on the arm, and the arm and torso can be calculated in real time. In recent years, athlete performance analysis has received widespread attention as a new anti-doping auxiliary judgment strategy, but many researchers have not had a clear understanding of this strategy in theory and practice. Literature [12] conducted in-depth research on performance analysis through literature review and inductive research methods. The literature takes some well-known athletes as examples and analyzes the results. The results show that whether there are athletes using doping can be quickly distinguished from the performance of the athletes, which can improve the efficiency of sports excitement detection. The purpose of the literature [13] is to determine which morphological indicators and how to affect postural stability and control through special tests. The results of the literature [14] can be used to enhance the digital human modeling motion generated for human motion simulation. Literature [15] analyzed the EMG response and joint movement of the legs in subjects who stood on a sinusoidal treadmill with their eyes closed.

2. Theory Introduction

2.1. The Status Quo of Rural Sports Development. At present, China's rural sports venues are few and of low quality, and some areas even lack suitable venues for villagers' activities. Rural sports venues and infrastructure are generally in poor condition; some villages have stadiums, but they have been idle for too long and no one is used. Even crops have already been planted, and the overall situation is not optimistic. This also causes farmers to watch TV as their main activity during leisure time, so conditions are not allowed to a certain extent, which limits the enthusiasm of villagers to participate in sports. Therefore, the relevant departments must take measures to solve these problems. The villagers do not have a deep understanding of the problem of sports and cultural exercises, and it is generally young people who participate in sports. Relevant governments have taken measures to solve these problems, but despite this, rural sports activities are still a weak link in China's sports industry. The increasing sports health requirements in rural areas and the serious shortage of public sports venues in rural areas have restricted rural sports.

2.2. Classification of Human Motion Posture. The posture of the human body movement is the form displayed by the human body in the process of daily life activities. Whether a person's body is healthy or not is closely related to the posture of the human body movement, so the posture of the human body movement has been widely concerned by the majority of researchers. The increase in user needs and people's requirements for the quality-of-life force researchers to speed up the research on human body movement postures. These studies are of great significance to the timely discovery of the human body's health [16]. The basic forms displayed by the human body in the process of daily life activities include lying, standing upright, sitting, walking, and running. In some complicated situations, it may be due to some irresistible external factors, or some injury or illness, etc., which may cause people to fall. Under normal circumstances, people call the most basic postures displayed by the human body in the process of daily life activities, including lying, standing upright, sitting, walking, and running, as ADL. In the process of life activities, some basic activities have to be carried out to take care of themselves and their families, protect the family and social environment, or participate in some social activities. These activities of daily life are basic life postures that human beings must always repeat to survive and live in this society. Each posture can be subdivided into many types, such as standing posture, which can be subdivided into standing upright, standing tilted forward, and standing tilted backward; lying flat includes lying on your back, lying on the left, lying on the right, and lying on the left and right sides. Sitting posture can be subdivided into sitting upright, leaning forward when sitting, leaning backward when sitting, and so on. Like walking, running is also affected by the surrounding environment, road conditions, and the physical condition of the runner. Running can also be subdivided into even running, slow running, and fast running. In some special circumstances, due to some complicated reasons, it may be due to some irresistible external factors, or some injuries or illnesses, etc., which may cause people to fall. The fall mentioned here refers to the uncontrolled fall of the body to the ground or to another plane that is not controlled by humans, occurs suddenly without preparation, or falls to another plane [17]. The World Health Organization has classified "falls" (including falls), as shown in Table 1.

2.3. Human Body Motion Posture Detection Algorithm. To carry out a three-dimensional simulation of the athlete's movement posture to adjust the training method and improve the training level, this study studies the application of unlabeled 3D pose estimation method in training assistance system [18, 19]. While athletes interact with the computer through limb movement, it is difficult to establish a human body posture database because there is no corresponding marking technology support to provide a robust observation method for the computer. Therefore, this article adopts a partial estimation method, which divides the athlete's overall posture into multiple partial postures, and estimates the posture of each part separately. The algorithm block diagram is shown in Figure 1.

3. Method

3.1. Deep Learning Features Based on Motion Information. Deep learning has been widely used in recent years [20, 21]. The time template can extract all the motion sequences of an image frame, and the difference between the video frames is used to calculate the motion information between the frames. The calculation formula of the time template is as follows [19]:

$$TT = \left(\frac{1}{255}\right)\sum_{i=2}^{n}\omega_i \cdot m(i). \tag{1}$$

Among them, n represents the number of video frames, $m(i)$ represents the motion information of the ith frame, ω_i represents the weight value of the ith frame [22], and the value range of the weight value is [0, 255]. Formula (1) is transformed to get the following:

$$TT = \sum_{i=2}^{n}\left(\frac{\omega_i}{255}\right) \cdot m(i). \tag{2}$$

A fuzzy membership function $\mu(i)$ is replaced to get the following:

$$TT = \sum_{i=2}^{n}\mu(i) \cdot m(i). \tag{3}$$

The appropriate $\mu(i)$ is selected, to enhance the saliency of the temporal motion information in the time template [23]; the model diagram of $\mu(i)$ is shown in Figure 2.

