Basketball Free Throw Posture Analysis and Hit Probability Prediction System Based on Deep Learning

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***Abstract*—With the continuous progress of basketball technology and tactics, educators need to adopt new teaching methods to cultivate high-quality athletes who meet the needs of modern basketball development. In basketball teaching, the accuracy of free throw techniques directly affects teaching effectiveness. Therefore, the automated prediction of free throw hits is of great significance for reducing manual labor and improving training efficiency. In order to automatically predict the free throw hits and reduce manual fatigue, the study conducts an in-depth analysis for the criticality of free throw in basketball. In this study, the target detection model of target basketball players is constructed based on YOLOv5 and CBAM, and the basketball free throw hit prediction model is constructed based on the OpenPose algorithm. The main quantitative results showed that the proposed model could accurately recognize the athlete posture in free throw actions and save them as video frames in practical applications. Specifically, when using the free throw keyframe limb angle as features, the model achieved a prediction accuracy of 71% and a recall rate of 86% in internal testing. In external testing, the prediction accuracy was improved to 89% and the recall rate was 77%. In addition, combining the relative position difference and angle characteristics of joint points, the accuracy of internal testing was significantly improved to 80%, and the recall rate was increased to 96%. The accuracy of external testing was improved to 95%, with a recall rate of 75%. The experimental results showed that the various functional modules of the system basically meet the expectations, confirming that the basketball penalty posture analysis and hit probability prediction system based on deep learning can effectively assist basketball teaching and meet the practical teaching application needs. The contribution of the research lies in providing a scientific basketball free throw training tool, which helps coaches and athletes better understand and improve free throw techniques, thereby improving free throw hits accuracy. Meanwhile, this study also provides new theoretical and practical references for the application of deep learning in motor skill analysis and training, which has potential value for updating the basketball education system and reducing teacher workload.**

***Keywords*—Deep learning; CBAM; OpenPose; Free throws; Posture analysis**

I. Introduction

A. Basketball and Technological Progress

As a popular sport around the world, the continuous improvement of basketball technology and tactics requires increasingly high technical requirements from athletes. The improvement of free throw skills is not only an important part of basketball technical training, but also a reflection of precision and repetition training in physical education.

B. The Application of Deep Learning in Basketball Training

From the perspective of social science, the application of deep learning technology to basketball free throw posture analysis and hit rate prediction demonstrates sports science and technology progress. It is also a concrete application of modern physical education teaching concepts. It advocates a training approach based on the data and science, which helps coaches and teachers shift from traditional empiricism to more quantitative and objective training strategies. It is important for the scientific development of personalized athlete training and physical education [1-2].

C. Challenges and Objectives of Research

Zhao et al. proposed a novel real-time shooting prediction method that combines visual sensors and trajectory learning. Four machine learning algorithms were used for analysis, providing data support for prediction accuracy. However, the computational efficiency or real-time performance of the model was not mentioned. In addition, there were still some shortcomings in combining different features [3]. Scholars such as Oltenu focused on improving basketball free throw skills by setting up experimental and control groups to evaluate the effectiveness of training programs. Three different tests were used to evaluate the training effectiveness of athletes, increasing the comprehensiveness of the research. However, the universal applicability of the research results or how they can be applied to different training environments was not discussed, and the maintenance of free throw skills after training was not evaluated [4].

D. Overview of Research Content and Innovation Points

The innovation of the research lies in developing a deep learning system for analyzing the free throw posture of basketball players and predicting the free throw hits. The core innovation of the system includes: adopting multimodal feature fusion technology, combining limb angle and joint position difference to improve prediction accuracy. YOLOv5 and CBAM modules are integrated to enhance small object detection capabilities. Based on the improved OpenPose

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algorithm, it is possible to accurately capture the posture changes of athletes through trajectory optimization and feature fusion. The SVM classifier is applied to effectively handle small sample learning tasks. In addition, the study comprehensively evaluates the application effect of the system in actual basketball training, ensuring its practicality.

E. Research Expectations

The research is expected to provide basketball players and coaches with a scientific and efficient free throw training tool to help them better understand and improve free throw shooting techniques, so as to improve free throw hits. At the same time, the research will also provide new theoretical and practical references for deep learning in sports skill analysis and training, update the basketball education system, and reduce the teacher workload.

F. Article Structure

The research is divided into four parts. The first part introduces basketball free throw and deep learning algorithm. The second part uses You Only Look Once version 5 (YOLOv5) network and OpenPose to build a basketball free throw posture analysis and hit probability prediction system. The third part tests and analyzes the model performance. The fourth part summarizes the above contents.

II. Related Works

The OpenPose model is often used to extract and estimate human pose. Therefore, Zhang et al. proposed a novel end-to-end Point-to-Pose Mesh fitting Network (P2P-MeshNet) based on OpenPose 3D joint dataset to estimate body joint rotation. The average position error, percentage of correct keys (PCK), and area under the curve (AUC) of each joint within the calibration threshold were tested using 0-60 mm Proclustes. The estimated error was 11.31 mm, the success rate was 99.7%, and the AUC was 80.9% [5]. Zhu et al. introduced a method to quickly and accurately classify human motion by utilizing skeletal key points as descriptors of motion characteristics. The OpenPose was employed to extract human skeleton point information as the primary features, followed by deep learning techniques for further classification and identification of action features. The results demonstrated that this approach achieved an impressive accuracy of 86.1% in fall detection using publicly available datasets [6]. Kim et al. proposed an OpenPose-based ergonomic posture evaluation system for calculating joint angles and RULA/REBA scores, validating them with reference motion capture systems, as well as comparing performance with Kinect-based systems. The records of 12 experimental tasks completed by 10 participants under different conditions were analyzed. The OpenPose performed well in all task conditions, while the Kinect performed significantly worse than OpenPose in body occlusion or non-frontal tracking [7].

