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Article

Research on Artificial Intelligence Application Strategies in the Integration of Physical Education Teaching and Athletic Training for College Students in Higher Education

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Abstract: In this paper, the hourglass network is used to extract the key points of human skeleton of students during physical education teaching and sports training, and to estimate the students' single movement posture characteristics by eliminating the abnormal frames and coordinate transformations, parameter calculations, and division of possible movement intervals. Based on the differences in the movement posture features, the DTW algorithm is used to calculate the similarity between the student's movements and the teacher's movements during physical education and sports training, and score them accordingly. In the key action posture matching, the matching success rate of this paper's method for six types of actions is between 70.52% and 90.43%, which is higher than that of other methods. The classification accuracy calculated by this paper's method based on similarity is high, and the number of classification errors for the 6 classes of actions is mostly in the range of 0-3 times. The number of model parameters of this paper's method on 2 validation sets is only 13.1M, which is lightweight. In the motion pose matching deviation rate experiments, the scoring deviation rate of this paper's method for the excellent and unqualified phases ranges from 3.16% to 5.56%, and the overall scoring deviation is in line with expectations.

Keywords: single person pose estimation; hourglass network; DTW algorithm; key movement poses; similarity calculation

1. Introduction

In the context of the new era, college students' physical education teaching and sports training must take some innovative measures to adapt to the development of society and ensure the educational effect [1-2]. Unprecedented technological development has given rise to artificial intelligence, and artificial intelligence technology has begun to be applied and developed in physical education teaching and sports training, providing new ideas for the cultivation of sports athletes in good condition [3-6].

The traditional way of teaching sports often relies on the teacher's experience and guidance, while the application of artificial intelligence technology brings new possibilities for sports teaching [7-8]. Through the use of AI technology, students' motor skills, postures and movements can be efficiently monitored and analyzed, so that students' problems can be found in time and targeted guidance can be given [9-12]. Artificial intelligence technology can also tailor the best learning and training programs for students according to their individual needs and characteristics, making teaching more accurate and effective [13-15]. Although the application of AI technology in physical education has brought much convenience and progress in teaching, training and health management [16-18]. However, the current application of AI technology in physical education is still in the primary stage and still faces many challenges and problems, with the accuracy and reliability of data as well as privacy and security being the key issues [19-21]. If the collected data are in error or incomplete, it may lead to biased analysis results and wrong decisions, and the application of AI technology may also raise some ethical and moral issues, such as the protection of athletes' privacy and fairness controversy due to technology dependence [22-25].

Literature [26] applied research methods such as documentation to discuss the value and dilemmas of Al technology in sports, and based on the current situation and characteristics of sports development in China, it put forward feasible suggestions for the application of AI in sports, aiming to enhance the cultivation of sports talents. Literature [27] investigated the transformative impact of technology integration on physical education and sports training, revealing that the integration of traditional coaching methods with technology has revolutionized athlete preparation and performance, but also brought challenges, including fair access and ethical considerations. Literature [28] proposed an AI-based multi-feature fuzzy evaluation model to provide an efficient framework for acquiring teaching methods, demonstrating the effectiveness of the framework in improving physical education teaching methods and helping to advance teaching practices in the field. Literature [29] analyzed the application of AI technology in the field of physical education teaching in the context of the current situation of physical education teaching in colleges and universities, highlighting the positive impacts of AI including accurate diagnostic capabilities and personalized learning support, and pointing out the barriers encountered. Literature [30] explored the importance of personalization in the school physical education teaching environment and the role of artificial intelligence (Al) in assisting teachers to customize their curriculum. Literature [31] analyzes the current status quo of physical education teaching quality evaluation in colleges and universities, proposes a method to construct a basic framework through an expert system, and tests it to ensure the reliability and correctness of the system logic. Literature [32] describes the application of artificial intelligence in physical education, emphasizing that artificial intelligence not only stimulates students' interest in sports, but also improves students' sports skills, which has a positive impact on the teaching of physical education in colleges and universities. Literature [33] designed an interactive teaching system for physical education based on artificial intelligence, and by further improving the relevant system to make it have safety and accuracy, so as to improve the efficiency of the system and enhance the integrity of teaching. Literature [34] combined loT and AI to analyze the application mode of innovative practice teaching in college sports teaching, emphasizing the qualitative improvement of teaching efficiency and teaching quality under this teaching mode, which provides a reference for the further development of loT and AI in teaching. The analysis of the development and application of literature [35] educational artificial intelligence explores the value of combining artificial intelligence technology and sports. In particular, the application of AI in physical education teaching. Literature [36] designed the intelligent service platform for the intelligent sports classroom in colleges and universities, the platform can find and solve the problems of students in the process of physical education teaching, which is conducive to in improving physical education classroom teaching, and provides a practical basis for the reform of physical education teaching. Literature [37] discusses the advantages, difficulties and implementation strategies of the application of artificial intelligence technology in college sports teaching, and elaborates that artificial intelligence technology can provide a personalized learning experience in university physical education, effectively improve teaching efficiency, and has great potential. Literature [38], in order to promote the construction of college physical education network courses and the evaluation of course teaching effect, combined with the three-dimensional reconstruction technology in computer vision, constructed a human body morphology reconstruction model, and applied it to physical training exercises and teaching effect evaluation tasks. The above studies explored the application of AI in college physical education teaching and physical training, and acknowledged the positive impacts of AI, the personalized teaching provided by it improved the learning effect of students, and also contributed to the overall quality of teaching in colleges and universities, and individual studies also mentioned the challenges of AI in the process, such as the existence of ethics.

