

## *Retraction*

# **Retracted: Research on Pose Recognition Algorithm for Sports Players Based on Machine Learning of Sensor Data**

## **Security and Communication Networks**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## **References**

- [1] C. Zhang and H. He, "Research on Pose Recognition Algorithm for Sports Players Based on Machine Learning of Sensor Data," *Security and Communication Networks*, vol. 2021, Article ID 9327619, 8 pages, 2021.

## Research Article

# Research on Pose Recognition Algorithm for Sports Players Based on Machine Learning of Sensor Data

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The existing motion recognition system has a low athlete tracking recognition accuracy due to the poor processing effect of recognition algorithm for edge detection. A machine vision-based gymnast pose-tracking recognition system is designed for the above problem. The software part mainly optimizes the tracking recognition algorithm and uses the spatiotemporal graph convolution algorithm to construct the sequence graph structure of human joints, completes the strategy of label subset division, and completes the pose tracking according to the change of information dimension. The results of the system performance test show that the designed machine vision-based gymnast posture tracking recognition system can enhance the accuracy of tracking recognition and reduce the convergence time compared with the original system.

## 1. Introduction

In sport competitions, the body data of athletes are very important, especially gymnasts. Because the structure of human limbs is special, so there is no regularity in the process of movement, and the athletes' movement changes fast [1–3], which cannot be accurately identified by human eyes alone, resulting in the lack of posture identification of fitness gymnasts in the process of competition [4]. With the development of technology, some posture tracking recognition systems gradually applied in the fitness gymnastics competition and showed a certain effect. The existing system is relatively fast and effective in the process of athlete limb monitoring, but due to the existence of various factors in the process of athletes in the competition, fitness gymnastics in the process of the competition in general, there are many scores, and when the athlete's posture is detected, the regions with large pixel values in the image will respond, resulting in detection errors in the process of tracking the athlete. The athlete tracking recognition accuracy is low [5]. To address the above problems, a machine vision-based gymnast pose-tracking recognition system is designed.

In this paper, the inertial sensor technology is applied to the pose recognition in basketball and in order to improve the accuracy of the pose solution and reduce the noise interference in the ready detection process, this paper applies the extended Kalman filter algorithm to the pose solution and realizes the data fusion of multiple sensors; in order to solve the problems of complex and space limitation of optical motion capture data processing in sports training, this paper builds a virtual human model in the upper body to realize the human body [6]. In order to solve the problems of complex optical motion capture data processing and space limitation in sports training, this paper builds a virtual human model in the upper body to realize the reproduction of human motion posture and initially completes the display of human lower limb movement and upper limb movement; based on the above research, the recognition method of basketball motion posture is proposed.

In this paper, we analyzed the behavioral performance of leg and arm movements and the corresponding signal waveform features in nine basketball movements: walking, running, jumping, standing dribbling, walking dribbling, running dribbling, shooting, passing, and catching, proposed a two-stage data division method for basketball,

extracted unit movement data for analysis, realized feature extraction, and selected the most suitable classifier for basketball gesture recognition. The constructed feature vectors are trained with four different classifiers to construct different classifiers to realize the action classification. The experiments show that the experimental method designed in this paper for nine kinds of postures in basketball can obtain the basketball action information of the detected person in real time, realize the accurate extraction of individual action data, and complete the recognition of basketball postures, and its average accuracy rate can reach 98.85%, which has certain practical value in basketball posture recognition.

## 2. Theoretical Foundation

**2.1. Overview of Posture Recognition.** As a branch of pattern recognition, human pose recognition has received extensive attention and development in recent years [7]. With the increasing maturity of microelectronics technology, human pose recognition based on inertial sensors has gradually become a research hotspot, and on the basis of pattern recognition, many researchers have applied image-based recognition technology to the field of human pose recognition based on wearable devices [8]. Figure 1 shows the process of human pose recognition based on inertial sensors, which is mainly divided into five stages: data acquisition, data preprocessing, data segmentation, feature extraction, and classifier training. In the data acquisition stage, the physical or physiological signals of human body, such as acceleration, angular velocity, heart rate, and body temperature, are collected by the sensor device; in the data preprocessing stage, the data are processed such as dedrying and normalization to meet the system requirements; in the data segmentation stage, the data are extracted in the time domain and frequency domain for individual analysis [9]. The feature extraction stage mainly completes the analysis of the unit action and calculates and extracts the relevant attribute features as the sample data; finally, in the classifier stage, the collected samples are constructed into classification models according to different classification principles, and then the classification of unknown samples is realized [10].