In image recognition, YOLO series has attracted significant attention from researchers. To address the low accuracy and slow speed in traditional coal gangue identification methods, Yan et al. combined YOLOv5 and multispectral imaging technology. Experimental results demonstrated that the YOLOv5.1 model achieved an impressive average detection accuracy of 98.34% for coal gangue. This method not only accurately identified coal gangue but also provided information about its relative position, making it highly effective for coal gangue identification purposes [8]. Wei Jia et al. proposed a motorcycle helmet detection method using YOLOv5 to detect motorcycle drivers' helmets through video surveillance. It achieved 97.7% mAP, 92.7% F1 score, and 63 frames per second [9]. To improve the performance of robots in classifying lower limb movements, Bingzhu et al. analyzed using different features, including feature signals combining lying and sitting postures. sEMG feature extraction and pattern recognition obtained the trained motion decoder, and then sent control instructions to the robot to drive the lower limbs for corresponding rehabilitation training. The results verified the effectiveness of the control method based on sEMG signal [10]. Researchers such as Mcdonough D designed a controlled experiment to improve the intervention effect of school dance and physical education models and improve the enjoyment and self-efficacy of urban ethnic minority students. Through experiments, it was found that urban ethnic minority students were happier in the group exercise mode, which was an effective intervention mode for dance sports games [11]. Liu S et al. analyzed the effectiveness of the Small Private Online Course (SPOC) teaching model and conducted experiments using the embryology course as an example. Results showed that SPOC teaching improved students' average professional performance and enhanced students' enthusiasm for learning. This indicated that the SPOC teaching model was scientific and reasonable. It was popularized and applied in medical courses [12].

In summary, previous studies have improved the accuracy of human pose detection. A large number of algorithms are used to optimize datasets and feature extraction. However, there are still few pose analysis and hit probability prediction systems that have high-speed computational efficiency and are suitable for basketball detection. These two have strong potential application value in improving the detection efficiency of basketball games.

III. Construction of Penalty Attitude Analysis and Hit Probability Prediction System using Deep Learning Algorithm

In this study, the target detection model of target basketball players based on YOLOv5 and the basketball free throw hit prediction model based on the OpenPose algorithm are constructed. The aim is to improve the accuracy and efficiency of free throw technical analysis, provide a new perspective for the impact of basketball on physical education, and improve the effectiveness of basketball teaching.

A. Construction of Basketball Player Target Detection Model Based on YOLOv5

As an important part of the school physical education curriculum, basketball plays a role in cultivating students' physical fitness, teamwork spirit, and competitive spirit. The scientific analysis of basketball free throw posture can not only improve students' motor skills, but also help physical education teachers to diagnose and correct students' movements more accurately in the teaching. It helps to promote the modernization of basketball education methods.

In addition, as a social and cultural activity, the teaching and training process of basketball also reflects the social and cultural attributes of the educational concept, emphasizing the respect for individual differences and the integration of cultural diversity. Therefore, the application of deep learning technology to basketball free throw teaching can be regarded as a part of educational innovation, which can help improve the teaching quality and educational value of physical education courses. Then, YOLOv5 is selected as the baseline network to construct a target detection model for target basketball players. As the latest generation of fast object detection algorithm, the main advantages of YOLOv5 are its efficient real-time processing capability and excellent detection accuracy. It achieves faster processing speed and higher accuracy through optimized network structure and algorithm innovation. Compared with Faster Region-Convolutional Neural Network (Faster R-CNN), YOLOv5 significantly reduces the computational resource requirement while maintaining high accuracy [13-14]. This makes it excellent in various application scenarios, especially in situations that require fast real-time processing, such as traffic monitoring, human behavior analysis, and industrial automation [15-18]. The YOLOv5 network structure is shown in Fig. 1.

In Fig. 1, YOLOv5 is an efficient real-time object detection system consisting of multiple key modules, aiming to achieve high-precision detection with less computing resources. The network consists of several main components: an input layer, which preprocesses the image data to standardize the input size, and a backbone, which consists of multiple convolutional layers to extract image features. Backbone network output is connected to the neck network, which includes a Feature Pyramid Network (FPN) and a Path Aggregation Network (PAN) structure, merging feature maps at different scales and detecting small objects. Finally, the Detection Head performs object localization, classification, and confidence prediction based on the feature map. YOLOv5 uses the Anchors strategy to predict the bounding box. Anchors with different scales and sizes are used to improve the objects detection accuracy of various shapes. The entire network is optimized through a loss function, combining classification, localization, and confidence loss to improve detection performance. In the traditional YOLOv5 network, the Generalized Intersection over Union (GIoU) loss function is used to optimize the confidence error calculation of the candidate box. The gradient of the Intersection over Union (IoU) loss is 0 when the two boxes do not overlap, which cannot be optimized. The distance relationship between the two boxes cannot be accurately judged. At the same time, it does not accurately reflect the degree of overlap between frames. Even if the IoU values are the same, the positioning effect may differ. The GIoU loss function is used to better reflect the degree of overlap. The GIoU computation diagram is shown in Fig. 2.

