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Article

Basketball Training Movement Pattern Recognition and Personalized Teaching Strategy Design Based on Multidimensional Data Analysis

Yu Lei *

School of Physical Education, Huazhong University of Science and Technology, Wuhan 430074, Hubei, China; ray9889@126.com

Abstract: Basketball is a sport with a broad grassroots following, and its scientific research value has also garnered significant attention. Currently, most basketball training content is based on coaches' experience and intuition when training athletes, lacking unified standards and personalized guidance. To address the issues of disorganized data and unclear objectives during training, this paper proposes a method that integrates a dual-stream convolutional neural network with a long short-term memory network, based on video analysis techniques, motion trajectory tracking, and knowledge graph construction technology. It also employs a diffusion probability model for player synthesis, a Monte Carlo optimization model for shot strategy decision-making, and multi-object tracking technology to resolve the issue of mutual obstruction between players, the ball, and the court during games. Through actual testing, it was found that the model and algorithms constructed in this paper not only improve training effectiveness but also provide personalized, targeted technical improvement suggestions for different individuals. By fully utilizing mechanical analysis and motion trajectory tracking methods, as well as machine learning and computer vision algorithms, this study enhances the scientific nature of basketball training and provides new insights and methods for technical analysis research and training content development in other sports fields.

Keywords: basketball training; multidimensional data analysis; motion pattern recognition; personalized instruction; machine learning

1. Introduction

1.1. Research Background and Significance

Basketball is one of the most popular sports worldwide, not only promoting physical and mental health and fostering positive interpersonal relationships but also contributing to sports science research. As basketball continues to evolve, there is an increasing demand for scientifically sound training methods and personalized approaches tailored to individual athletes' needs. Particularly, how to enhance basketball training methods and overall basketball skills has become a central focus in current basketball training [1-2]. Traditionally, coaches have evaluated and guided training methods based on their own experience and intuitive understanding, without a measurable standard or a scientific and effective evaluation system [3-4]. Especially since basketball training is a sport with high difficulty and diversity in movements, and athletes have individual differences, it is challenging to achieve personalized training for each athlete [5].

In recent years, with the development of artificial intelligence technology and data statistical analysis technology, training methods based on multi-dimensional data analysis have gradually been incorporated into basketball training [6]. The vast amounts of data generated by players during training activities, including video data, motion data, and movement trajectory data, can serve as reference data for evaluating players' athletic performance and tactical abilities [7-8]. Through advanced deep learning technologies and computer vision methods, valuable data content can be extracted from large datasets,

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enabling precise and personalized training guidance for athletes. The analysis of movement trajectory data and video data provides a foundation for tactical action recognition and pattern recognition in basketball training, enabling the precise capture of players' movement details and behavioral patterns [9-11]. By analyzing and interpreting the tactical and technical movement patterns of players' training in a more accurate and objective manner, it is possible to design reasonable and effective tactical and technical training programs based on the specific circumstances of the players, thereby better promoting the improvement and development of their skills.

In addition, the integration of knowledge graphs and multimodal data allows for a more comprehensive and multidimensional combination of information during the training process [12]. In basketball, combining video information, movement trajectory information, and professional knowledge enables more comprehensive and intelligent training, and can effectively help athletes with personalized training by creating customized training plans for each player.

1.2. Innovative Aspects of This Study

First, through statistical analysis of a large number of basketball players' movement videos, it was found that current data mining techniques struggle to accurately capture athletes' movement details through single-dimensional data analysis. Therefore, a multi-dimensional data analysis research scheme was proposed to address this issue, comprehensively utilizing data video, data trajectory, and data knowledge graph analysis techniques. The multi-dimensional data employed in this experimental scheme includes an improved dual-stream neural network model. The spatial stream branch of this neural network structure adopts a multi-scale feature fusion network architecture to capture more precise movement details, while the temporal stream branch utilizes a bidirectional attention mechanism to identify additional movement trajectory information. To address the challenges in modeling and analyzing athletes' movement states, a diffusion probability model is incorporated into the framework. The behavioral modeling of basketball athletes is processed using layer-wise diffusion techniques, combined with historical game data from professional basketball leagues and tactical knowledge models learned from data training, through a Gaussian mixture algorithm. The tactical distributions learned by machine learning are optimized to achieve a maximum value (reward). To meet the requirements for evaluating movement actions, a convolutional memory network combined with an improved Gaussian mixture network is used to establish a corresponding visual spatio-temporal evaluation mechanism.