**2.2. Signal Acquisition Solutions.** In order to realize the recognition of human posture, it is necessary to grasp the information of arm and leg motion posture during human movement, and Aminian pointed out that most of the planes of arm and leg oscillation are vector surfaces parallel to the center of the human body, and their angular velocity and acceleration can best reflect the oscillation of the subject, and the angular velocity data of the leg during linear walking can be observed through the data waveform to have the most regular change [11]. The angular velocity of the legs during linear walking is the most regular. Moreover, the human body movement process involves many body parts, so the more the sensor nodes placed in the body, the richer the acquired posture information; this paper takes the legs and arms as the key parts of the human movement process, by

observing the movement of the limbs and then inferring the human posture, so the placement of sensors is shown in Figure 2. In this paper, four sensor nodes, attached to the human arms and legs, are used to detect the upper limb movement and lower limb movement conditions in human motion, and through wireless communication protocol, the collected data information is sent to the base station [12]. The base station completes the data acquisition and uploads it to the host computer through the serial port for further analysis of the data.

**2.3. Basketball Stance Definition.** The human body movements included in basketball are complex, and Figure 3 shows the analysis of the composition of basketball postures. According to the state of the limb, the basketball poster is divided into the static state and the motor state [13]. The static state refers to the state in which the limb posture is unchanged, while the motion state refers to the state in which the limb performs the basketball action, for example, when catching the ball, the athlete's leg posture remains unchanged, and the leg is in a static state, while the arm performing the catching action is in a motion state. If the upper limb shooting, catching, passing, and dribbling and the lower limb jumping, walking, and running are defined as unitary movements, the movements can be divided into transient and continuous movements according to whether they are periodic or not in the movement state [14, 15]. Transient action is not periodic, it contains only one unit action, such as shooting and catching the ball. Continuous action is periodic; it contains several consecutive unit actions, such as dribbling and walking, for a period of time. Therefore, in basketball gesture recognition, the division of upper and lower limb unit actions is crucial for recognition, for which a division method based on unit action extraction is proposed in this paper.

Figure 4 demonstrates the comparison of angular velocity and angle during walking dribbling, in which the horizontal coordinates represent time, the vertical coordinates of subplots (1) and (3) represent the angular velocity of the small arm and the small leg, respectively, and the vertical coordinates of subplots (2) and (4) represent the angle of the small arm and the small leg, respectively. From subplots (1) and (3), we can see that there are more noise signals in the angular velocity signal and the curves are not smooth enough; while the angular signal curves in subplots (2) and (4) are smoother, so the unit action division based on angle can reduce the complexity of implementation.

**2.4. Athlete Pose-Tracking Recognition System Based on Machine Vision.** The main task of the system is to implement the posture tracking and recognition of athletes in a sports competition arena environment [15]. In the overall structure of the system, the motion state of the gymnast needs to be collected first and processed and judged on the PC using machine vision algorithms. Through the wireless serial port to send control commands to the camera to complete the camera in the dynamic scene of the target tracking, since the body movements of the gymnasts are