Four $\mu(i)$ are set to $\mu 1 \sim \mu 4$, defined by the following formulas:

$$\mu_1(i) = 1, \quad \forall i \in [0, n], \tag{4}$$

$$\mu_2(i) = \frac{i}{n}, \quad \forall i \in [0, n], \tag{5}$$

$$\mu_3(i) = 1 - \frac{i}{n}, \quad \forall i \in [0, n], \tag{6}$$

$$\mu_4(i) = \begin{cases} \dfrac{2i}{n}, & 0 \le i \le \dfrac{n}{2}, \\ 2 - \dfrac{2i}{n}, & \dfrac{n}{2} \le i \le n. \end{cases} \tag{7}$$

3.2. Human Motion Gesture Recognition. The motion detection of the human body is carried out by detecting the confidence map S of the joint points of the human body and the affinity domain L of the human joint points of a two-

Table 1: Classification of falls.

Fall classification	Fall classification
Fall on the same plane of ice and snow	Falls and falls on stairs and steps
Sliding, tripping, and falling on the same plane	Falls and falls on the ladder
Falling while skating, skiing, or roller skating	Falls and falls on scaffolding
Other falls on the same plane caused by being hit or pushed by others	Falling or falling out of the house or building structure
Falling while being transported or supported by others	Injuries caused by diving or diving, excluding drowning and sinking
Fell on wheelchair	Other drops from one plane to another
Falling in bed	Other falls on the same plane
Falling on the chair	Falling on sports facilities
Falling on other furniture	Unspecified fall

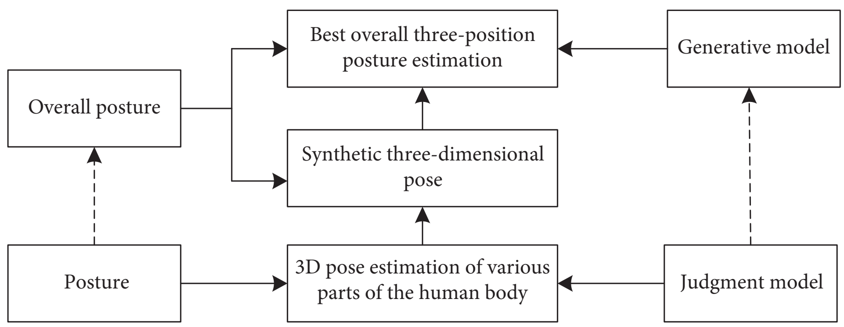


Figure 1: Frame diagram of a three-dimensional pose estimation method.

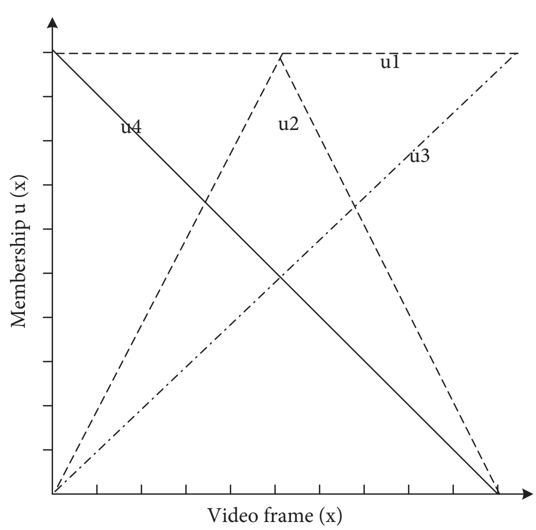


Figure 2: Graphs of 4 fuzzy membership functions.

dimensional vector [24], and the calculation formula is as follows:

$$\begin{aligned} S^t &= \rho^t\left(F^t, S^{t-1}, L^{t-1}\right), \quad \forall t \geq 2, \\ L^t &= \rho^t\left(F^t, S^{t-1}, L^{t-1}\right), \quad \forall t \geq 2. \end{aligned} \tag{8}$$

Each loss function is weighted, and the loss function is as follows:

$$\begin{aligned} f_S^t &= \sum_{j=1}^{J} \sum_{P} w(p) \cdot \left\| S_j^t p - S_j^*(p) \right\|_2^2, \\ f_L^t &= \sum_{c=1}^{C} \sum_{P} w(p) \cdot \left\| S_c^t p - S_c^*(p) \right\|_2^2. \end{aligned} \tag{9}$$