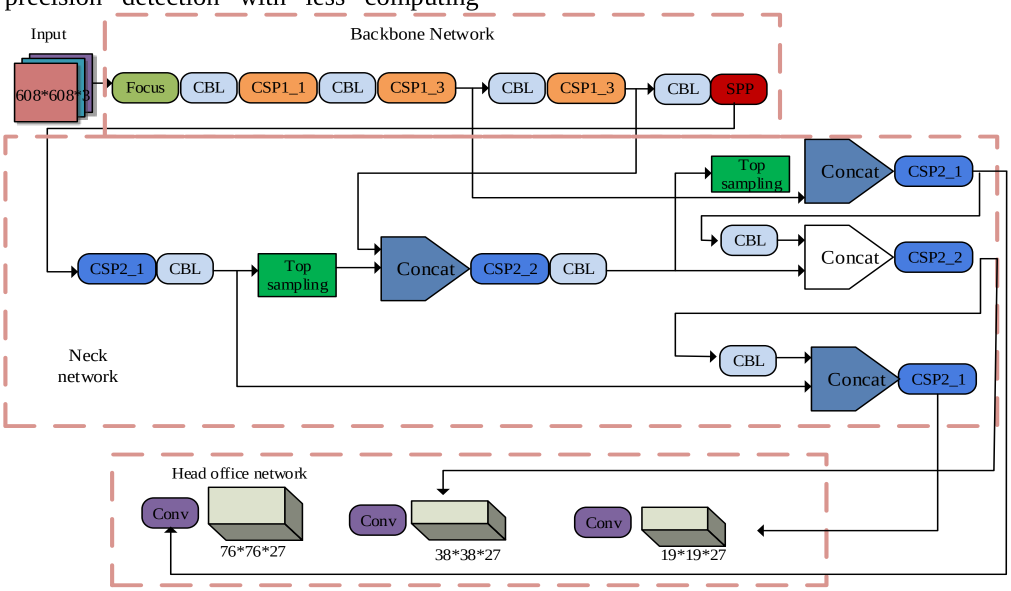
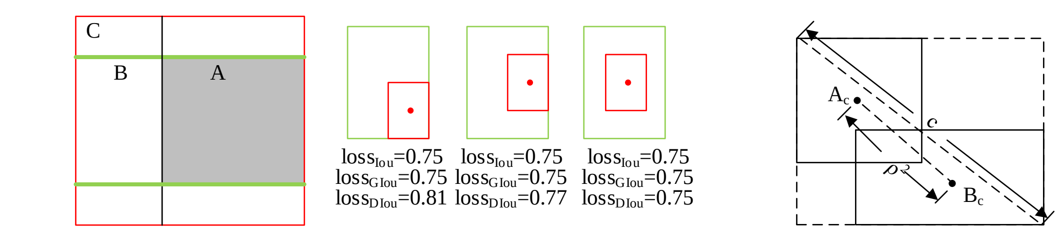


Fig. 1. YOLOv5 network architecture.



(a) Schematic diagram of the minimal outer rectangle of A and B

(b) GIoU same cannot distinguish relative positions

(c) Schematic diagram of DIoU calculation

Fig. 2. Schematic diagram of GIoU computation.

As shown in Fig. 2, the minimum circumscribed rectangle is C. The IoU is calculated in Eq. (1).

$$L_{IoU} = 1 - IoU(A,B) \tag{1}$$

In Eq. (1), L_{IoU} represents the IoU loss function. The $IoU(A,B)$ is calculated in equation (2).

$$IoU(A,B) = \frac{A \cap B}{A \cup B} \tag{2}$$

From Eq. (2), it can be seen that when two bounding boxes do not intersect, the IoU is zero. This makes it impossible to measure the relationship between the prediction box and the target box by the IoU loss and hinders the learning process, because there is no gradient for post-back. Therefore, the GIoU loss function is introduced, which adds a penalty term on the basis of IoU. It can effectively solve the gradient disappearance problem when the bounding boxes do not overlap, so as to improve the training efficiency and the accuracy of regression effect.

A penalty term is introduced on the basis of IoU, and GIoU can be obtained, as shown in Eq. (3).

$$L_{GIoU} = 1 - IoU(A,B) + \frac{\left|C / \left(A \cup B\right)\right|}{|C|} \tag{3}$$

The GIoU loss value ranges from -1 to 1, which can solve the gradient vanishing when the boxes do not intersect. However, it relies too much on the IoU term, which makes it impossible to distinguish the relative position relationship when the real box completely contains the prediction box, and may slow down the convergence. Distance Intersection over Union (DIoU) can solve these problems. The DIoU adds the distance between the center point of the prediction box and the real box on the basis of IoU to improve the positioning accuracy in the object detection task. The DIoU loss function is calculated in Eq. (4).

$$L_{DIoU} = 1 - IoU(A,B) + \frac{\rho^2(A_c, B_c)}{c^2} \tag{4}$$

In Eq. (4), A_c and B_c represent the center point of the prediction frame and the target box. $\rho^2()$ represents the Euclidean distance calculation. c represents the diagonal distance that encloses the minimum area of the prediction frame and the target box, which can provide an optimization scheme for the bounding box and improve the convergence speed when both boxes do not overlap. In view of the small fluctuation in the aspect ratio of the prediction box in the target detection of basketball penalty players, the Complete Intersection over Union (CIoU) loss function is selected to optimize the model. The CIoU loss function utilizes DIoU to increase the aspect ratio factor. Based on the characteristics of basketball free throw player target detection, the guidance of bounding box optimization direction and the convergence speed of distance between center points have been improved. The CIoU is calculated in Eq. (5).

$$L_{CIoU} = 1 - IoU(A,B) + \frac{\rho^2(A_c + B_c)}{C^2} + \alpha v \tag{5}$$

In Eq. (5), α is a weight function. v measures the similarity between the target box and the detection box, as is shown in Eq. (6).