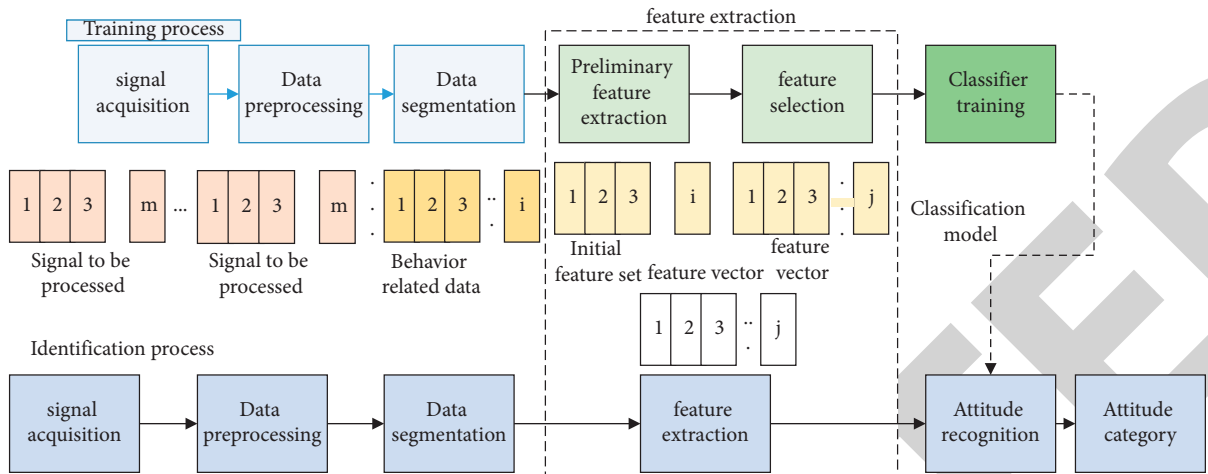


FIGURE 1: Flowchart of human posture recognition method based on inertial sensor.

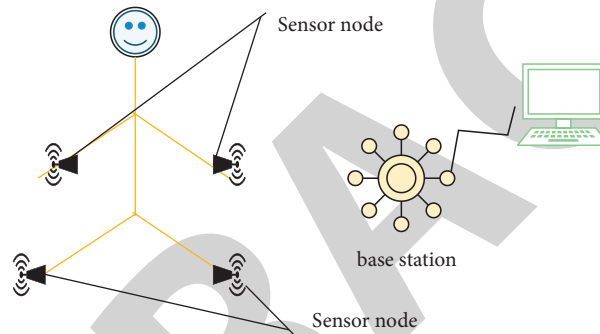


FIGURE 2: System topology diagram.

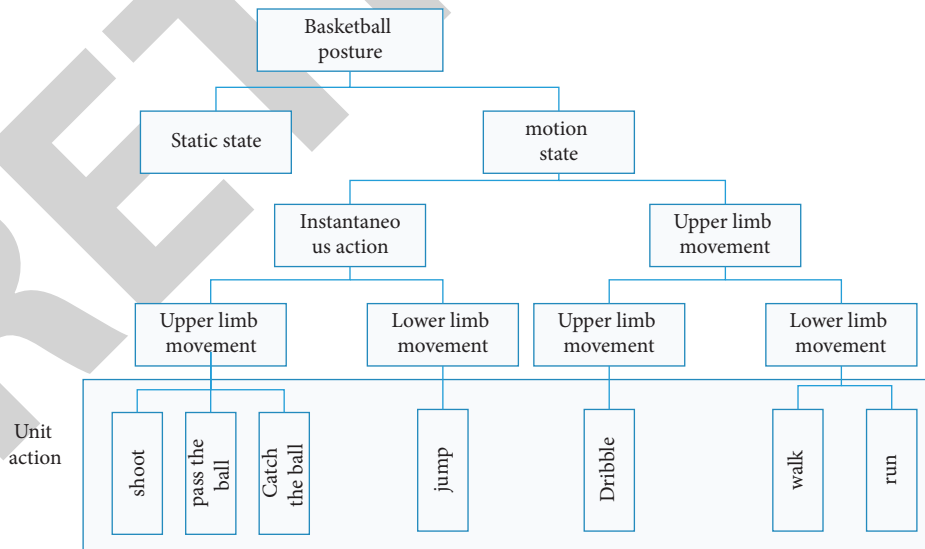


FIGURE 3: Composition of basketball stance.

relatively random and the speed and direction of movement during the competition are unknown, the athletes need to be analyzed using machine vision algorithms [16]. For the analysis of the above system functions, it is able to design the overall structure of the system, as shown in Figure 5.

In Figure 5, the gymnast identification and tracking system are mainly composed of two parts: hardware for image information data acquisition and software for machine vision identification and tracking [17, 18].