Among them, $S_j^*(p)$ and $S_c^*(p)$ are the actual labeled values, and the final objective function is as follows:

$$f = \sum_{t=1}^{T} \left(f_S^t + f_L^t \right). \tag{10}$$

3.2.1. Confidence Graph Detection of Nodes. First, the confidence map of the kth person is $S_{jk}^*(p)$, and $x_{j,k}$ is the true value of the kth joint point for the jth person, and the predicted value $S_{jk}^*(p)$ at the p point is expressed as a Gaussian function [25]:

$$S_{j,k}^*(p) = \exp - \frac{\left\| p - x_{j,k} \right\|_2^2}{\sigma^2}, \quad x_{j,k} \in R^2. \tag{11}$$

The maximum operation is performed:

$$S_j^*(p) = \max_k S_{j,k}^*(p). \tag{12}$$

As shown in Figure 3, $x_{j_1,k}, x_{j_2,k}$ represent the real position of the kth person's joint point j_1 and joint point j_2 on the limb c, and the vector field [26] at p is as follows:

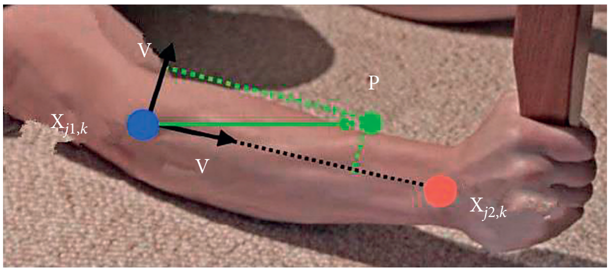


FIGURE 3: Connection diagram of key nodes.

$$L_{c,k}^{*}(p)=\begin{cases}V, & \text{If point } p \text{ is on lim } bc,\\ 0, & \text{else.}\end{cases} \tag{13}$$

Here,

$$V=\frac{\left(x_{j_2,k}-x_{j_1,k}\right)}{\left\|x_{j_{2,k}}-x_{j_1,k}\right\|_2}. \tag{14}$$

The unit vector p representing the direction of the limbs satisfies the formula:

$$\begin{aligned}&0\le V\cdot\left(p-x_{j_1,k}\right)\le l_{c,k},\\ &\left|V_{\perp}\cdot\left(p-x_{j_1,k}\right)\right|\le\sigma_l.\end{aligned} \tag{15}$$

Limb length $l_{c,k}$ is calculated as follows:

$$l_{c,k}=\left\|x_{j_2,k}-x_{j_2,k}\right\|_2. \tag{16}$$

Mean processing is calculated as follows:

$$L_c^{*}(p)=\frac{1}{n_c(p)}\sum_k L_{c,k}^{*}(p). \tag{17}$$

The link reliability of the affinity domain L_c along the line segment between two points E is calculated as follows:

$$\begin{aligned}E&=\int_{u=0}^{u=1}L_c((u))\cdot\frac{d_{j_2}-d_{j_1}}{\left\|d_{j_2}-d_{j_1}\right\|_2}\mathrm{d}u,\\ p(u)&=(1-u)d_{j_1}+ud_{j_2}.\end{aligned} \tag{18}$$

Limb prediction results are as follows:

$$\max_Z E=\sum_{c=1}^{c}\max_{Z_c}E_c. \tag{19}$$

3.2.2. Human Motion Gesture Recognition. For the training data set (x, y), where each sample x includes n-dimensional feature, namely $x=(x_1,x_2,\cdots,x_n)$, the class label set has k categories, namely $y=(y_1,y_2,\cdots,y_k)$ [27]; according to Bayes' theorem:

$$p(y_k\mid x)=\frac{p(x\mid y_k)p(x)}{p(x)}. \tag{20}$$

According to the total probability formula:

$$p(y_k\mid x)=\frac{p(x\mid y_k)p(x)}{\sum_k p(x\mid y_k)p(y_k)}. \tag{21}$$

$p(x\mid y_k)$ can be converted to:

$$p(x\mid y_k)=p(x_1,x_2,\ldots x_n\mid y_k)=\prod_{i=1}^{n}p(x_i|y_k). \tag{22}$$

The naive Bayes classification model is as follows:

$$\begin{aligned}f(x)&=\operatorname{argmax}_{y_k}p(y_k\mid x)\\ &=\operatorname{argmax}_{y_k}p(y_k)\frac{\prod_{i=1}^{n}p(x_i\mid y)}{\sum_k p(y_k)\prod_{i=1}^{n}p(x_i y_k).}\end{aligned} \tag{23}$$

It is converted to:

$$f(x)=\arg\max p(y_k)\prod_{i=1}^{n}p(x_i y_k). \tag{24}$$

4. Simulation Experiment and Data Analysis

4.1. Data Preprocessing. The article proposes a human body gesture recognition algorithm based on BP neural network, as well as the modified AEC-BP, ABC-BP, and ABC-AEC-BP algorithms. AEC-BP regards continuous video frames as a box and uses a three-dimensional convolution kernel for convolution. Through this structure, action information can be captured; ABC-BP uses single frame data and optical flow data, thus capturing motion information; ABC-AEC-BP is a convolutional neural network using two data streams for video behavior recognition. The video is divided into a static frame data stream and an inter-frame dynamic data stream. The static frame data stream can use single frame data, the inter-frame dynamic data stream uses optical flow data, and each data use a deep convolutional neural network for feature extraction. The BP algorithm is used to record the body's action decomposition during walking and running, as shown in Figures 4 and 5.