In this paper, the key points corresponding to the joints are selected after outputting the heat map using hourglass network and organized into human body key points. By eliminating abnormal frames and coordinate transformation, the normalization matrix based on human joints is obtained. Different parameter values are calculated for different actions in sports training. After that the valid frames are categorized to get the corresponding dataset. Based on the differences in the gesture characteristics of different categories of actions, the DTW algorithm is applied to calculate the similarity between the student's actions and the teacher's actions. Through several comparison experiments, the key action pose matching success rate, classification accuracy rate, model collection, and motion pose matching deviation rate of this paper's method are obtained to verify the applicability of this paper's comprehensive method in college physical education teaching and sports training.

2. Analysis of the research methodology of sports posture

The key points of the human body are obtained using hourglass network extraction. The normalization matrix based on the human body joints is obtained by eliminating the abnormal frames and coordinate transformation, which makes the data collected at different places can be compared and analyzed. For different motion actions, this paper needs to select suitable calculation parameters. The effective movements are divided.

2.1. Data set and organization of research ideas

This paper focuses on analyzing the application of single target tracking and single person pose estimation in sports. The data we processed are daily training videos such as sit-ups and triple jumps for a university, each video is about 6s, and the pre-processing of the videos is done by using a cross-platform computer vision library to convert the videos into image form. These daily training videos are processed to finally get the homemade sports action dataset for the research of this paper. The resolution of the image is 1920*1080 pixels, which is relatively large, and the background of the athlete's training site is more cluttered, the number of people, and the light will have a greater impact on the extraction of the main target features. For the data with large overall resolution but small main target resolution, if we choose the direct target detection method, the problem of inaccurate and incomplete detection will occur, and secondly, in the case of only focusing on the main target and ignoring other targets in the background, we choose the single-target tracking method for feature extraction given the initial frame, so that we can complete the tracking and key-point extraction tasks with continuous iteration based on the initial value. The top-down method is based on target detection, the hourglass network can be used for single target detection tracking, there is the generation of target frame, and it is frame by frame to complete the detection, at the same time, inspired by the process of attitude processing, the detection-tracking-attitude estimation process is taken as the processing idea of this paper, which not only solves the problem of the matching algorithm's low accuracy, but also avoids the problem of the detection accuracy caused by the too high resolution.

2.2. Single person pose estimation based on hourglass network

2.2.1. Key point extraction

DeepPose is a transition method from classical to CNN in pose estimation, using the network to directly regress the coordinates of keypoints, and another class of methods to obtain heat maps of keypoints through multi-scale feature fusion. The Hourglass Network builds on both, exploring how to capture information across scales and adapting its approach to fuse features of different resolutions, using simple nearest-neighbor up-sampling and layer-hopping connectivity structures to achieve top-down processing. The hourglass network processes and merges all scale features based on pooling and up-sampling successive operations, and then obtains a pixel-by-pixel output, pooling to low-resolution features and then up-sampling to high-resolution, while fusing the features of the same resolution in the corresponding pooling descent process to avoid losing information. In addition, the symmetric topology of hourglass network realizes that forward and reverse direction prediction can improve the attitude estimation accuracy. The hourglass network outputs a set of heat maps, takes the highest-scoring point on each heat map as the key point of each corresponding joint, and then combines these key points to get the key points of the whole human body.

2.2.2. Elimination of anomalous frames and coordinate transformations

After obtaining the 3D joint data, these 3D joint coordinates are stored into a matrix. Taking the sit-up movement as an example, it can be regarded as a combination of movements with the hip as the fulcrum and the rest of the joints moving around the hip. Therefore, this paper focuses on the hip coordinate points under each frame in the coordinate matrix. If the hip coordinates do not exist in a particular frame, the entire coordinate information representing that frame is anomalous and it is eliminated. This operation can reduce the phenomenon of human body grid jitter when rendering videos and improve the accuracy of motion detection and counting.

Subsequently, a clear coordinate matrix is obtained which follows the image pixel coordinate system. However, this coordinate matrix cannot be directly used to recognize actions because different internal camera parameters, or different shooting distances and angles, may lead to inaccurate calculation of subsequent parameters. Therefore, the coordinate matrix needs to be converted into a normalized matrix based on human joints.

Most exercises have a unique fixed axis point of motion. For the sit-up movement, this paper uses the hips as the axis point and translates the coordinate system with the horizontal floor to the right as the x-axis. This transformation allows the algorithm to describe the motion in a relatively consistent manner, independent of the angle and distance of the shot.

By converting the coordinate matrix to a normalized matrix based on the joints of the human body, it is possible to more accurately describe the movement. This process involves calculating the position and orientation of each joint and describing them with a uniform coordinate system. This normalization process allows data collected in different locations to be compared and analyzed. In addition, this choice of coordinate system allows for easier classification and identification of different movements, which improves the performance of the model.