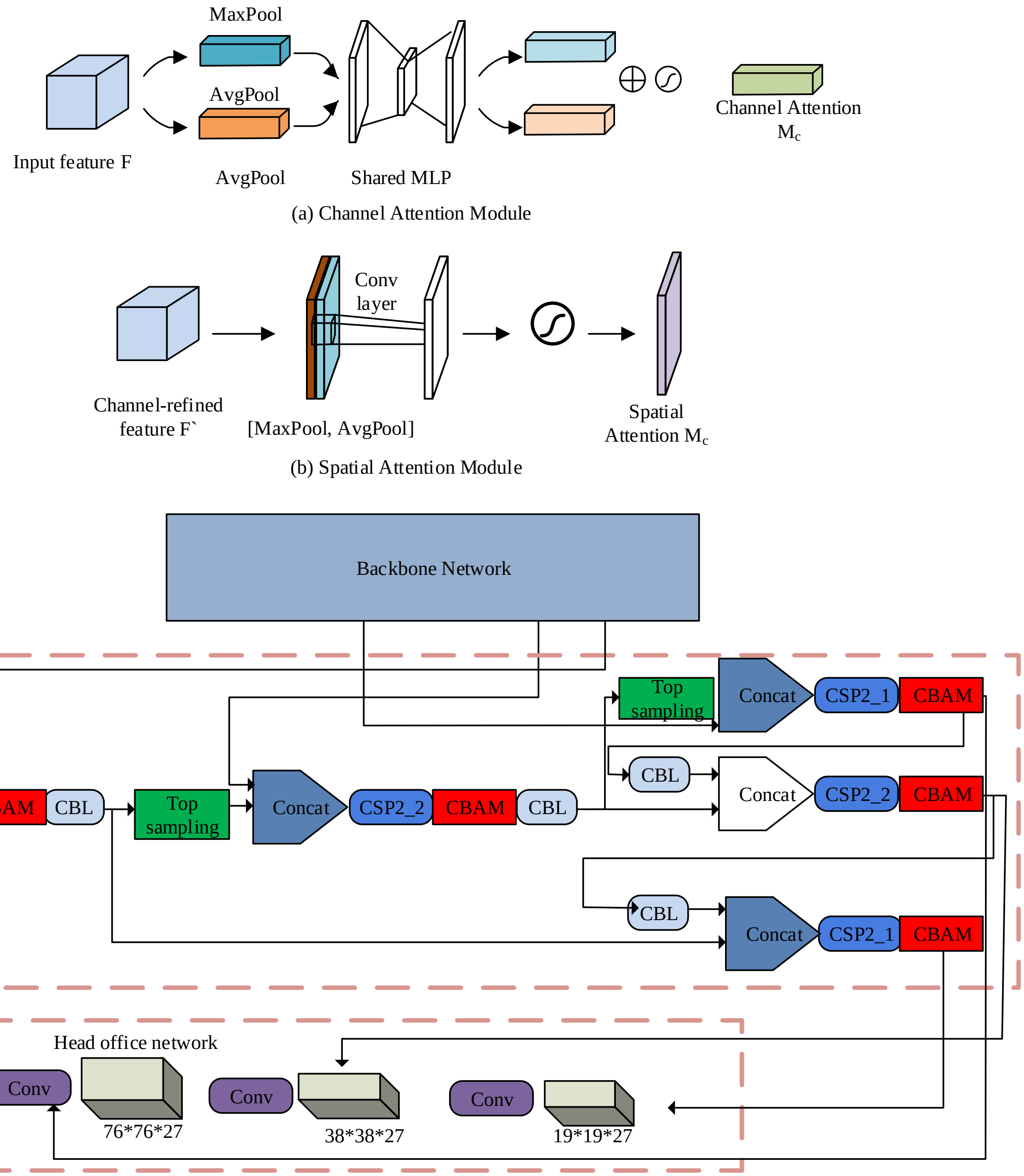
$$v = \frac{4}{\pi^2}(\arctan\frac{w_A}{h_A} - \arctan\frac{w_B}{h_B})^2 \tag{6}$$

In Eq. (6), w_A and w_B represent the width of the two boxes A and B. h_A and h_B represent the height of the two boxes. Then, a lightweight Convolutional Block Attention Module (CBAM) is inserted into the network structure to optimize the object detection accuracy and strengthen the attention to the detected target, thereby reducing the detection accuracy degradation caused by complex environment [19-22]. The structure and optimization of CBAM are shown in Fig. 3.

In Fig. 3, CBAM combines spatial attention and Channel Attention to improve the performance of convolutional neural networks. By mining the feature dependencies between different channels, the channel attention module assigns different importance weights to different channels, so as to enhance the response of the model to the information-rich channels. The spatial attention module focuses on the importance of different spatial locations in the feature map, and highlights the important spatial regions through feature aggregation in the spatial context, so as to further improving the ability to capture key spatial information. CBAM can adaptively assign different attention weights to different parts of the network, thus helping the network better capture and utilize important information about the input features. In this way, CBAM improves the performance of convolutional neural networks on tasks. It is introduced into the Neck structure of YOLOv5s to solve the challenges in small target detection, such as small target, dense target, noisy and background interference. Therefore, CBAM is introduced after each CSP2 module in Neck to enhance attention to small targets.

B. Construction of Basketball Free Throw Hits Prediction Model Based on OpenPose Algorithm

While discussing the free throw posture and hit probability prediction in basketball, the study also considers the importance of basketball in the field of education. Basketball, as a team sport, not only demonstrates the physical fitness and technical level of students, but also embodies teamwork and competitive spirit, which promote communication and cooperation between groups in an educational environment. Through an in-depth analysis of the correlation between basketball free throw posture and shooting rate, this study is committed to optimizing the physical education teaching strategy in colleges and universities. Fee throw hit prediction depends on the recognition and detection of human posture. Based on the previously proposed object detection model, the human pose estimation of the target object extracted by the model is carried out. Human pose estimation methods are divided into single and multi-person pose estimation, which are suitable for both image and video scenarios. Key challenges include occlusion interference, light and environmental changing effects, and identification of different angles and scales. Compared with static images, video analysis can obtain richer dynamic body information. There are two human pose estimation methods: top-down and bottom-up. The former relies on human detection results, and the latter first recognizes joint information and then constructs posture. Based on the OpenPose algorithm, a recognition method using trajectory optimization is proposed, which combines the angle transformation and feature fusion of limb features. Then the SVM classifier is used to predict the penalty action, and then analyzes the importance of limb features, and puts forward optimization suggestions for the free throw action [23-25]. Firstly, the feature information of the key points of the joint when shooting the target object is extracted by OpenPose. Fig. 4 shows the OpenPose network structure.



(a) Channel Attention Module

(b) Spatial Attention Module

(c) Improvement programmes

Fig. 3. CBAM structure.

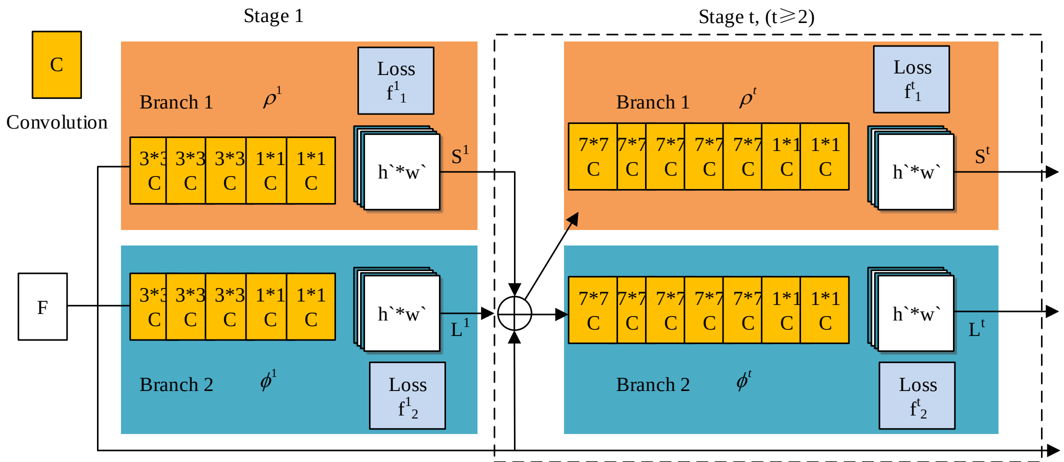


Fig. 4. OpenPose network structure.