To further enhance the system's operability, a knowledge-based multimodal video commentary generation network is studied. Under the synergistic effect of its cross-modal alignment and hierarchical knowledge injection modules, it effectively integrates video information and professional knowledge. A tracking algorithm based on trajectory and appearance feature fusion achieves good results in addressing complex target tracking in court obstructions. Based on the aforementioned new technologies and algorithms, a real-time commentary video intelligent teaching strategy system based on Monte Carlo tree search is designed and studied. Specifically, the system relies on Monte Carlo tree search technology and a reinforcement learning framework to dynamically analyze athletes' competition situations and formulate corresponding training guidance strategies in real time based on athletes' current video feedback. The system has been applied to different training scenarios and is of great significance for the scientific analysis of basketball training and other training techniques.

2. Literature Review

2.1. Theoretical Basis of the Study

Neural network structures play a key role in basketball motion recognition research. The local connections and weight sharing mechanisms of convolutional neural networks lay a solid foundation for visual feature extraction [13]. Local features are effectively captured through the dot product operation between the convolutional layer and the input data. Let the input feature map be x , the convolutional kernel be w , and the bias term be b . The output y of the convolutional layer can be expressed as:

$$y = f\left(\sum_{i,j} w_{ij} x_{i+m,j+n} + b\right) \tag{1}$$

In the equation, the activation function f and the center coordinates (m,n) of the convolution kernel work together to enable the convolutional neural network to perform excellently in spatial feature extraction. For video sequence modeling requirements, the long short-term memory network relies on its unique gating mechanism and the update mechanism of the memory unit c_t , namely:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{2}$$

To handle temporal relationships, the collaborative work of the forget gate f_t, input gate i_t, and candidate memory unit $\tilde{c}_t$ makes action sequence analysis more accurate. The diffusion probability model synthesizes player behavior by adding Gaussian noise and learning the reverse diffusion process. The model training objective is expressed as:

$$L = E_{x_0,\epsilon}[\|\epsilon - \epsilon_\theta(x_t,t)\|^2] \tag{3}$$

The combination of standard Gaussian noise ϵ and neural network prediction noise ϵ_θ provides a new approach to action generation.

In action pattern clustering research, Gaussian mixture models describe data distributions as weighted combinations of multiple Gaussian distributions, which can be expressed as:

$$p(x) = \sum_{k=1}^{K} \pi_k N(x \mid \mu_k, \Sigma_k) \tag{4}$$

In the formula, the mixing weights π_k and Gaussian distribution parameters μ_k, Σ_k are optimized through the expectation maximization algorithm, enabling automatic classification of basketball movements. At the data integration level, multimodal fusion technology uses attention mechanisms to process different types of information. The cross-modal attention calculation formula is:

$$A = softmax(\frac{QK^T}{\sqrt{d}})V \tag{5}$$

The query Q, key-value pair K, V, and feature dimension d in the formula jointly construct the adaptive attention mechanism.

To address the problem of multiple people blocking the field of view, the multi-target tracking algorithm uses the Hungarian algorithm for target association by minimizing the problem.

$$\min \sum_{i,j} C_{ij} x_{ij}, \text{subject to} \sum_i x_{ij} = 1, \sum_j x_{ij} = 1 \tag{6}$$

To optimize the allocation relationship between detection boxes and trajectories, the design of the cost matrix c_{ij} and allocation variable x_{ij} ensures tracking effectiveness.