2.2.3. Parameter calculations

Under the current step, for different exercise movements, this paper needs to select suitable calculation parameters. Taking sit-up movement as an example, rotation can be detected by calculating cosine similarity and distance by calculating Euclidean distance. The cosine similarity calculation is shown in equation (1):

$$\theta_i = \cos^{-1}\left(\frac{\vec{t}_i \times \vec{y}_i}{\|\vec{t}_i\| \times \|\vec{y}_i\|}\right) \tag{1}$$

where $\vec{t}_i$ and $\vec{y}_i$ denote the vectors on which the lines connecting the joints are located, respectively, and θ_i denotes the angle between the vectors less than 180°, and the Euclidean distance is calculated as shown in Equation (2):

$$d\left(\vec{t}_i, \vec{y}_i\right) = \sqrt{\sum_{j=1}^{3}\left(\vec{t}_{i,j} - \vec{y}_{i,j}\right)^2} \tag{2}$$

where $\vec{t}_{i,j}$, $\vec{y}_{i,j}$ denote the intercept between two points in each direction. The side of the joint (left or right) is distinguished according to the orientation of the body. Several major joint angles are calculated:

$\alpha_{body} = \angle p1p2p4$ denotes the angle of the torso during movement;

$\alpha_{knee} = \angle p3p2p4$ indicates the angle of the knee to the ground during movement;

$\alpha_{ankle} = \angle p4'p2p4$ indicates the angle of the ankle to the ground during movement;

$\alpha_{wrist} = \angle p5p2p1$ represents the angle of the wrist to the upper body during movement.

2.2.4. Classification of possible action intervals

In the sit-up exercise, $\alpha_{body} = \angle p1p2p4$ is the main criterion for determining whether a sit-up procedure is passable or not. Once the key parameters are calculated for each frame, the effective frames in the video are started to be divided into multiple sets of candidate event frame datasets. Each frame dataset consists of a portion of frames belonging to a sit-up event. The process is as follows:

(1) Tentatively, the torso angle of the sit-up maneuver when sitting up is 95°, which is called the standard end-frame angle α_{end}. First, the first frame is defined as the start frame f_s;

(2) Then check whether angle α_{body} is less than the standard end-frame angle α_{end} frame by frame backward from start frame f_s. If a frame is found, the current loop stops and defines this frame as e_i. Subscript i denotes the serial number of the frame data set;

(3) Angle α_{body} is then checked within $\left(f_s, e_i\right)$, looking forward from frame e_i to the start frame $s_i\left(\alpha_{body} \geq \alpha_{start}\right)$, where α_{start} denotes the standard start angle, representing the torso angle when lying flat in a supine position, which is tentatively set at 160° here.

(4) If s_i is obtained in step (3), divide the current possible action frame interval into $F_i = (s_i, e_i)$. If s_i is not found, it means that the current frame set is not a valid sit-up action and the possible action frame interval will not be divided.

(5) If e_i is not the last frame of the video, e_i is used as the start frame f_s. Then the current loop ends and jumps back to step (2) to loop again. If e_i is the last frame, the algorithm jumps to step (6).

(6) Under the current step, it means that all frames are checked and the whole detection process is finished. $F = (F_1, F_2, \cdot, \cdot, F_n)$ denotes the set of possible motion frame intervals, and n is the number of possible complete motion processes.

2.3. Dynamic Time Warping (DTW) algorithm based on attitude feature differences

2.3.1. Description of the DTW algorithm based on differences in attitude features

The DTW algorithm is based on the idea of dynamic programming, which can be similar to the extension or shortening operation for two time series of different lengths, and the similarity between them is measured by the obtained regularized path distance, which is expressed by using the sum of the distances between all similar points. Figure 1 shows two sequences over a period of time. As shown in Figure 1, the two dark solid lines above and below on the two time series, and the light dashed line connecting the two points in the middle represent the points that are similar among them:

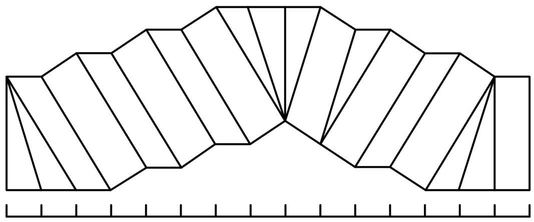

Figure 1. Two sequences over time

Assuming that it consists of two time series of lengths $X = \{x_1, x_2, \ldots, x_n\}$ and $Y = \{y_1, y_2, \ldots, y_m\}$, respectively, and lengths $|X| = n$ and $|Y| = m$, respectively, and defining its regularized path $W = \{w_1, w_2, \ldots, w_k\}$, where $\max(n,m) \le k \le n+m$, w_k is of the form (i, j), where i denotes the i coordinates in X the matrix, i.e., the i th element of sequence X, and j denotes the j coordinates in Y the matrix, i.e., the j th element of sequence Y, the computation of sequence similarity for DTW calculations of X and Y is as follows :

(1) Construct a matrix D of size $n \times m$ with matrix elements $d_{ij} = dist(x_i, y_j)$. where $dist$ denotes the distance computation function, d_{ij} is the degree of difference between the features in frame i of the action to be matched and the features in frame j of the template action, whose value is usually expressed as the Euclidean distance between the two features, with smaller values indicating that the actions in the two frames are more similar.

(2) Search for the shortest path from d_{11} to d_{nm} in matrix D, at position d_{ij}, the regularized path search must start at $w_1 = (1,1)$ and end at $w_k = (n,m)$ to ensure that every element in X and Y occurs in W, and additionally i and j of $w_{ij} = (i, j)$ in W must be monotonically increasing to ensure that the dotted lines do not intersect in Fig. 1, and to ensure that the monotonically increasing condition is as shown in Eq. (3).

$$w_k = (i, j), w_{k+1} = (i', j') i \le i' \le i+1, j \le j' \le j+1 \tag{3}$$

(3) Take the minimum value of Euclidean distance i.e. $\min\left[d_{i+1,j}, d_{i,j+1}, d_{i+1,j+1}\right]$ as the next node of the regularized path in the three search directions until the search ends with d_{nm}.