The Openpose network includes two main parts. The first part is a convolutional neural network, which is responsible for extracting features and predicting the confidence graph of key points. The second part is Part Affinity Fields (PAFs), which is used to predict the direction of connections between various parts of the body. These two parts are alternated in a multi-stage convolutional network. The prediction results are gradually refined, ensuring the accurate positioning of key points and the correct association of various parts of the body [26-27]. Considering that the human pose estimation method is easy to cause false detection of joint points due to obstacle occlusion in complex background, the wrong joint points identified are repaired to reduce the impact of missed detection and false detection on pose recognition. The poses in adjacent frames of the video are represented by k_1 and k_2, respectively. k_1^i and k_2^i represent the i-th body part appearing in k_1 and k_2, respectively. Bounding boxes B_1^i and B_2^i are extracted, respectively. From B_1^i, x_i feature points can be extracted, while B_2^i represents y_i feature points. The calculation for the distance between frames with k_1 and k_2 is shown in Eq. (7).

$$d(k_1,k_2)=\sum_i \frac{y_i}{x_i} \tag{7}$$

Based on the distance calculation in Eq. (7), the target object in the video can be tracked and judged. When the reliability of the body position is lower than th_b, the bounding box B_i of the joint point action is magnified by one time, two times, and three times in turn, and each multiple is tr_1, tr_2, tr_3, respectively. If the threshold is still lower than the threshold, the similarity between the pose of the previous frame and the current pose is calculated, as shown in Eq. (8).

$$Sc_{g,h}^i=\alpha*\sum_i \frac{n_i}{m_i}+(1-\alpha)*\left\|H_g-H_h\right\|_2 \tag{8}$$

In Eq. (8), the number of feature points in the bounding box of the i joint point in the g frame is described as m_i. The h frame is described as n_i, when the similarity is greater than th_b, the joint point of the previous frame is selected as the candidate node. Otherwise, the corresponding joint point information in the frame is cleared. In this study, the hit rate is predicted by analyzing the changes in the bending angle of each joint in the body of basketball players when they make free throws. The angles between the thigh and the calf, the upper arm and the lower arm, and the upper arm and the torso are the key features, reducing the error caused by the difference in body shape and improving the prediction stability. The schematic diagram and key points of the joint angle are shown in Fig. 5.

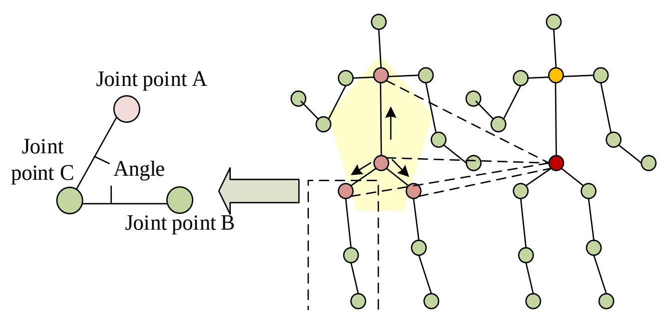


Fig. 5. Schematic diagram of joint pinch angle and key points.

For the analysis of key features, the three key points on the leg are represented as two vectors. The three joint points are connected, and the angle formed at the middle joint point is the angle of the key part. The coordinates of the right wrist, elbow, and shoulder joint points are $R_t(x_0,y_0)$, $R_b(x_1,y_1)$, $R_m(x_2,y_2)$, respectively. The vector representations of the right forearm and right arm are shown in Eq. (9).

$$\begin{cases} l_1 = (x_0 - x_1, y_0 - y_1) \\ l_2 = (x_2 - x_1, y_2 - y_1) \end{cases} \tag{9}$$

From Eq. (9), the angle of the right arm is shown in Eq. (10).

$$\beta = \cos^{-1}\left(\frac{l_1 - l_2}{\|l_1\|\|l_2\|}\right) \tag{10}$$

By converting the absolute position coordinates of basketball players' joint points into angular features, this study focuses on the squat and ascent phases in the free throws. The variation in the leg joint point is used to judge the shooting phase, in which the thigh calf angle decreases to a minimum during a squat and increases to a maximum when rising. At the same time, the characteristics of arm joint points are also considered. Namely, the angle between the large arm and the small arm remain stable in the squat stage, while the angle between the small arm and the torso of the large arm gradually increases with the rise of the arm joint point in the ascending stage. These angular features are used to predict free throw movements and improve the prediction accuracy. Free throw outcome prediction is essentially a categorical problem, divided into two categories: hit or miss. Classification problems are one of the core tasks in machine learning, which aims to find a function to discriminate and classify input data. This involves converting input values into discrete output values, including binary and multi-classification problems. SVM is an effective binary classification model, which is widely used in text classification, action classification and result prediction. Based on a given sample set, it looks for an optimal hyper-plane that can distinguish two categories in the sample space, and transforms the classification task into finding the best interface, so as to achieve accurate classification. The equation for dividing the hyper-plane in the sample space is shown in Eq. (11).

$$\omega^T X + b = 0 \tag{11}$$

In Eq. (11), $X = (x_1, x_2, \cdots, x_n)$ represents the input data, that is, the converted limb angle characteristics of the penalty shooter, n represents the dimension. ω represents the normal vector of the hyper-plane, and b represents the offset term. The calculation for the distance from the shooting posture to the super-plane in the data sample is shown in Eq. (12).