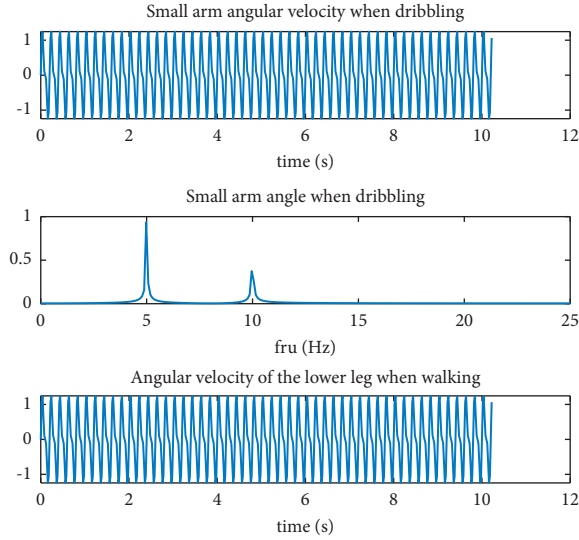


FIGURE 4: Comparison of the angle and angular velocity of small-arm dribbling and small-leg walking.

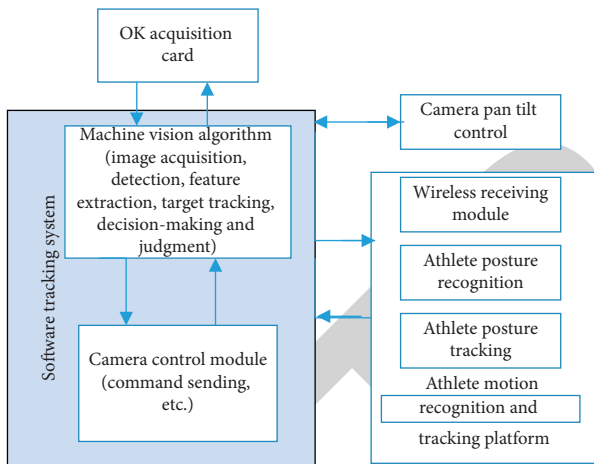


FIGURE 5: Overall system architecture.

**2.5. Optimized Tracking Recognition Algorithm.** In the process of gymnast's pose-tracking recognition, many original systems are based on HOG and SIFT [19, 20] for feature extraction and implicit modeling of athlete's pose, but this algorithm is less effective for edge extraction, which affects the accuracy and efficiency of tracking recognition to some extent [21, 22]. With the development of machine vision, it is proposed to use recurrent neural networks to train the video frames of the athlete's body movements and the surrounding environment [23]. In the process of optimizing the tracking recognition algorithm in this paper, the reference is the spatiotemporal CNN, after collecting and calibrating the dataset of the relevant parameters of the athlete's game and performing migration learning [24]. Algorithm recognition flow of this paper is shown in Figure 6.

The gesture sequences of the athlete's body captured by the hardware are divided by the spatiotemporal graph convolution method shown above, and the joint points and

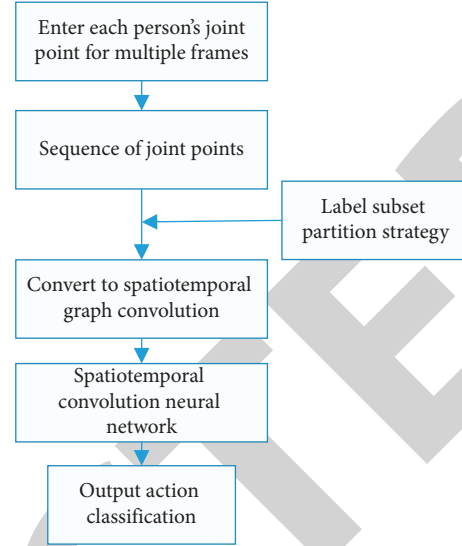


FIGURE 6: Athlete posture recognition tracking process.

link relationships are divided according to label subsets. For the matching algorithm of joints, the data structure can be used as the basis for modeling the athlete's joint points and limbs, extending their temporal dimension and modeling the action consisting of multiple poses using the spatiotemporal data structure [25, 26]. For a given spatiotemporal graph convolution, the mapping of labels can be implemented according to uniform division, distance division, and division in space. In order to realize the pose recognition classification of athletes, the corresponding feature information obtained from the output of the stacking module needs to be mapped, and finally, the posttracking is completed based on the change of the information dimension. This completes the design of machine vision-based gymnast pose-tracking recognition system.