Taking a certain rural area as an example, we recorded the sports postures of rural athletes in five different states: stationary, going upstairs, going downstairs, walking, and running. The recognition results are as follows:

(a) AFC-BP algorithm in Table 2
(b) ABC-BP algorithm in Table 3
(c) ABC-AFC-BP algorithm in Table 4

Comparing the recognition rate and training time of the BP neural network algorithm, ABC-BP algorithm, AFS-BP algorithm, and ABC-AFS-BP algorithm, it can be seen from Table 5 that in terms of recognition rate, ABC-AFS-BP algorithm, AFS-BP algorithm, and ABC-BP algorithm are better than the traditional BP algorithm. Among them, the recognition rate of ABC-AFS-BP algorithm is higher than that of ABC-BP algorithm, but it takes slightly more time than the ABC-BP algorithm. In terms of training time, the ABC-BP algorithm takes less time, but the accuracy is lower than the ABC-AFS-BP algorithm. The error curves of the four algorithms are shown in Figure 7.

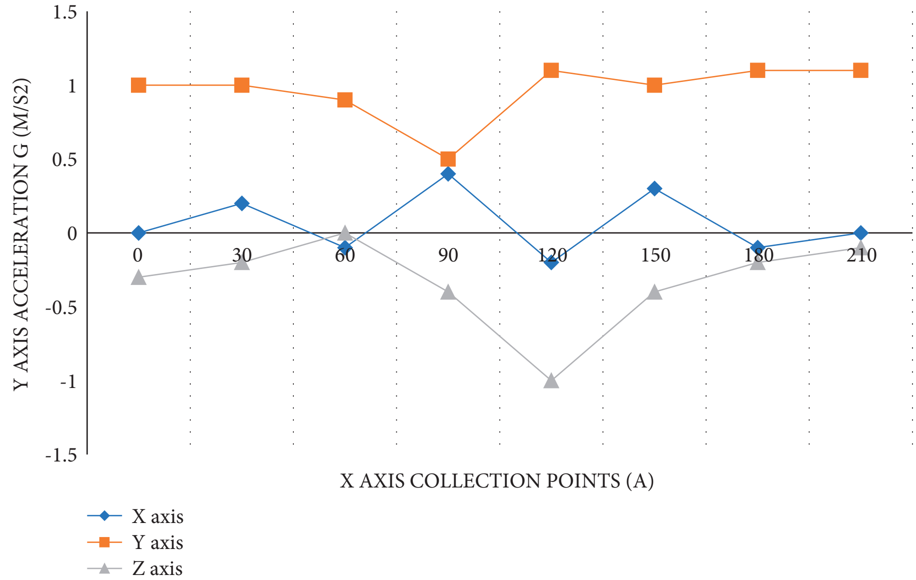


Figure 4: Exploded view of walking action.

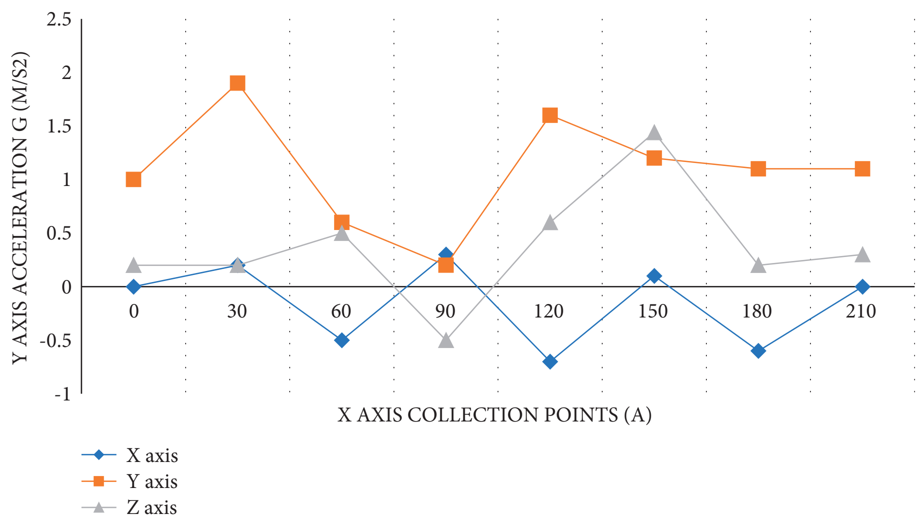


Figure 5: Exploded view of running action.