$$l = \frac{|\omega^T X + b|}{\|\omega\|} \tag{12}$$

When the free throw is hit, the sample point is located above the super-plane and vice versa below, as shown in Eq. (13) for classification problems.

$$\begin{cases} \omega^T x_i + b \geq 1, \ \ y_i = +1 \\ \omega^T x_i + b \leq -1, \ \ y_i = -1 \end{cases} \tag{13}$$

The SVM is the points in the sample set that satisfies the above equation and satisfies the equality sign. The distance from these points to the hyper-plane is the spacing, so the basic model of the SVM is shown in Eq. (14).

$$\begin{cases} \min\limits_{\omega,b} \frac{1}{2}\|\omega\|^2 \\ s.t. y_i(\omega^T x_i + b) \geq +1, i = 1, 2, \cdots, n \end{cases} \tag{14}$$

Based on solid mathematical theory, SVM simplifies classification problems, focuses on key sample positioning, and avoids dimensionality problems caused by large sample sizes. The disadvantage is that the training time is longer. Therefore, it is more suitable for small-sample tasks, and the computational complexity increases when the number of key samples increases.

C. *Basketball Free Throw Posture Analysis and Hit Probability Prediction System Design*

Based on the above model, a free throw probability prediction system in basketball game scenarios is constructed. It aims to provide target detection and pose estimation functions for free throw players in individual enthusiasts and basketball teams, so as to assist in training and improving free throw skills. Users can upload videos of single or multiple free throws. The system will detect the player's position and predict the result of the free throw. The main functional modules include the browser side (video input, historical query, user help), application server (object detection, image information output, information forwarding), GPU server (video processing, result output) and database (storage of body and penalty data). Non-functional requirements emphasize ease of use and scalability to optimize the user experience and adapt to changed data and needs. The system design is simple and intuitive, ensuring easy user operation. The modular design allows for subsequent expansion and adaptation. Fig. 6 shows the overall system logical framework.

In Fig. 6, the free throw prediction system based on B/S architecture designed by the research involves a local environment and a remote GPU server, including a multi-layer structure, and a storage layer connected to the database management system. Various necessary files such as pre-trained models and user information are stored. The front-end and back-end interaction and Ajax asynchronous technology are used to feed back the results, and the GPU server side is responsible for body pose estimation and shooting result prediction. The front-end interaction layer acts as the user interface, which is responsible for receiving video input and presenting the results. The browser module is mainly used to display the prediction results. The interface design is simple, using html and JavaScript, which is divided into three modules: information input, result prediction, and record prediction. The information input module is used to upload videos and player information and save them in the database. The result prediction module processes the video and displays the prediction results. The record prediction module allows the user to manually correct and save the results for subsequent model training. The application server coordinates the work of each module, receives video and information, implements object detection, sends data to the GPU server, obtains the prediction results, and delivers the front-end page and database storage. The entire system architecture is designed to improve the accuracy of penalty prediction, while ensuring the ease of use of the user interface and the scalability of the system. The database management system uses MySQL. The data is presented in the form of a table in Table I.

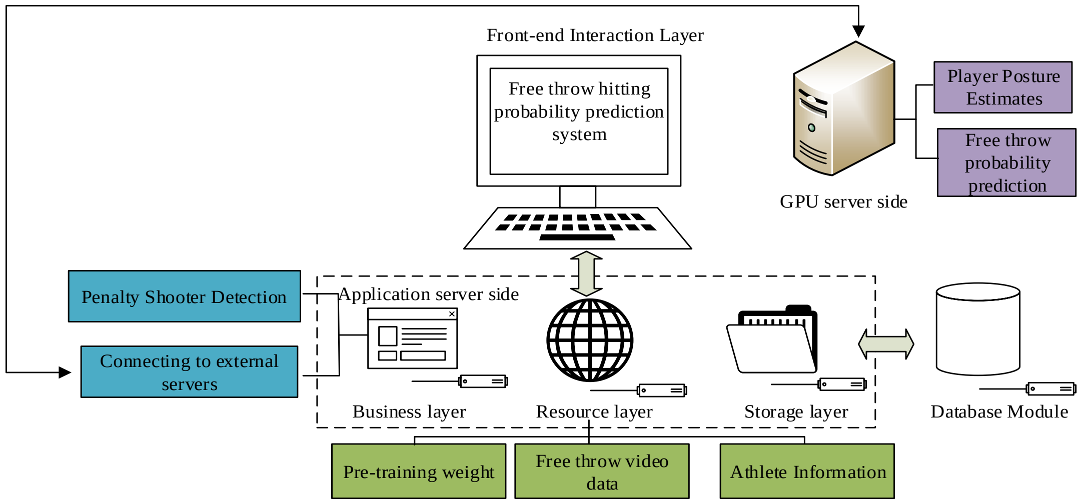


Fig. 6. Overall logical framework of the system.

TABLE I. DATABASE TABLES AND DATA TYPES

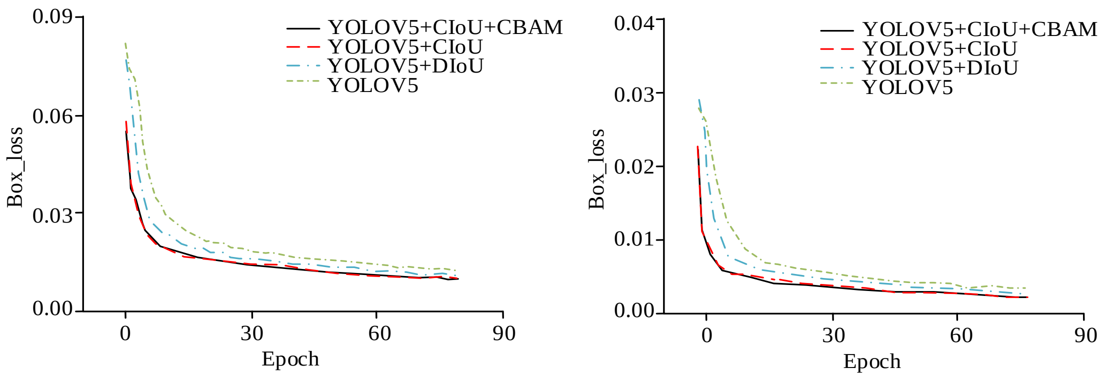
Field name	Data type	Austerity	Clarification
Id	1nt	Primary key; self-incrementing	Primary Key ID
Name	Varchar(30)		User name and surname
Height	Float		Height of an athlete (i.e. person's height)
Weight	Float		Athlete weight
Text	Var char(100)		Remarks on information
Img	Var char(100)		Screenshot of the game video
Info	Var char(100)		Human joint position information is saved in JSON format
Res_video_path	Var char(100)		Video after prediction
Change_time	Datetime		Modify Time