### 3. System Testing

**3.1. Building System Test Environment.** In order to verify that the designed system has certain effectiveness, a part of the video of the gymnastic athletes' competition scene was collected in the system testing session, and it was used as the experimental data for system testing. The system test equipment and related parameters are shown in Table 1.

In the above parametric environment, the 3D point data in the video are extracted using the Google tracking-related API of Kinect SDK [27, 28], the video mainly includes the gymnast's competition video and Weizmann human behavior database; the ratio of training data and test data is about 1 : 1, where the relevant gymnastic postures are mainly walking, jumping, prone, squatting, standing, and raising hands. The calibrated joint point diagram is shown in Figure 7.

In order to better identify the athlete's pose, the pose image needs to be joint calibrated, and the obtained pose joints can convert the pose image sequence into a set of joint point feature vectors and combine the file transfer stream technology to write the obtained 3D key point data into a file

TABLE 1: The system test equipment and related parameters.

Testing environment	Project	Parameter
Test PC	Operating system	Windows 8
	Processor	Intel(R) Core(TM) 15-4200
	Memory	4G
	Dominant frequency	2.6 GHz
	Sensor	Microsoft Kinect for Windows
Test development environment	Operating system	Windows 8
	Program development environment	Visual Studio 2010
	Development language	C language
	Development framework	WPF
	Development package	Kinect SDK vl. 7

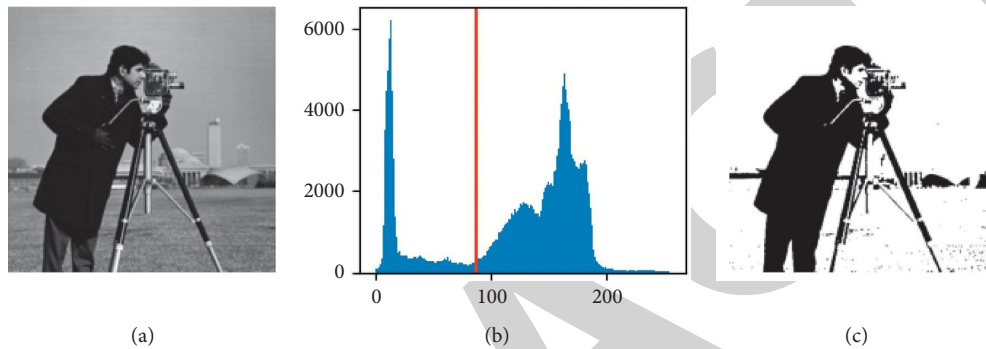


FIGURE 7: Posture joint calibration diagram. (a) Original. (b) Histogram. (c) Thresholded.

and can be opened directly in the software for data processing.

**3.2. Designing the System Testing Process.** The testing process of the system is mainly composed of two parts: edge detection and image integration detection of human limbs [29]. At the beginning of the test, in a given video of a gymnast performance, each frame is used to get the limb or suspected limb area in the image by edge detection, as shown in Figure 8.

Based on the above image, the right arm tracking and recognition are performed using the designed system and the conventional system for the above image, respectively, and the experimental results of the two systems are compared and analyzed.

**3.3. Clustering Experiment Results and Analysis.** Under the abovementioned experimental conditions, the tracking recognition results of both systems for the right arm of the athlete were obtained, as shown in Figure 9.

Figure 9 shows the tracking recognition results obtained by the original system and the tracking recognition results obtained by this system. After testing a series of videos in the database for different items, tracking recognition accuracy comparison results obtained by the two systems are shown in Table 2.