(4) The sum of the shortest path distances from d_{11} to d_{nm} in matrix D is taken as the regularized path distance by the previous step, i.e., it is the similarity of the sequences of X and Y,

and the dynamic planning process is shown in Equation (4).

$$D(i,j) = dist(i,j) + \min[D(i-1,j), D(i,j-1), D(i-1,j-1)] \tag{4}$$

(5) Finally, the shortest regularized path W is obtained with a regularized path distance of $D(n,m)$.

2.3.2. Implementation of DTW algorithm based on attitude feature differences

In the sports-oriented basic movement teaching research, the teacher's movement is referred to evaluate whether the student's movement is correct or not, and the similarity between the student's movement and the teacher's movement is calculated with the DTW algorithm based on the difference of gesture features as described above, and the smaller the distance between the regularized paths of the data sequences of the two movements, the higher the similarity degree of the two movements is.

The sequence of action gesture features to be matched $P = \{p_1, p_2, \ldots p_i, \ldots, p_n\}$ and the sequence of template action gesture features $Q = \{q_1, q_2, \ldots q_j, \ldots, q_m\}$, where p_i and q_j are the human body difference gesture feature vectors of the action in the frame, i.e., $p_i = (x_{i1}, x_{i2}, \ldots, x_{i21})$ and $q_j = (y_{j1}, y_{j2}, \ldots, y_{j21})$, respectively, and the similarity of the two frames of the action is judged by solving the Euclidean distance between the gesture features of the action, then the Euclidean distance similarity of the action in the i th frame of the sequence to be matched to the action in the j th frame of the template sequence is represented as shown in Eq. (5).

$$d(i,j) = \frac{1}{21}\sqrt{(x_{i1}-y_{j1})^2 + (x_{i2}-y_{j2})^2 + \cdots + (x_{i21}-y_{j21})^2} \tag{5}$$

The Euclidean distance is used to indicate the similarity of two features, the smaller the distance means the more similar, the larger the distance means the less similar. When the distance is 0 in the ideal standard case, it means that the two features are exactly the same, and it can be determined that the two actions are exactly the same; the posture feature information is standardized radian system data, and the distance is less than 2π in the extreme non-standard case, and the DTW algorithm matching with Euclidean distance as similarity can be very good for the optimal regular path search, but it is difficult to quantitatively score the different people doing the same action, so Redefine the search conditions of the maximum matching principle of the regularized path, score the Euclidean distance to convert the similarity measure to between $[0,1]$, that is: the smaller the distance, the greater the similarity, the specific calculation is shown in Equation (6).

$$sim(i,j) = \frac{1}{1+d(i,j)} \tag{6}$$

The above equation takes $sim(i,j) = 1$ at distance $d(i,j) = 0$ in the ideal case and further multiplies it by 100, with a percentization value of 100, indicating that the action in frame i of the sequence to be matched has an action score of $Score(i,j)$ with respect to the action in frame j of the template sequence, as shown in Eq. (7).

$$score(i,j) = sim(i,j) \times 100 \tag{7}$$

Replacing the original Euclidean distance as the basis of similarity judgment in the matching process with the action score $score(i,j)$ as the basis, then the complete implementation process of the DTW algorithm based on the difference of gesture features is:

(1) Construct matrix S of size $n \times m$ and matrix element $s_{ij} = score(p_i, q_j)$, the larger value means the more similar the actions in the two frames.

(2) Search for the shortest path from s_{11} to s_{nm} in matrix S and store it in path array W with the same search direction and monotonicity principle.

(3) Take the maximum value of the action score in the three search directions, i.e., $\max[s_{i+1,j}, s_{i,j+1}, s_{i+1,j+1}]$, as the next node of the regularized path until the search ends at s_{nm}.

(4) The sum of the scores of the shortest paths from s_{11} to s_{nm} in matrix S is taken as the distance of the regularized path, i.e., the similarity of the sequences of X and Y, and the dynamic

planning process is changed as shown in Eq. (8).

$$S(i,j) = score(i,j) + \max[S(i-1,j), S(i,j-1), S(i-1,j-1)] \tag{8}$$

(5) obtain $S(i,j)$ as the sum of all frame scores of the action sequence to be matched relative to the template action sequence, and use the length of the sequence to be matched n to find the weighting value as the final score of the action sequence for Equation (9), and round the score result.

$$Grade = \frac{S(i,j)}{n} \tag{9}$$

We can stipulate that when a frame action score is lower than 60 points to judge the frame in the action does not meet the standard, but also can design the system to add their own set standard score S_0 , so that you can arbitrarily get the video frames that do not meet the preset standard score, get the deviation of the action of the larger video frame where the picture, and hope to get the deviation of the action of the larger parts of the body, give tips.

The DTW algorithm for features can get the objective results of the degree of gesture matching, to get the score of each frame and the overall score of the whole action process, when a reasonable threshold is set as the basis for judging the correctness of the action, it has a very good differentiation effect on the correct and incorrect action in the movement process, and its advantage is that it can avoid the effect of the different lengths of the sequence to be matched and the template sequence, and in the process of searching for regularized paths, through the action The advantage is that it can avoid the effect of the difference between the length of the sequence to be matched and the template sequence, and in the process of searching the regular path, through the action score, it can get the frames with large action errors.

3. Hourglass network with DTW algorithm application

This section utilizes the hourglass network to output a sequence of human skeletal keypoints. Matching experiments and analysis of key action postures are performed. Classify 6 types of actions based on similarity calculation. Compare the number of parameters of this paper's model with other models. Select student volunteers for the study of movement posture matching deviation rate.