IV. Performance Test of Basketball Free Throw Attitude Analysis and Hit Probability Prediction System Based on YOLOv5 Network and OpenPose Algorithm

The study analyzes the free throw action in basketball game through object detection technology. Various game scene videos are selected, including offline shooting and online collection. In order to enhance the training samples and improve the generalization ability, a data augmentation method is adopted.

A. *Performance Test of Target Basketball Player Object Detection model Based on YOLOv5*

Through an in-depth analysis of the correlation between basketball free throw stance and shooting rate, this paper is committed to optimizing the teaching strategy of college physical education. This study not only has practical significance for the improvement of sports technology, but also reflects the trend of social science in physical education. It aims to provide students with personalized guidance through data-driven teaching methods, promote the innovation of physical education teaching mode, and improve the quality and efficiency of students' physical education learning. After constructing the experimental dataset, 80% of the images are selected as the training set, and 20% as the test set. Dataset preparation includes not only image information collection, but also manual annotation of specific objects in the image, including species and location information. According to the format of the VOC dataset, the collected video is first converted into a single-frame picture. Then the players performing the penalty action in the picture are labeled by Labeling software, and the labeling result is saved as an xml format file. These files detail the location of the penalty player in the picture, including the coordinates of the upper left and lower right corners. To adapt to the VOC format, the type information and location information in the xml file are further extracted for the training process. Compared with the 80 categories and 255-dimensional output tensors of the COCO dataset, the object detection in this study focuses on three types: penalty players, ordinary athletes, and spectators. To reduce the computation and improve the detection accuracy and speed, the YOLOv5 classifier is modified to only recognize penalty players. Therefore, the dimensionality of the output tensor is adjusted to 3*(5+1)=18 to better adapt to the needs of match detection and optimize the model performance. Fig. 7 shows the loss function curve.



(a) Cross-parity loss diagrams (b) Target detection loss graphs

Fig. 7. Loss function curve.

In Fig. 7(a) and Fig. 7(b), the loss function changes of different versions of YOLOv5 algorithm in object detection tasks are presented. box_loss corresponds to matching loss between the target and the prediction box, while the obj_loss corresponds to object detection loss. Overall comparison showed that YOLOv5 had the lowest loss value when combined with CIoU and CBAM, indicating the effectiveness of the improved method. In both loss functions, this combination consistently maintained a faster downward trend and reached a lower stable value in the later training stages. In the box_loss, YOLOv5+CIoU+CBAM decreased rapidly at the beginning and continued to maintain a loss value below 0.02, while the standard YOLOv5 loss was slightly higher. Since only the penalty player category was set in this experiment, and the class loss (cls_loss) was 0, the cls_loss value was not considered in the analysis. These results show that YOLOv5 combined with CIoU and CBAM can perform more accurate target detection, which has better convergence performance. The experimental average accuracy curve is shown in Fig. 8.

Fig. 8 shows the average accuracy curve of the original YOLOv5 and the model after introducing DIoU, CIoU loss function and attention mechanism. The experiment is conducted with 80 rounds in the same configuration. The observations showed that the models converged rapidly from the 30th round and tended to stabilize after the 60th round. The black curve of CIoU loss function and attention mechanism showed that the improved model outperformed the original YOLOv5 model in terms of average accuracy and recognition. In order to verify the recognition effect, three frames of video are selected for comparison, as shown in Fig. 9.

As shown in Fig. 9, in the first frame, although both models could detect the penalty player, the original model had a low confidence level. The recognition was not ideal, and the target was not detected in the last frame. In contrast, the improved model exhibited high recognition accuracy and stability, which accurately identified the athlete's posture throughout the penalty action and saved it as a video frame.

B. *Performance Test of Basketball Free Throw Hit Prediction Model Based on OpenPose Algorithm*

In this study, the limb angle and the relative position gap and angle of the joint point of the key frame in the free throw are combined as feature inputs. The comparison results of accuracy and recall before and after algorithm optimization are shown in Fig. 10.

In Fig. 10, the pre-improvement test results showed that the goal prediction accuracy was 71% inside (in) and 89% outside (out), and the recall rates were 86% and 77%, respectively, when the free throw key frame limb angle was used as the feature. The improved model was characterized by the combination of the relative position gap and the angle of the joint points. The accuracy was significantly improved to 80% internally and 95% externally. The recall rate was also increased to 96% and 75%, respectively. This significant improvement, especially the significant increase in internal recall, shows that the prediction bias caused by different body types of athletes can be effectively reduced by comprehensively considering the relative position gap and angle information of joint points. In addition, the F1-score and accuracy of the improved model also reached 88% and 86% internally, and 84% and 86% externally, respectively, which verified the effectiveness of the feature optimization strategy and demonstrated the efficiency of the model in recognizing basketball free throws. In previous studies, the human pose estimation method was used to extract the relative coordinates of human bone points, and the free throw posture was input into the classifier as a static feature for prediction. The method not repairing the joint points in the shooting process is used as the comparison object, which is named the static input. The ROC curve comparison results are shown in Fig. 11.