Since the clustering algorithm in the original system needs to determine the number of clusters that need to be clustered in advance in order to achieve clustering, the designed system, in order to improve the tracking recognition performance in the actual application process, is

tested on the same test data on the assumption that the original system has obtained the clustering a priori, and the tracking recognition results of the two systems are compared; as can be seen from Table 2, the clustering accuracy of the original system is much lower than that of the system in this paper, and the clustering results in the original system are very different, compared to the system in this paper. The accuracy rate is higher with the same dataset [30].

**3.4. Analysis and Discussion of Experimental Results.** Taking basketball as a benchmark, the completion of basketball movements is mainly done through the overall movement of the player's upper and lower limbs in a coordinated manner, so when identifying basketball movements, the upper and lower limb movements need to be discussed separately [16, 27, 31]. In the process of data acquisition, the collected data of upper limb movements and lower limb movements are discussed and recognized separately according to the different positions of sensor nodes placed on the body. The results were analyzed in terms of accuracy and recall, as shown in Table 3. The whole experiment was implemented on the Weka platform, and the ten-fold cross-validation method was used.

From Table 4, it can be seen that for the action classification of different limbs, the BP artificial neural network achieves better recognition results, with the average accuracy of 93.2% and the average recall of 93.2% for upper limb actions and 99.2% and the average recall of 99.2% for lower limb actions. As shown in Table 4, the average recognition rate of upper limb movement of dribbling in place, walking



FIGURE 8: Video raw image.



FIGURE 9: Comparison of tracking recognition results of the two systems.

TABLE 2: Comparison of the tracking recognition accuracy of the two systems.

Test items	Accuracy of the original system		Accuracy of this system	
	Highest	Minimum		
LrIs dataset	73.3%	51.3%		%
Wine dataset	61.5%	58.6%		%
Trunk and noise	81.6%	54.9%		%
Lower limbs and noise	75.6%	50.9%		%

TABLE 3: Classification results of different classification algorithms for lower limb movements.

Behavior	C4.5 accuracy	C4.5 recall rate	SVM accuracy	SVM recall rate	BN accuracy	BN recall rate	BP-ANN accuracy	BP-ANN recall rate
Jumpthrun	0.997	0.994	0.983	0.999	0.979	0.976	0.985	0.999
Run	0.983	0.981	0.998	0.979	0.955	0.975	0.997	0.985
Walk	0.971	0.971	0.988	0.996	0.981	0.958	0.993	0.994
Average	0.984	0.984	0.990	0.990	0.970	0.970	0.992	0.992

Table 3 is reproduced from [32].

TABLE 4: Different classification for the combined upper limb movements.

Behavior	C4.5 accuracy	C4.5 recall rate	SVM accuracy	SVM recall rate	BN accuracy	BN recall rate	BP-ANN accuracy	BP-ANN recall rate
Catch the ball	0.923	0.911	0.928	0.913	0.846	0.945	0.984	0.984
Pass the ball	0.917	0.939	0.976	0.990	0.943	0.959	0.990	0.990
Dribble	0.984	0.985	0.997	0.990	0.997	0.985	0.996	0.993
Shoot	0.944	0.924	0.985	0.994	0.955	0.909	0.973	0.985
Average	0.963	0.963	0.988	0.988	0.963	0.963	0.990	0.990

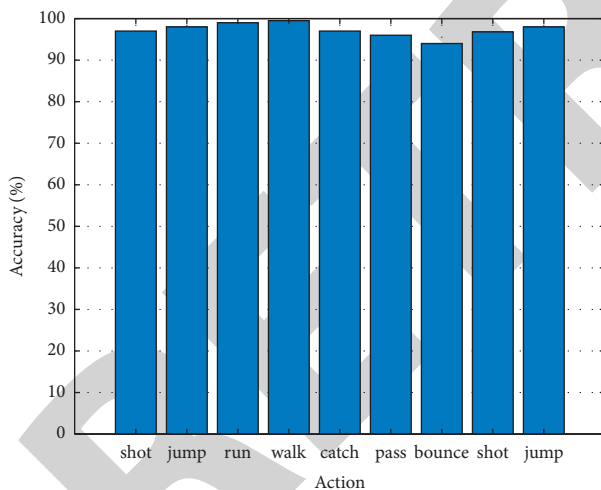


FIGURE 10: BP-ANN recognition results for basketball posture.

dribbling, and running dribbling as a movement state can reach up to 99%, and the average recall rate can reach up to 99%.