3.1. Hourglass network based key point sequence extraction for human skeleton

The hourglass network can output the key point data of human skeleton from the BODY-25 model.The BODY-25 model has more key point data than other models, so the BODY-25 model can provide more accurate posture detection results when dealing with complex human postures. Table 1 shows the correspondence between the main key point labeling of the BODY-25 model and the joint parts of the human body. In this paper, BODY-25 model is chosen as the output format of human body posture.

Table 1. Correspond to key points of the human skeleton in BODY-25 model

Serial number	Position	Serial number	Position	Serial number	Position
0	Nose	5	L Shoulder	10	R Knee
1	Neck	6	L Elbow	11	R Ankle
2	R Shoulder	7	L Wrist	12	L Hip
3	R Elbow	8	Mid Hip	13	L Knee
4	R Wrist	9	R Hip	14	L Ankle

3.2. Experiments and Analysis of Key Action Posture Matching

The method of comparative experiments is used to understand whether the combined hourglass network of DTW algorithm has an advantage in matching success rate in different actions. The method of this paper, the direct matching method, and the RISE algorithm are chosen to match the action poses of all data samples in the homemade sports action dataset, and after the matching is completed, the matched action pose frames are compared with the human-calibrated key action pose frames, and it is intuitively judged whether the matching is successful or not by determining whether there exists a more suitable matching frame.

Figure 2 shows the matching success rate of the three methods in six types of movements: standing long jump, deep squat jump, open and close jump, lunge jump, high leg lift and knee hold jump. Among them, the horizontal coordinate numbers 1-6 represent the six types of movements of standing long jump, deep squat jump, open and close jump, lunge jump, high leg lift and knee hold jump, respectively. From the results, it can be seen that the matching success rate of this paper's method for the six types of movements, namely, standing long jump, deep squat jump, open and close jump, lunge jump, high leg raise and knee-hold jump, ranges from 70.52% to 90.43%, which is better than that of the direct matching method, which is 21.39% to 43.21%, and that of the RISE algorithm, which is 60.32% to 82.66%, and the more complicated the movements are, the more difference there is between the matching success rate of this paper's method and that of the other methods. The more complex the action, the greater the difference between the matching success rate of this paper's method and that of the other methods. The fundamental reason is that the direct matching method directly matches each element in the input human joint angle sequence and the template human joint angle feature sequence in sequence, and does not solve the problem of time axis difference. While the RISE algorithm solves the problem of timeline difference by temporal ordering of the human skeleton key point sequence, it does not solve the problem of inconsistent size of the human skeleton caused by the differences in camera distance and human body size. Therefore, the effect is not ideal when matching alignment for action videos with inconsistent camera distance and large differences in human body size.

Meanwhile, from the results, it can be observed that the matching success rate of this paper's method for five types of actions, namely, standing long jump, high leg lift, open and close jump, push-up and lunge jump, does not exceed 90%, which is due to the fact that some of the samples of the action videos in the motion data set are not shot in a frontal perspective, which makes the extracted human joint angle features not able to express the human body's action gesture information in the action video well, resulting in The success rate of matching key action frames in this part of the action video is not high enough. Therefore, when applying the method of this paper to assist teaching and research, college physical education teachers need to pay attention to the problem of the shooting angle of students' exercise videos, in order to improve the matching success rate of this paper's method, so as to better make the corresponding training adjustment program.

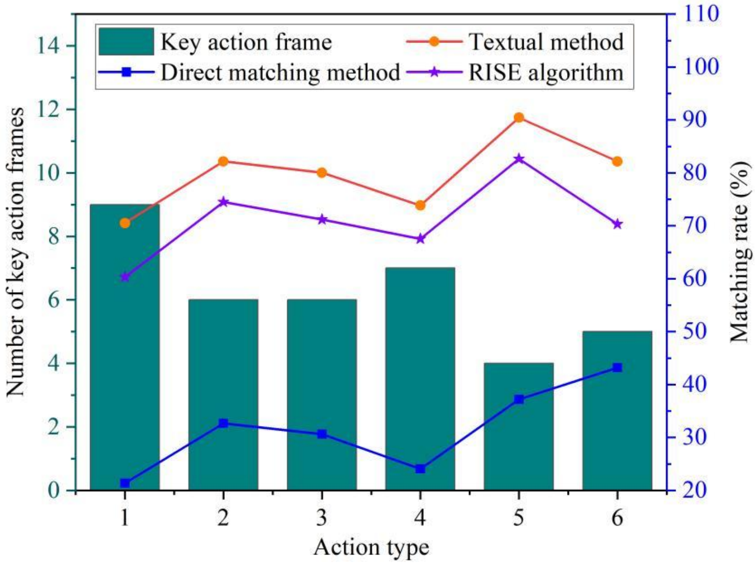

Figure 2. The success rate of key action posture matching of the three methods

3.3. Classification accuracy study based on similarity calculation

Based on the idea of minimum distance classification, for the homemade exercise action dataset in the previous section, the canonical human actions corresponding to the 6 action categories selected in subsection 3.2 are used as template actions, and the 6 categories of actions in the homemade exercise action dataset are categorized by the method of this paper. That is, under this paper's method, each test action sample is calculated with the 6 template actions for action similarity respectively, and the template action with the largest similarity is identified as the action category identification result. Figure 3 shows the confusion matrix of the classification results of this paper's method, in which the horizontal coordinates 1-6 represent the six categories of movements, namely, standing long jump, deep squat jump, open and close jump, lunge jump, high leg raise and knee-hold jump, respectively. It can be seen that the method in this paper achieves better classification results in the homemade sports movement data set. For the 4 categories of standing long jump, squat jump, open and close jump, lunge jump, the number of classification errors is 0, 0, 2, 0, but in the 2 categories of leg raising and knee-holding jump, the number of errors reaches 9 and 10 times. Analyzing the reason, it may be that the 4 types of movements such as standing long jump have obvious technical movement characteristics, so it is easier to discriminate and the classification accuracy is higher; while the technical movement characteristics of high leg raising and knee-holding jump are closer to each other, and for the videos of movements that are not filmed from the frontal viewpoint, the angle recognition error will occur.