Table 2: AFC-BP recognition results.

Sports posture	Standstill	Go upstairs	Go downstairs	Walk	Run
Still	189	5	2	2	3
Go upstairs	3	114	6	4	4
Go downstairs	2	15	185	10	5
Walk	1	9	5	161	6
Run	2	6	11	5	218

Table 3: ABC-BP recognition results.

Sports posture	Standstill	Go upstairs	Go downstairs	Walk	Run
Still	190	5	2	1	3
Go upstairs	3	115	7	2	4
Go downstairs	2	13	189	6	7
Walk	2	5	3	164	8
Run	1	8	7	8	218

Through the comparison of Figure 7, it can be found that after 500 iterations of the training part, the iteration error value of the ABC-AFS-BP algorithm is the smallest, reaching the set accuracy, and the local searchability is strong, followed by BP neural network. The algorithm has the largest iterative error value, which is much different from the set accuracy, and the searchability is poor, which proves that the error is smaller when the ABC-AFS-BP algorithm neural network is used for data training and the training effect is better. At the same time, the ABC-AFS-BP algorithm and the ABC-BP algorithm curve decline faster, and a smaller error value is reached after fewer

Table 4: ABC-AFC-BP recognition results.

Sports posture	Standstill	Go upstairs	Go downstairs	Walk	Run
Still	191	3	2	2	3
Go upstairs	1	120	5	2	3
Go downstairs	3	6	203	3	2
Walk	0	3	3	171	5
Run	1	9	9	5	222

We recorded the recognition rate and training time of different algorithms, as shown in Table 5 and Figure 6.

Table 5: Recognition rate and recognition results of the algorithm.

Classification algorithm	Recognition rate (%)	Training time
BP	86.23	00:18:83
ABC-BP	90.03	00:08:36
AFC-BP	89.11	00:33:26
ABC-AFC-BP	93.21	00:10:12

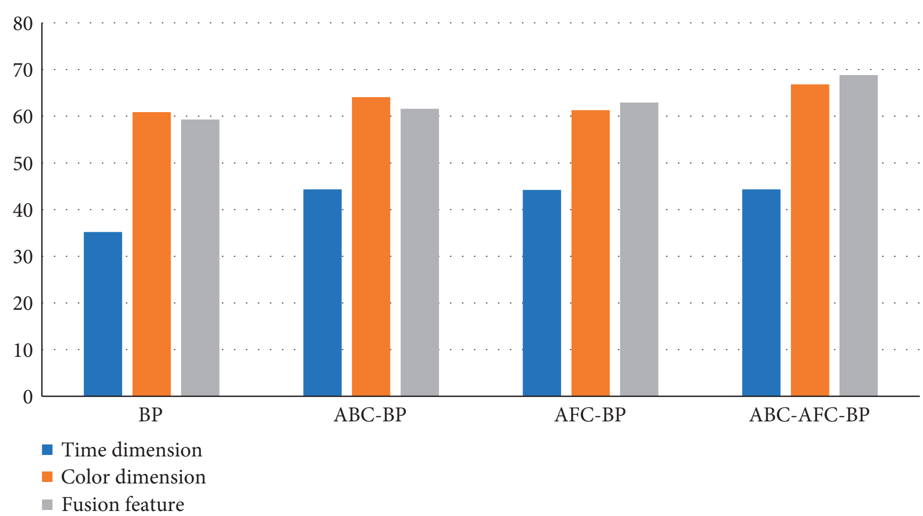


Figure 6: Recognition accuracy rate of different dimensions.