As shown in Figure 10, the horizontal coordinates indicate the action types and the vertical coordinates indicate the accuracy rate, and the recognition accuracy of each basketball action exceeded 95%, and the average accuracy rate reached 98.85%.

#### 4. Conclusions

Tracking recognition of human movement posture is a hot research problem at present. Due to the special physiological

structure of the human body, it causes the movement posture to be more difficult in the calculation process of recognition tracking. Due to the influence of external factors such as some relatively intense lighting during the aerobics competition, the accuracy of the original system in the process of recognition tracking is low. Therefore, with the support of machine vision technology, a new posture tracking recognition system for calisthenics athletes is designed. The system camera is designed and calibrated to ensure that the acquired image data do not have errors, and the software is optimized for the recognition and tracking algorithm.

#### Data Availability

The dataset used in this paper are available from the corresponding author upon request.

#### Conflicts of Interest

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

#### References

- [1] J. Li and D. Gu, "Research on basketball players' action recognition based on interactive system and machine learning," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 2029–2039, 2021.
- [2] J. Wang and X. H. Liu, "Human posture recognition method based on skeleton vector with depth sensor," *IOP Conference*



- Series: Materials Science and Engineering*, vol. 806, no. 1, Article ID 012035, 2020.
- [3] N. Rommers, R. Rössler, E. Verhagen et al., "A machine learning approach to assess injury risk in elite youth football players," *Medicine & Science in Sports & Exercise*, vol. 52, no. 8, pp. 1745–1751, 2020.
  - [4] J. L. Oliver, F. Ayala, M. B. A. D. S. Croix, R. S. Lloyd, G. D. Myer, and P. J. Read, "Using machine learning to improve our understanding of injury risk and prediction in elite male youth football players," *Journal of Science and Medicine in Sport*, vol. 23, no. 11, pp. 1044–1048, 2020.
  - [5] M. Oytun, C. Tinazci, B. Sekeroglu, C. Acikada, and H. U. Yavuz, "Performance prediction and evaluation in female handball players using machine learning models," *IEEE Access*, vol. 8, pp. 116321–116335, 2020.
  - [6] W. Gu, K. Foster, J. Shang, and L. Wei, "A game-predicting expert system using big data and machine learning," *Expert Systems with Applications*, vol. 130, pp. 293–305, 2019.
  - [7] J. Taborri, L. Molinaro, A. Santospagnuolo, M. Vetrano, M. C. Vulpiani, and S. Rossi, "A machine-learning approach to measure the anterior cruciate ligament injury risk in female basketball players," *Sensors*, vol. 21, no. 9, p. 3141, 2021.
  - [8] S. Wilkens, "Sports prediction and betting models in the machine learning age: the case of tennis," *Journal of Sports Analytics*, vol. 7, pp. 99–117, 2021.
  - [9] G. Liu, W. Zhu, and O. Schulte, "Interpreting deep sports analytics: valuing actions and players in the NHL," in *Proceedings of the International Workshop on Machine Learning and Data Mining for Sports Analytics*, pp. 69–81, Springer, Dublin, Ireland, September 2018.
  - [10] P. Wang and Z. Q. Liu, "Research on evaluation of vehicle dangerous traveling state based on information fusion method," *Advanced Materials Research*, vol. 791–793, pp. 1018–1022, 2013.
  - [11] T. Xie, C. Zhang, and Z. Zhang, "Utilizing active sensor nodes in smart environments for optimal communication coverage," *IEEE Access*, vol. 7, pp. 11338–11348, 2018.
  - [12] T. Li, J. Sun, and L. Wang, "An intelligent optimization method of motion management system based on BP neural network," *Neural Computing & Applications*, vol. 33, no. 2, pp. 707–722, 2021.
  - [13] B. Barshan and M. C. Yükek, "Recognizing daily and sports activities in two open source machine learning environments using body-worn sensor units," *The Computer Journal*, vol. 57, no. 11, pp. 1649–1667, 2014.