2.2. Current State of Research

In the field of motion recognition in basketball training: Reference [14] employs wearable devices equipped with inertial sensors to capture posture data from basketball players across multiple dimensions during movement. Principal component analysis is introduced to modify a basic convolutional neural network for posture recognition, achieving an accuracy rate as high as 99.4%. Reference [15] employed decision trees, naive Bayes, support vector machines, and backpropagation artificial neural networks to intelligently recognize athletes' limb movements (catching, passing, dribbling, and shooting) during basketball training. The backpropagation artificial neural network achieved the best recognition performance, with upper and lower limb recognition accuracies of 93.3% and 99.4%, respectively. Reference [16] established a region selection strategy and constructed static and dynamic detail models to recognize basketball movements. These models were tested under a region-filtered dual-stream model, a channel-domain attention mechanism model, and a 3D attention feature fusion module model, resulting in improved recognition accuracy while preserving the integrity of local regional information, thereby achieving a precise basketball movement recognition framework. Literature [17] applied deep convolutional neural networks in deep learning to extract features from image datasets of basketball player movements and recognize their actions, not only accelerating recognition efficiency but also improving recognition accuracy. Literature [18] combined various physical parameters from basketball movement trajectories, using computer vision and Kalman filters to develop a basketball self-shot posture tracking algorithm capable of identifying lazy postures and estimating trajectories. Literature [19] utilized computer vision image processing technology to process image data in basketball movement adaptation, followed by key point detection using the DeepLabCut model to identify athlete movements. The results were analyzed and validated using biomechanical indicators. Reference [20] constructed a basketball technical movement recognition model by integrating three-dimensional convolutional and long short-term memory networks to extract spatio-temporal relationships and temporal data from movements. The model was optimized using an adaptive learning rate, enabling accurate recognition under different lighting conditions.

In terms of personalized training strategies for basketball: Literature [21] reported that female basketball athletes, after undergoing personalized shooting training programs, corrected biomechanical defects, improved the accuracy and consistency of their shooting skills, and enhanced their confidence and motivation. Reference [22] developed an artificial intelligence coaching system that uses deep visual tracking technology and a human joint relationship model to capture human posture and posture estimation. By combining anomaly detection and visual cues from reference cases to correct the captured posture, the system generates personalized training plans. Literature [23] developed a novel intelligent cheetah optimizer supported by a flexible recurrent neural network. This system primarily acquires athletes' physiological and motion data via sensors, preprocesses the data, and then uses Z-score normalization and linear discriminant analysis to remove abnormal data and capture features, thereby identifying athletes' strengths and weaknesses to formulate personalized training strategies for basketball players.

3. Research Methods

3.1. Data Collection and Preprocessing

The experiment established a database of 4,477 hours of high-definition game video information from 40 different countries and regions based on the BASKET database. In the preprocessing and noise reduction of the original video data, signal noise reduction technology was used to suppress video noise caused by camera vibration and uneven backgrounds. The data was standardized by setting the frame rate to 30 Hz and the image resolution to 1920 × 1080. Object detection technology based on the YOLO framework was used to extract player rectangular bounding boxes, and a deep convolutional neural network-based method was employed to annotate player poses, thereby obtaining technical action annotation data information for 10 categories of motor skills. Movement trajectory information was collected using the SportVU tracking system, which recorded the spatial coordinate values of players and the ball using six high-speed cameras installed around the stadium. Due to the high degree of dispersion in the raw movement trajectory data, which includes trajectory noise and missing values, Kalman filtering is used to smooth the movement trajectory data, and cubic spline interpolation is employed to fill in missing values. Player speed and acceleration are calculated using the central difference method, i.e.,:

$$v_t = \frac{x_{t+1} - x_{t-1}}{2\Delta t}, \quad a_t = \frac{v_{t+1} - v_{t-1}}{2\Delta t} \tag{7}$$

For the acquisition of perspective information captured by head-mounted cameras, a 60Hz acquisition frequency is used to capture high-speed motion details, and a video stabilization algorithm based on optical flow is implemented to eliminate head shaking. The affine transformation matrix H between adjacent frames is used to achieve smooth processing of continuous frame videos, i.e.,:

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \tag{8}$$

During the construction of the NBA 2022 Knowledge Graph (KG_NBA_2022), a text entity recognition model based on deep learning was proposed to automatically parse professional knowledge from text data, combining player data, game data, and expert commentary. Through ontology mapping and association, a semantic knowledge graph was established for 286 players and 9 types of shooting actions. For multi-object tracking, video data from multiple fixed camera angles were obtained. Using multi-view calibration technology, a mapping relationship was established between world coordinates and image coordinates, i.e.,:

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = K[R \mid t] \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{9}$$

In the formula, K represents the camera's internal parameter matrix, and $[R \mid t]$ represents the external parameter matrix.