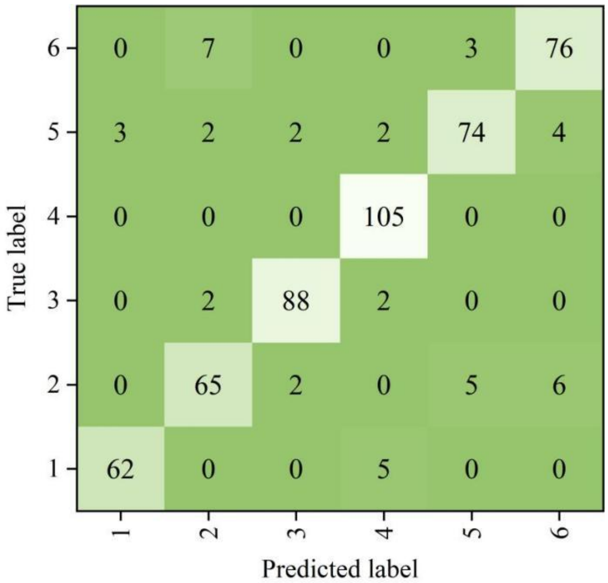

Figure 3. Confusion matrix of the classification results of this method

3.4. Comparative analysis of the number of model participants

Due to the small amount of data in the homemade motion action dataset of this paper, the performance of the optimized hourglass network is further compared and investigated in this section using the val2018 validation set and test2018 test set, which have a larger amount of data. Table 2 demonstrates the performance results obtained for the optimized hourglass network with multiple human pose estimation networks on the val2018 validation set. Since the fixed input size for this experiment is 1920*1080 pixel size image, the same input size is used for the comparison network.

By analyzing the experimental results of different network models on the val2018 validation set, it can be concluded that the optimized hourglass network is the least in terms of the number of parameters when the input size is the same, with a model parameter count of only 13.1 M. Compared to the Hourglass model and the CPN model, the optimized hourglass network parameter counts have been reduced by 12.1 M and 14 M, respectively. The optimized hourglass network reduces the number of parameters by 41M compared to SimpleBascline. The reduction in the number of model parameters does not have much effect on the detection accuracy of the optimized hourglass network, and the AP values are all higher than those of Hourglass, CPN, and SimpleBascline. Overall, the optimized hourglass network combines both model lightweight and high level of keypoint recognition accuracy, and outperforms most of the human posture estimation models. The lighter the network model, the more advantageous it is when embedded in a mobile device when helping college teachers to make corrections to students' movement postures.

Table 2. Experimental results of val2018 verification set

Model	Argument	GFLOPs	AP	AP^{50}	AP^{75}	AP^{M}	AP^{L}	AR
Hourglass	25.2M	14.2	66.8	-	-	-	-	-
CPN	27.1M	6.3	68.7	-	-	-	-	-
CPN+OHKM	27.1M	6.3	69.5	-	-	-	-	-
SimpleBascline	54.1M	12.5	71.5	89.4	79.4	68.2	78.2	77.2
Hourglass+DTW	13.1M	6.1	73.9	89.9	81.3	70.2	80.4	79.4
HRNet	63.7M	14.7	75.2	90.7	82.3	71.4	81.9	80.5

Table 3 shows the experimental results of the optimized hourglass network with multiple human pose estimation network models on the test2018 test set. In the test2018 test set experiments, the top-down optimized hourglass network significantly outperforms the bottom-up human posture estimation model, with an AP value 12.2% higher than the OpenPose model. The number of parameters of the optimized hourglass network also dominates compared to other top-down models.

Table 3. Experimental results of test2018 verification set

Model	Argument	GFLOPs	AP	AP^{50}	AP^{75}	AP^{M}	AP^{L}	AR
OpenPose	-	-	61.5	84.8	67.6	57.2	68.3	66.6
Mask-RCNN	-	-	63.2	87.4	68.8	57.9	71.5	-
IPR	45.1M	11.1	67.9	88.3	74.9	63.8	74.1	-
CPN	27.1M	6.3	72.2	91.5	80.1	68.8	77.3	78.6
G-RMI	42.7M	57.1	64.8	85.6	71.2	62.4	70.1	69.8
Hourglass+DTW	13.1M	6.3	73.7	89.6	81.2	70.3	79.4	78.8

3.5. Motion Attitude Matching Deviation Rate Study

After extracting the key points of the human skeleton through the hourglass network and extracting the posture matching features based on the key point information, the DTW algorithm was used to match and calculate the scoring of the human movement postures. The matching movements used in the test included wide stance deep squat, lunge front squat, lunge spread and lunge turn. In order to make the matching results more realistic, three students with different body types were selected as testers for the posture comparison experiment.