  - [14] C. Zhang, T. Xie, K. Yang et al., "Positioning optimisation based on particle quality prediction in wireless sensor networks," *IET Networks*, vol. 8, no. 2, pp. 107–113, 2019.
  - [15] G. Chunfeng, "Research on pre-competition emotion recognition of student athletes based on improved machine learning," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 4, pp. 5687–5698, 2020.
  - [16] Q. Ding and Z. Ding, "Machine learning model for feature recognition of sports competition based on improved TLD algorithm," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 1, pp. 1–12, 2020.
  - [17] P. Li and J. Cai, "Research on image recognition from wireless sensor data based on deep learning," *Journal of Critical Care*, vol. 42, no. 6, pp. 2607–2612, 2017.
  - [18] S. L. Colyer, M. Evans, D. P. Cosker, and A. I. T. Salo, "A review of the evolution of vision-based motion analysis and the integration of advanced computer vision methods towards developing a markerless system," *Sports Medicine-Open*, vol. 4, no. 1, pp. 1–15, 2018.
  - [19] D. P. P. Nagalakshmi Vallabhaneni, "The analysis of the impact of yoga on healthcare and conventional strategies for human pose recognition," *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, vol. 12, no. 6, pp. 1772–1783, 2021.
  - [20] L. Zhu, "Computer vision-driven evaluation system for assisted decision-making in sports training," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 1865538, 7 pages, 2021.
  - [21] D. Pan, H. Liu, D. Qu, and Z. Zhang, "Human falling detection algorithm based on multisensor data fusion with SVM," *Mobile Information Systems*, vol. 2020, Article ID 8826088, 9 pages, 2020.
  - [22] C. Gao, J. Su, B. Wang, W. Zhuang, and Y. Chen, "Design of human activity recognition algorithms based on a single wearable IMU sensor," *International Journal of Sensor Networks*, vol. 30, no. 3, p. 193, 2019.
  - [23] L. Yan, M. Shen, W. Yao, M. Lu, L. Liu, and A. Xiao, "Recognition method of lactating sows' posture based on sensor MPU6050," *Transactions of the Chinese Society for Agricultural Machinery*, vol. 46, no. 5, pp. 279–285, 2015.
  - [24] M. Zhang, Y. Yang, and N. Cheng, "Research on activity recognition method based on human motion trajectory features," *Journal of Convergence Information Technology*, vol. 7, no. 1, pp. 79–85, 2012.
  - [25] H. U. Xiao-Yan and Y. Zhang, "Study of face detection algorithm based on complexion," *Journal of Hefei University of Technology*, vol. 35, no. 7, pp. 908–912, 2012.
  - [26] X. Bu, "Human motion gesture recognition algorithm in video based on convolutional neural features of training images," *IEEE Access*, vol. 8, no. 99, p. 1, 2020.
  - [27] J. Qu, C. Wu, Q. Li, T. Wang, and A. Hamid salman, "Human fall detection algorithm design based on sensor fusion and multi-threshold comprehensive judgment," *Sensors and Materials*, vol. 32, no. 4, pp. 1209–1221, 2020.
  - [28] Y. Cui, W. Liu, Z. Zhao, Y. Ma, Y. Li, and W. Shu, "Research on data fusion algorithm and anti-collision algorithm based on internet of things," *Future Generation Computer Systems*, vol. 85, pp. 107–115, 2018.
  - [29] L. Xiao and G. Shenkai, "Research on sports retrieval recognition of action based on feature extraction and SVM classification algorithm," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 4, pp. 5797–5808, 2020.
  - [30] C. Ma, X. Sun, C. Yao, M. Tian, and L. Li, "Research on sheep recognition algorithm based on deep learning in animal husbandry," *Journal of Physics: Conference Series*, vol. 1651, Article ID 012129, 2020.
  - [31] R. Yuan, Z. Zhang, Y. Le, and E. Chen, "Adaptive recognition of motion posture in sports video based on evolution equation," *Advances in Mathematical Physics*, vol. 2021, Article ID 2148062, 12 pages, 2021.
  - [32] H. Ren and X. Wang, "Application of wearable inertial sensor in optimization of basketball player's human motion tracking method," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–15, 2021.