In this stage of data processing, a semi-automatic annotation tool was designed to use deep learning-based target detection and re-identification technologies to identify player numbers, positions, and action categories, thereby accelerating the annotation speed and ensuring annotation accuracy, which provided a guarantee for further subsequent mining.

3.2. Model Training and Evaluation

Based on a dual-stream neural network, the spatial stream backbone network uses an optimized ResNet-50 with a multi-scale feature pyramid model to better extract details. Its convolution layer basic calculation is:

$$y = f(W^{*} x + b) \tag{10}$$

In the equation, W is the weight matrix, b is the bias term, and f is the ReLU activation function.

During training, we selected the AdamW optimizer, set the initial learning rate to 0.001, decayed by 0.1 every 30 training cycles, and used a batch size of 32. The temporal stream branch is based on the design concept of the long short-term memory network. The core computation process includes input gates, forget gates, and output gates, expressed as:

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \end{aligned} \tag{11}$$

Memory unit updates follow:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)_{\psi} \tag{12}$$

The calculation expression for the hidden state is:

$$h_t = o_t * \tanh(C_t)_{\psi} \tag{13}$$

This branch performs exceptionally well in continuous action sequence recognition tasks. The motion trajectory analysis model is constructed based on a diffusion probability model, utilizing U-Net as the backbone network. During the training phase, the player position coordinates in the NBA motion trajectory dataset are standardized. Trajectory generation is learned through a process of progressive noise addition and denoising. To enhance the plausibility of the generated trajectories, constraints based on basketball rules are introduced, and reinforcement learning methods are employed to optimize the generation strategy.

In the first-person video analysis section, a convolutional LSTM network based on an attention mechanism is designed to focus on key actions such as shooting and passing. Visual spatio-temporal features are extracted and analyzed to achieve a quantitative assessment of player performance. The knowledge graph-supported multimodal video description generation network (KEANet) adopts a new hierarchical knowledge injection mechanism, where a pre-trained visual encoder extracts video features during training. Then, a cross-modal attention module aligns visual information with knowledge graph information, using cross-entropy and pre-trained language model distillation loss functions to obtain the accuracy and professionalism of the generated descriptions. The training design of the Basketball-SORT algorithm adopts an improved algorithm based on the Deep SORT framework, using Deep Association Metric to learn appearance features, combined with a Kalman filter to predict motion trajectories, and proposes a trajectory completion strategy based on field position to address issues such as complex occlusions.

During the testing phase, a professional evaluation team comprising professional coaches and athletes was assembled to conduct comprehensive testing from multiple aspects, including action judgment accuracy, trajectory prediction rationality, video description professionalism, and tracking stability. The system test results show that not only do all technical indicators meet the standards, but the training effects in actual applications also demonstrate strong adaptability and practicality. Through comparative experiments with traditional training methods, the training group using this system achieved a 23.5% increase in technical movement improvement, validating the system's effectiveness in actual basketball training.

4. Experimental Results

4.1. Basketball Action Recognition Performance

Based on the annotated dataset constructed in the preceding section, which includes 10 types of fine-grained technical movements, the basketball training movement model designed in this paper was used for basketball technical movement recognition. The results were compared with those of the baseline model, and the recognition accuracy rates of the proposed model for various basketball technical movements are shown in Table 1. In the table, ↑ indicates an improvement, and ↓ indicates a decrease.