Table 4 shows the results of the three testers' scores in the exercise posture matching test. The three testers did four groups of different types of exercise movements and got a total of 12 movement scores. The largest deviation rate was 26.2% for the A2 tester's matching test for the lunge spread movement. Overall the deviation rate of the scores for the excellent and unqualified phases was relatively low, ranging from 3% to 6%, while the deviation rate for the qualified phase was relatively high, basically above 9%. The reason for this phenomenon may lie in the wide range of scores in the passing stage, and the possibility of deviation between the calculated scores and the human scores is higher. After obtaining the overall motor posture similarity score, the teacher can extract the key frames of irregular movements from the lower-scoring movements, and target the improvement of students' motor posture accuracy by observing irregular body movements and combining them with the teacher's own standardized body movements.

Table 4. Scores of motion posture matching test

Action class	Tester	Action evaluation	Calculate score	Manual scoring	Deviation rate
Wide position squat	A1	Outstanding	91	94	3.19%
	A2	Up to standard	81	78	3.85%
	A3	Up to standard	66	70	5.71%
Lunge forward squat	A1	Up to standard	83	76	9.21%
	A2	Up to standard	77	83	7.23%
	A3	Outstanding	92	95	3.16%
Lunge spread	A1	Up to standard	83	75	10.7%
	A2	Up to standard	77	61	26.2%
	A3	Up to standard	72	82	12.2%
Lunge twist	A1	Outstanding	95	92	3.26%
	A2	Up to standard	80	89	10.1%
	A3	Below standard	57	54	5.56%

4. Conclusion

In this paper, the hourglass network and DTW algorithm are comprehensively applied to physical education teaching and sports training in colleges and universities, which is used as an auxiliary teaching resource to help teachers visualize and analyze the students' sports posture problems and give personalized guidance suggestions based on the scores. Through comparative experiments, it is found that the success rate of this paper's method in key action posture matching can reach up to 90.43%, and the lowest is more than 70%, which is higher than other posture matching methods. The classification accuracy of this paper's method is higher in action types with obvious technical action characteristics, and the number of classification errors is mostly at 0. In action types with more similar technical action characteristics, the number of classification errors increases, but overall, the classification accuracy of this paper's method is higher. In the test set, this paper's method is the least in the number of parameters, only 13.1M, and the AP value is higher than most of the comparison models, verifying that the hourglass network combined with the DTW algorithm combines the advantages of both model lightweight and high level of key point identification accuracy. In the study of motion pose matching deviation rate, it is found that the scoring deviation rate of this paper's method for excellent and unqualified stages is no more than 6%, which is relatively low. And due to the large range of qualified phases, the deviation rate for qualified phases basically exceeds 9%, which is relatively high. Overall, the deviation rate of sports posture matching of this paper's method is in the normal range.

Physical education teachers in colleges and universities can comprehensively use the hourglass network and DTW algorithm to extract students' human body keypoints and posture matching characteristics, and compare the students' posture characteristics with teachers' standard posture characteristics for scoring, thus judging the students' sports posture problems in the physical education courses and daily sports training, and carefully researching the corresponding posture corrective methods to help the students improve the sports posture problems, and improve the level of athletic and enthusiasm for sports.

References

1. Liu, J., Shangguan, R., Keating, X. D., Leitner, J., & Wu, Y. (2017). A conceptual physical education course and college freshmen’s health-related fitness. Health Education, 117(1), 53-68.
2. Huang, J., Wang, S., Zhu, J., Cai, J., & Jiang, B. (2024). Research on Teaching Idea Innovation of University Physical Education Teachers. Quality in Sport, 31, 56003-56003.
3. Zhang, Z., & Li, S. (2024). A Study on the Development of Professional Training in Physical Education in Colleges and Universities under Information Technology. Applied Mathematics and Nonlinear Sciences, 9(1).
4. huan, L. J. (2020, June). Discussion on the application of artificial intelligence technology in the construction of physical education class in higher vocational college. In 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) (pp. 297-300). IEEE.
5. Guo, H., & Zhang, L. (2021). Online evaluation system of college physical education students based on big data and artificial intelligence technology. In Frontier Computing: Proceedings of FC 2020 (pp. 459-465). Springer Singapore.
6. Hao, L., & Zhou, L. M. (2022). Evaluation index of school sports resources based on artificial intelligence and edge computing. Mobile Information Systems, 2022(1), 9925930.
7. Wan, J. (2024). Artificial Intelligence and Fuzzy Logic Approach Based Aerobic Physical Education Training in Colleges. Journal of Multiple-Valued Logic & Soft Computing, 42.
8. Li, N., & Xue, Y. (2022). Artificial Intelligence-Based Assessment of Physical Education and Training Effectiveness. Computer-Aided Design and Applications, 75-84.
9. Ma, Z., Xin, C., & Zheng, H. (2021). Construction of a teaching system based on big data and artificial intelligence to promote the physical health of primary school students. Mathematical Problems in Engineering, 2021(1), 9777862.
10. Sun, Q. (2021). Current school sports intelligence system based on artificial intelligence and Internet of things technology. In 2020 International Conference on Applications and Techniques in Cyber Intelligence: Applications and Techniques in Cyber Intelligence (ATCI 2020) (pp. 625-632). Springer International Publishing.
11. Ma, T., Huynh, T. N., Tran, V. C., Phan, B. C., Pham, N. K., & Do, T. N. (2023, October). PETSAI: Physical Education Teaching Support with Artificial Intelligence. In International Conference on Intelligent Systems and Data Science (pp. 227-242). Singapore: Springer Nature Singapore.
12. Lv, Z., & Song, S. (2020, August). Integration of artificial intelligence plus industry and sports industry: a research on the innovation and development strategy of sports industry. In 2020 International Conference on Sports Sciences, Physical Education and Health (ICSSPEH 2020) (pp. 7-12). Atlantis Press.
13. Su, Z. (2022). Artificial intelligence in the auxiliary guidance function of athletes’ movement standard training in physical education. Journal of circuits, systems and computers, 31(11), 2240001.