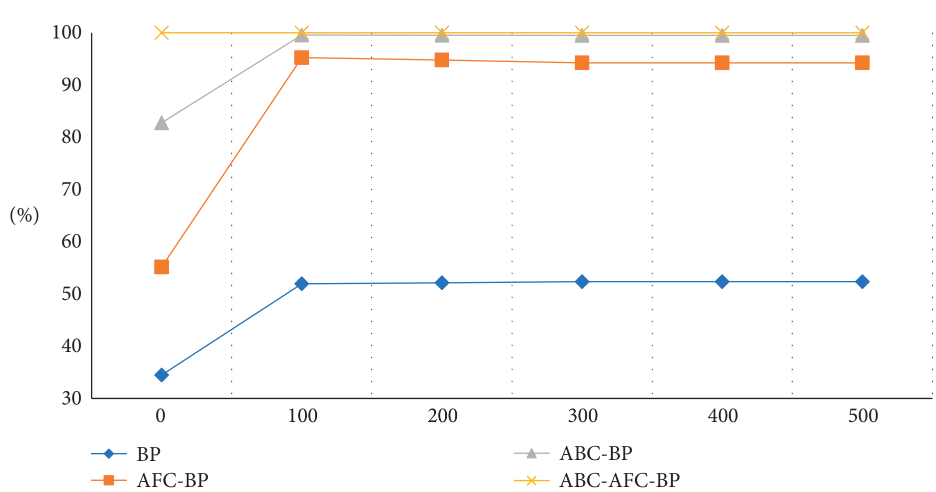
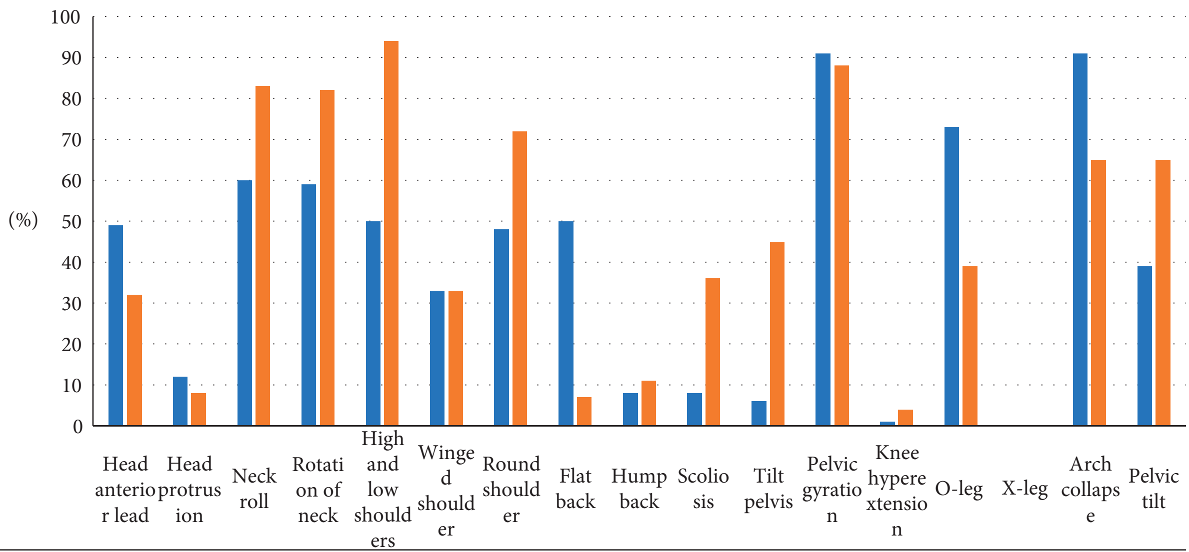


Figure 7: Error curve of the algorithm.

Table 6: Basic situation of athletes in different sports.

Sports	Source	Number of people	Age	Height (cm)	Weight (kg)	Sports years (years)
Football	Village 1	50	21.5	173.8	60.3	3.2
Basketball	Village 2	50	20.4	174.3	65.5	3.8
Aerobics	Village 3	50	20.8	166.4	50.4	3.4
Badminton	Village 4	50	21.2	170.7	53.4	2.8



	Head anterior lead	Head protrusion	Neck roll	Rotation of neck	High and low shoulders	Winged shoulder	Round shoulder	Flat back	Hump back	Scoliosis	Tilt pelvis	Pelvic gyration	Knee hyperextension	O-leg	X-leg	Arch collapse	Pelvic tilt
Football	49%	12%	60%	59%	50%	33%	48%	50%	8%	8%	6%	91%	1%	73%	0%	91%	39%
Basketball	32%	8%	83%	82%	94%	33%	72%	7%	11%	36%	45%	88%	4%	39%	0%	65%	65%

Figure 8: Total evaluation of abnormal posture results.

iterations. The simulation results confirm that the ABC-AFS-BP algorithm has better stability. The flexibility, fast convergence speed, and small error can largely avoid the problem of the BP neural network falling into local extreme value.

4.2. Simulation Experiment. We conducted a posture assessment of sports athletes from a certain team in rural areas. Because different sports have different power points, we selected football and basketball that consume more energy, as well as aerobics and badminton that consume relatively less energy. These 4 sports are taken as examples to study the effects of bad posture on the body in sports. We selected a total of 200 athletes. The experiment selected athletes whose gender, age, height, and weight were roughly the same, ignoring the influence of factors such as age, gender, and years of exercise on the athletes. The specific situation is shown in Table 6.

From the statistical data in Figure 8, we can conclude that bad postures in sports will have a certain impact on the athletes' bodies. Among them, more than 85% of athletes in football and basketball have the problem of pelvic rotation. The problem is more with football players; in 90% of the test sample, 60% of football players and basketball players have collapsed arches. Football players even reach 90% of the test sample, 77% of football players and 37% of basketball players have O-legs.