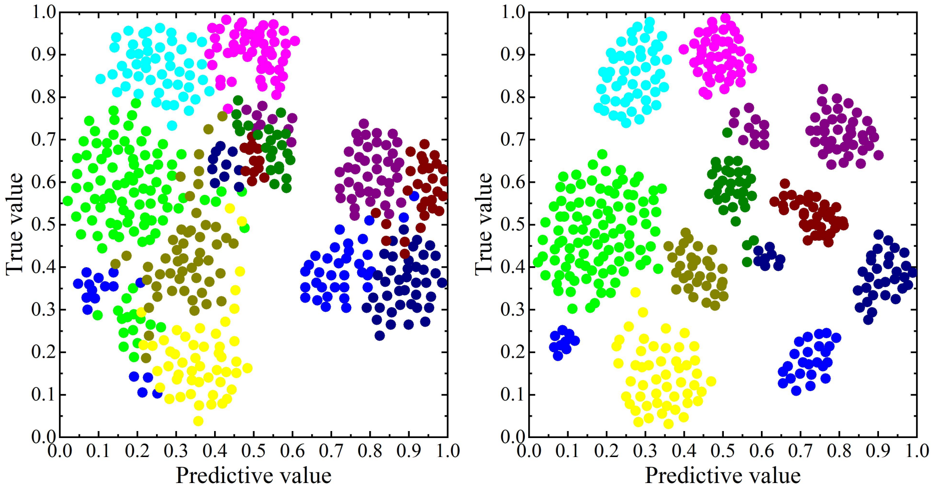
The average recognition accuracy (mAP) of the proposed model for the 10 different types of basketball technical actions reached 92.18%, an improvement of 4.71 percentage points compared to the baseline network (whose mAP was 87.47%). When identifying walking and no-action categories, these two types of actions exhibit less noticeable changes in player movements compared to other categories. In each video frame, players mostly maintain the same posture, and the correlation between frames is weak, resulting in no significant improvement in the model's recognition accuracy for these categories. However, when identifying actions such as blocking, running, dribbling, shooting, ball handling, and defense, the recognition accuracy of the proposed model significantly improved, increasing by 4.62%, 4.73%, 12.22%, 4.67%, 9.19%, and 9.97%, respectively. This is primarily because players exhibit greater movement variability during these actions, which contain rich dynamic information, resulting in a noticeable increase in temporal correlation between frames. Consequently, the model can effectively extract movement information and critical temporal information from video frames to enhance network performance.

Table 1. The recognition accuracy rate of basketball technical movements.

Type	Accuracy (%)		Change percentage point
	Baseline	This article	
Block	92.03	96.65	4.62 ↑
Pass	93.15	95.93	2.78 ↑
Run	87.73	92.46	4.73 ↑
Dribble	82.16	94.38	12.22 ↑
Shoot	86.94	91.61	4.67 ↑
Hold the ball	80.29	89.48	9.19 ↑
Defend	78.35	88.32	9.97 ↑
Block	93.04	93.51	0.47 ↑
Walk	89.93	89.46	0.47 ↓
No movement	91.06	89.95	1.11 ↓
mAP	87.47	92.18	4.71 ↑

To more intuitively assess the model's performance in recognizing basketball action videos, t-SNE was used to cluster and visualize the high-dimensional output features of the network's fully connected layer. The results are shown in Figure 1, with Figure 1(a) and (b) representing the recognition results of the baseline model and the model proposed in this paper, respectively. Points of the same color in the figure indicate data from the same action category.

As shown in Figure 1(a), when using the baseline model for recognition, the feature data of each category are not concentrated, and some category data are mixed together. For example, the green data representing dribbling actions and the purple data representing shooting actions are scattered in different parts of the figure, while the blue data representing passing and the brown data representing ball handling are intertwined. In contrast, as clearly shown in Figure 1(b), the basketball skill action recognition model proposed in this paper increases the inter-class distances and reduces the intra-class distances for each action category, spatially separating feature data from different categories while more tightly clustering data from the same category together, thereby facilitating the network's recognition of different actions. However, there are still a small number of data points mixed into other categories in Figure 1(b), leading to incorrect action recognition by the network. This is primarily due to the fact that some action video frames are quite similar, and the movement differences within the actions are not significant, thereby increasing the difficulty of recognition for the network.



(a) Baseline (b) This article

Figure 1. t-SNE visualization.

4.2. Motion Trajectory Tracking Error

A random video clip is selected from the dataset for image processing and computation. A virtual basketball court with dimensions of 30m in length, 13m in width, and 5m in height is drawn. The trajectory of the basketball jump shot is marked on the virtual court. Additionally, the method described earlier is applied to obtain the motion tracking trajectory of the basketball player, and the tracking trajectory is compared and analyzed with the actual trajectory. To further validate the feasibility of the method designed in this paper, ant colony algorithms, sensor technology, and regional growth algorithms for motion trajectory tracking were selected as comparisons. These were set as control groups A to C, with basketball trajectory tracking error as the experimental performance indicator, to more accurately analyze the tracking performance of the method. By calculating the error values between the four trajectory tracking methods and the actual trajectory, and tabulating the results, the computational results are shown in Table 2.