14. Ma, S. (2022). College sports intelligence using human–computer interaction system for education. International Journal of Human–Computer Interaction, 1-9.
15. Cao, Q., & Yu, Q. (2024). Application analysis of artificial intelligence virtual reality Technology in Fitness Training Teaching. International Journal of High Speed Electronics and Systems, 2440084.
16. Chen, R., Wang, T., & Kim, S. (2023). Optimizing teaching management in college physical education: A fuzzy neural network approach. Soft Computing, 27(24), 19299-19315.
17. Jiang, C. (2024). Hybrid Teaching Mode of Physical Education with Sports Games Based on Artificial Intelligence. KSII Transactions on Internet & Information Systems, 18(11).
18. Wen, J. (2021, April). Innovative application of artificial intelligence technology in college physical education. In Journal of Physics: Conference Series (Vol. 1881, No. 4, p. 042028). IOP Publishing.
19. Jiang, X., Du, Y., & Zheng, Y. (2024). Evaluation of physical education teaching effect using Random Forest model under artificial intelligence. Heliyon, 10(1).
20. Zhang, B., Jin, H., & Duan, X. (2022). Physical education movement and comprehensive health quality intervention under the background of artificial intelligence. Frontiers in Public Health, 10, 947731.
21. Wang, Y., & Wang, X. (2024). Artificial intelligence in physical education: comprehensive review and future teacher training strategies. Frontiers in Public Health, 12, 1484848.
22. Li, S., & Gu, X. (2023). A risk framework for human-centered artificial intelligence in education. Educational Technology & Society, 26(1), 187-202.
23. Tao, B., Díaz, V., & Guerra, Y. (2019). Artificial intelligence and education, challenges and disadvantages for the teacher. Arctic Journal, 72(12), 30-50.
24. Haldar, S. K. (2024, August). PRIVACY AND SECURITY IN AI EDUCATION FOR GENDER STUDIES. In ARTIFICIAL INTELLIGENCE IN EDUCATION (p. 39).
25. Rospigliosi, P. A. (2023). Artificial intelligence in teaching and learning: what questions should we ask of ChatGPT?. Interactive Learning Environments, 31(1), 1-3.
26. Zhang, H. (2020, April). Value and Development Ideas of the Application of Artificial Intelligence in Sports Training. In Journal of Physics: Conference Series (Vol. 1533, No. 3, p. 032049). IOP Publishing.
27. Choudhury, R. D. (2024). Exploring Technology Integration in Coaching and Training: A New Frontier in Physical Education and Sports. Modern Trends in Multi-Disciplinary Research (Vol-1).
28. Li, S., Wang, C., & Wang, Y. (2024). Fuzzy evaluation model for physical education teaching methods in colleges and universities using artificial intelligence. Scientific Reports, 14(1), 4788.
29. Jie, Y., Guangding, H., & Xiangyu, H. (2024). The Integration of Artificial Intelligence Technology in College Physical Education: Innovation and Challenges. Curriculum and Teaching Methodology, 7(3), 175-180.
30. Cudicio, A., Sangalli, S., Lucaccioni, L., & Borgogni, A. (2024). ARTIFICIAL INTELLIGENCE IN PERSONALIZING PHYSICAL EDUCATION: A TWO-YEAR STUDY. ITALIAN JOURNAL OF HEALTH EDUCATION, SPORT AND INCLUSIVE DIDACTICS, 8(2).
31. Guo, H. (2022). Research on the construction of the quality evaluation model system for the teaching reform of physical education students in colleges and universities under the background of artificial intelligence. Scientific Programming, 2022(1), 6556631.
32. Liu, Z., Wang, J. W. K. Z. Y., & Kuan, Q. L. G. (2024). Innovation and Opportunities of Artificial Intelligence in University Sports Education: A Review. Quality Physical Education in Active School and its Perspectives. Researches-Best Practices-Situation., 137.
33. Xu, M., Liu, D., & Zhang, Y. (2022). Design of interactive teaching system of physical training based on artificial intelligence. Journal of Information & Knowledge Management, 21(Supp02), 2240021.

34. Yu, H., & Mi, Y. (2023). Application model for innovative sports practice teaching in colleges using internet of things and artificial intelligence. Electronics, 12(4), 874.
35. Li, G. (2021, January). Research on AI Technology and the New Era of Physical Education. In 2021 International Conference on Information Technology and Contemporary Sports (TCS) (pp. 619-623). IEEE.
36. Cao, F., Lei, M., Lin, S., & Xiang, M. (2022). Application of Artificial Intelligence‐Based Big Data AI Technology in Physical Education Reform. Mobile Information Systems, 2022(1), 4017151.
37. Su, Z., Li, L., & Su, Y. (2024). Transforming College Physical Education: Exploring the Integration of Artificial Intelligence Technology. Fitness, Performance and Health Journal, 3(1), 29-38.
38. Guo, R. (2024). Analysis of artificial intelligence technology and its application in improving the effectiveness of physical education teaching. International Journal of Web-Based Learning and Teaching Technologies (IJWLTT), 19(1), 1-15.