From the data in Figure 9, we can conclude that the main problems of aerobic athletes are flat backs and collapsed arches. More than 90% of badminton athletes have high and low shoulder problems, and more than 80% have neck problems. Serious body posture problems and wrong exercise posture can cause damage to the body, so in the daily training process, you should pay attention to these problems.

4.3. Comparative Experiment. To test the flexibility of the BP posture detection algorithm proposed in the article, we have compared it with the traditional motion posture recording method. We tested the accuracy of recorded motion, missed detection rate, and recording time. The experimental results are shown in Table 7 and Table 8.

From the data in Figures 10 and 11, we can conclude that the missed detection rate of the BP attitude detection algorithm is low, basically maintained at about 2.0, and the accuracy of recording actions is relatively high, generally maintained above 98%, with a maximum of 99.15%. The recording time is shorter, keeping it at 3-4 minutes; the missed detection rate of the traditional attitude detection algorithm is relatively high compared with the BP attitude detection algorithm, which is kept at 4–6, and the accuracy of action is lower than that of the BP attitude detection algorithm. It is generally maintained at about 95%, and the recording time is maintained at 5-6 minutes. The BP detection algorithm is faster and more efficient.

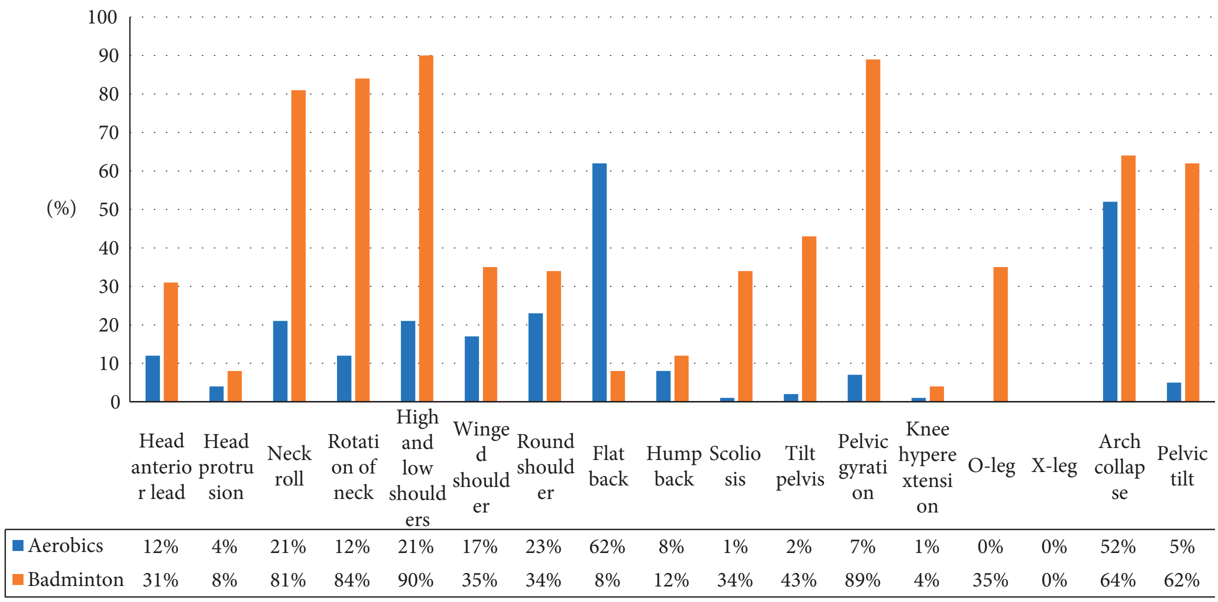


Figure 9: Total evaluation of abnormal posture results.

Table 7: BP attitude detection algorithm.

Target number	Goal 1	Goal 2	Goal 3	Goal 4	Goal 5	Goal 6	Goal 7	Goal 8
Total number of frames	752	752	752	752	752	752	752	752
Number of missed inspections	15	11	5	14	11	11	9	16
Missed detection rate (%)	2.0	1.5	0.7	1.9	1.5	1.5	1.2	2.1
Action accuracy	98.0%	98.6%	98.7%	98.6%	98.6%	98.9%	99.0%	99.15%
Recording time (minutes)	3.1	2.9	3.2	3.6	3.5	3.8	3.7	3.9

Table 8: Traditional pose detection algorithm.