As shown in the error calculation results in the table, when using the method proposed in this paper for basketball trajectory tracking, the average trajectory tracking error in 10-fold cross-validation is only 18.11 mm. In contrast, the average tracking trajectory errors obtained by the ant colony algorithm, sensor technology, and regional growth algorithm are 24.71 mm, 24.55 mm, and 24.41 mm, respectively. Which are 36.44%, 35.56%, and 34.79% higher than the average trajectory tracking error of the method proposed in this paper, respectively. This demonstrates that the real-time basketball trajectory tracking algorithm designed in this paper is more accurate than the conventional three methods, enabling the acquisition of more precise basketball trajectories, and can provide support for optimizing basketball training strategies.

Table 2. Motion trajectory tracking error (mm).

-	Ours	Control A	Control B	Control C
1	18.54	27.41	27.63	27.02
2	19.34	25.76	23.58	23.58
3	16.96	19.38	19.41	19.64
4	18.72	20.42	20.18	20.66
5	17.57	26.64	26.54	26.48
6	18.35	23.51	23.48	23.46
7	18.26	29.34	29.35	29.57
8	19.01	30.48	30.71	30.24
9	16.74	21.65	21.37	21.06
10	17.63	22.49	23.25	22.35

Means	18.11	24.71	24.55	24.41

5. Conclusion

The primary focus of this study is on basketball motion recognition based on multidimensional data analysis and the application of personalized teaching guidance strategies. The research on a multidimensional data analysis system based on a dual-stream neural network for basketball motion recognition involves training the network by inputting basketball video data as both spatial and temporal streams. This approach integrates video information into the training process and the extraction and recognition of motions. The recognition accuracy rate for 10 basic basketball tactical movements reached 92.18%, including 94.38% for dribbling, 91.61% for shooting, and 95.93% for passing.

Using the motion trajectory algorithm in the diffusion probability trajectory generation model, the system can effectively predict the motion trajectories of professional basketball players, with an average basketball motion trajectory tracking error of 18.11 mm. Additionally, in complex tactical combinations such as fast breaks, the system can effectively predict players' running trajectories, playing a crucial role in enhancing athletes' tactical decision-making.

The multi-dimensional data analysis system developed in this study has achieved good results when applied to action pattern recognition and personalized teaching strategy design in basketball training. However, the system has limitations in recognizing some complex actions. For example, while the recognition accuracy for actions such as shooting and dribbling is high, the accuracy for rapid, continuous actions (such as direction changes) is lower, with the lowest accuracy being 76.3%. This indicates that current deep learning models face challenges in processing high-speed and complex movements. Future improvements could be achieved by incorporating stronger temporal modeling techniques, such as optical flow estimation, to enhance the capture of temporal features.

In summary, the current system has achieved preliminary results in training efficiency and personalized instruction, but it still has certain limitations when dealing with complex movements, long sequence predictions, and multi-target tracking. Future work can focus on strengthening the collaboration of multi-modal information, improving the temporal modeling scheme in the model, and adopting training schemes with personalized customization effects. This will enable the system to be trained more efficiently and made more personalized, gradually making basketball training modes more scientific, effective, precise, and efficient.

References

1. Cong, J., & Endozo, A. N. (2022). Training methods in basketball players to increase their shooting percentage. *Revista Brasileira de Medicina do Esporte*, 28(6), 843-845.
2. Koryahin, V., Iedynak, G., Blavt, O., Galamandjuk, L., Ludovyk, T., Stadnyk, V., ... & Gavrilenko, M. (2019). The main aspects of the implementation of technical and physical training of basketball players. *Journal of physical education and sport*, 19, 358-362.
3. Zehao, D. (2021). The Construction and Optimization of Basketball Training Mode. *Journal of Human Movement Science*, 2(4), 30-33.
4. Jin, A. (2019, July). Basketball education and training system based on practical teaching method. In *2019 4th International Conference on Humanities Science and Society Development (ICHSSD 2019)* (pp. 196-199). *Atlantis Press.*
5. Cañadas, M., Gómez, M. Á., García-Rubio, J., & Ibáñez, S. J. (2018). Analysis of training plans in basketball: gender and formation stage differences. *Journal of human kinetics*, 62, 123.
6. Qiang, S. (2019). Formulation of physical education and training program based on multidimensional education data mining. *Cluster Computing*, 22(Suppl 2), 5017-5023.
7. He, W., & Li, B. (2025). The impact of data-driven metrics on training programs to improve the performance of elite basketball players. *Journal of Computational Methods in Sciences and Engineering*, 14727978251337989.
8. Demenius, J., & Kreivytė, R. (2017). The benefits of advanced data analytics in basketball: Approach of managers and coaches of lithuanian basketball league teams. *Baltic journal of sport and health sciences*, 1(104).
9. Tsai, T. Y., Lin, Y. Y., Jeng, S. K., & Liao, H. Y. M. (2021). End-to-end key-player-based group activity recognition network applied to basketball offensive tactic identification in limited data scenarios. *IEEE Access*, 9, 104395-104404.
10. Song, X., & Fan, L. (2022). Pattern recognition characteristics and neural mechanism of basketball players' dribbling tactics based on artificial intelligence and deep learning. *Mathematical Problems in Engineering*, 2022(1), 1673969.
11. Qin, Z., Zhong, Q., & Liu, M. (2025, February). Research on Basketball Technical Movement Recognition and Training Feedback System Based on Deep Learning. In *2025 International Conference on Digital Analysis and Processing, Intelligent Computation (DAPIC)* (pp. 641-645). *IEEE.*

12. Zhu, X., Li, Z., Wang, X., Jiang, X., Sun, P., Wang, X., ... & Yuan, N. J. (2022). Multi-modal knowledge graph construction and application: A survey. *IEEE Transactions on Knowledge and Data Engineering*, 36(2), 715-735.
13. Liu, R., Liu, Z., & Liu, S. (2021). Recognition of basketball player's shooting action based on the convolutional neural network. *Scientific Programming*, 2021(1), 3045418.
14. Jiang, L., & Zhang, D. (2023). Deep learning algorithm based wearable device for basketball stance recognition in basketball. *International Journal of Advanced Computer Science and Applications*, 14(3).
15. Cheng, Y., Liang, X., Xu, Y., & Kuang, X. (2022). Artificial intelligence technology in basketball training action recognition. *Frontiers in Neurorobotics*, 16, 819784.
16. Zhang, L. (2024). Deep learning based fine-grained recognition technology for basketball movements. *Systems and Soft Computing*, 6, 200134.
17. Wang, Q., Tao, B., Han, F., & Wei, W. (2021). Extraction and recognition method of basketball players' dynamic human actions based on deep learning. *Mobile Information Systems*, 2021(1), 4437146.
18. Egi, Y. (2022). Basketball self training shooting posture recognition and trajectory estimation using computer vision and Kalman filter. *Journal of Electrical Engineering*, 73(1), 19-27.
19. Pang, H., & Zhang, D. (2025). Actions of basketball players integrating computer vision and sports biomechanics. *Journal of Computational Methods in Sciences and Engineering*, 14727978251322050.
20. Wang, J., Zuo, L., & Cordente Martínez, C. (2024). Basketball technique action recognition using 3D convolutional neural networks. *Scientific Reports*, 14(1), 13156.
21. Bayu, W. I., Solahuddin, S., Mohamad, N. I., Nanda, F. A., & Yusfi, H. (2025). Personalised BEEF shooting training for female basketball players: Enhancing accuracy and consistency. *Journal Sport Area*, 10(1), 148-155.
22. Wang, J., Qiu, K., Peng, H., Fu, J., & Zhu, J. (2019, October). Ai coach: Deep human pose estimation and analysis for personalized athletic training assistance. In *Proceedings of the 27th ACM international conference on multimedia* (pp. 374-382).
23. Li, B., & He, W. (2025). Research the role of artificial intelligence in developing personalized training plans to maximize the potential of basketball players. *Journal of Computational Methods in Sciences and Engineering*, 14727978251337959.