Target number	Goal 1	Goal 2	Goal 3	Goal 4	Goal 5	Goal 6	Goal 7	Goal 8
Total number of frames	204	204	204	204	204	204	204	204
Number of missed inspections	9	11	12	10	13	8	7	9
Missed detection rate (%)	4.6	5.4	5.9	4.9	6.4	3.9	3.4	4.4
Action accuracy	95.0%	93.6%	94.7%	94.6%	93.6%	93.9%	94.0%	95.1%
Recording time (minutes)	5.1	5.3	5.5	5.4	5.5	5.7	5.9	5.8

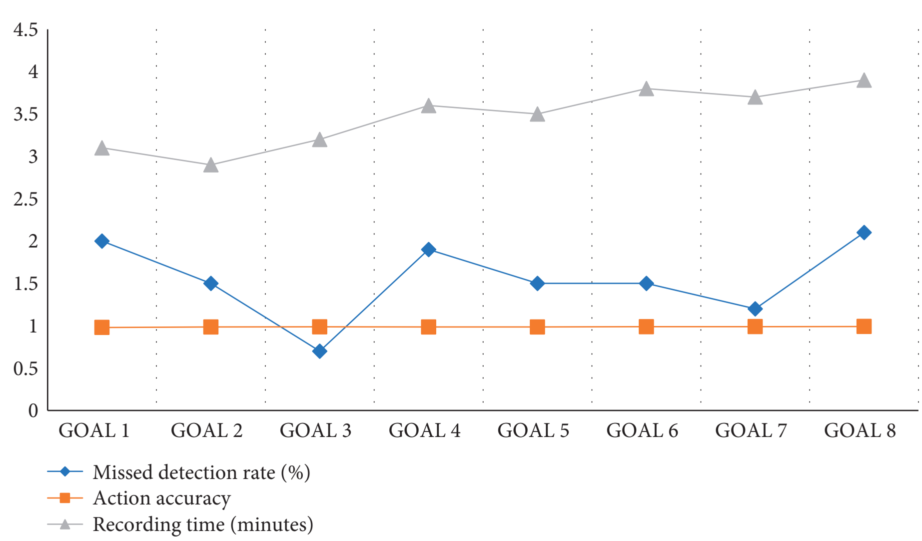


Figure 10: BP attitude efficiency graph.

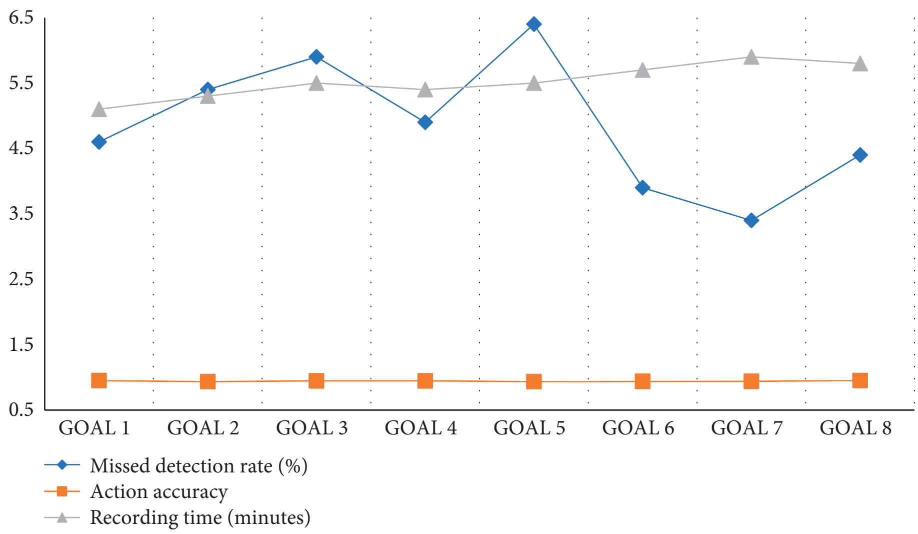


Figure 11: Traditional attitude efficiency graph.

5. Conclusion

The integrated development of urban and rural sports is the basic basis for the development of sports in China. Urban sports should promote the citizenization of migrant workers with its inclusiveness, and rural sports should attract urban residents to the countryside with its ecological nature, to meet the different needs of urban and rural residents for a better life. At this stage, focusing on creating rural ecological sports, promoting the two-way flow of urban and rural sports resources, then promoting the integrated development of urban and rural sports, and contributing to rural revitalization and the construction of new urbanization are the historical responsibility given to us by the new era. The model proposed in the article uses the powerful data processing, mining, and analysis functions of deep learning to train the massive data generated in competitive sports training and apply it to competitive sports training. It is committed to promoting the accuracy and analysis of competitive sports training. Refinement provides technical guidance for athletes' training, promotes the scientific and information development of competitive sports training in China, and provides some reference methods for the research and application of deep learning in competitive sports training. The human body poses that estimation has a good application prospect in sports analysis, but the truly appropriate matching method still needs to be adjusted according to specific data sets and specific applications. In addition, how to effectively use these data after getting the key points of the human body is also a question that requires in-depth thinking. The article only applies basic mathematical operations to get some simple metrics, which is relatively rough. There can be two directions for further research: one is to continue to improve the accuracy of key point extraction, the other is to fully tap the value of the obtained data, make full use of information to explain the actual needs of sports, and help athletes better improve their training.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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