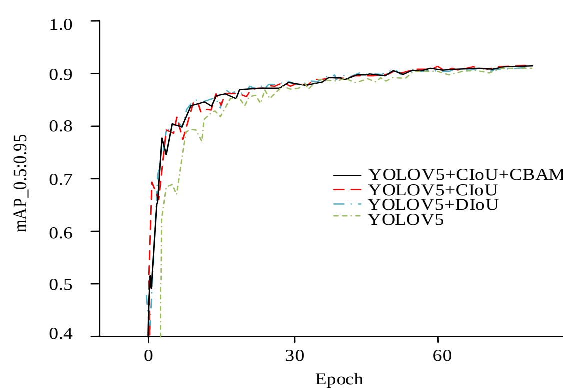
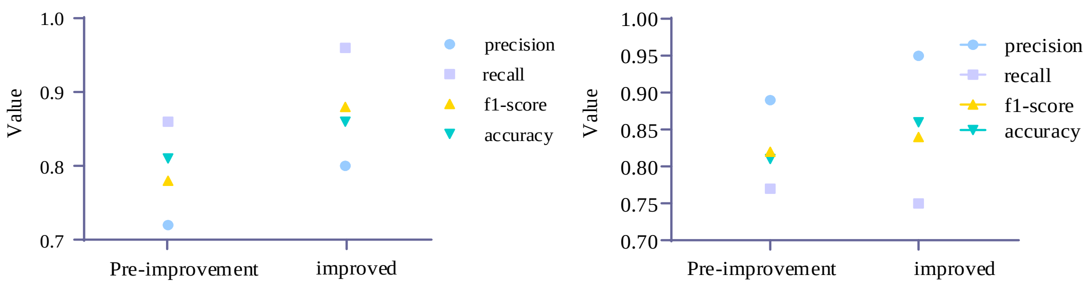


Fig. 8. Experimental average precision curve.

(a) Baseline network identification before improvement

(b) Improved

Fig. 9. Detection results visualization.



(a) Comparison of input values before and after improvement

(b) Comparison of output values before and after improvement

Fig. 10. Comparison of accuracy and recall.

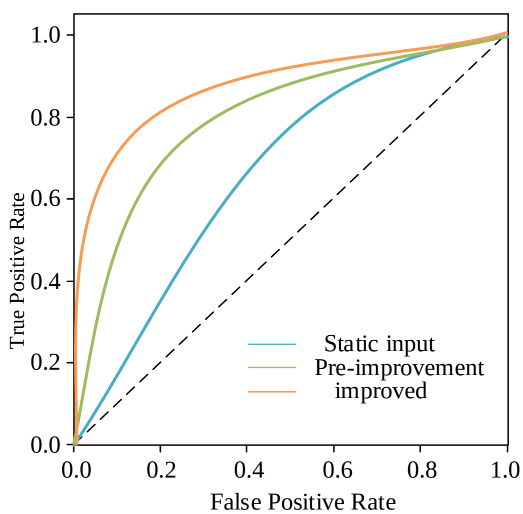


Fig. 11. ROC curve comparison.

Fig. 11 shows a comparison of the Receiver Operational Signature (ROC) curves for the three methods. A curve closer to the upper left indicates better prediction performance. From the figure, the ROC curve of the method combining the relative position characteristics of joint points and the characteristics of angular change (orange curve) was higher than that of the other two methods, indicating that this method achieved higher value in the True Positive Rate and maintained lower False Positive Rate. Therefore, it is better than the other methods in terms of prediction effect. These results indicate that the proposed method significantly improved the accuracy of free throw prediction. In this study, the key features in the shooting process were studied by observing the influence of different limb angle features on the prediction results of free throws. Table II shows the influence of different features on the prediction results.

The experimental results showed that the angle between the thigh and calf during the free throw, the angle between the shooter's big arm and the angle of the assistive hand had a significant impact on the free throw hit, all of which were more than 6%. In contrast, the calf foot angle and the torso-thigh hip angle had less effect. A successful free throw basket sample showed that the athlete had an angle of about 120 degrees between the thigh and calf when squatting, about 80 degrees between the upper arm and lower arm when shooting, and about 130 degrees between the upper arm and torso after the shot. These three angles were key features to improve free throw hit and should be taken into account in free throw drills. The corresponding angles of the missed samples are often large or small, suggesting that these critical angles should be normalized during training.

C. Posture Analysis and Hit Probability Prediction System Test

The functional demonstration of the basketball free throw posture analysis and hit probability prediction system using deep learning are shown in Fig. 12.

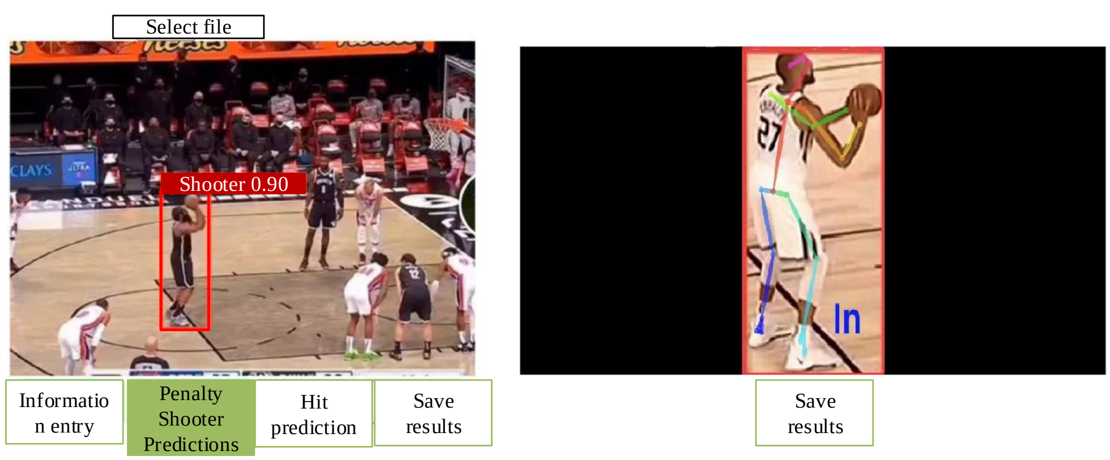
As shown in Fig. 12, the penalty player detection module shown in Fig. 12(a) allows the user to input information through the interface button in order to identify the player in the uploaded free throw video. The system identified the location of the penalty player, and extracted the video clip with the player as the main body for subsequent attitude evaluation. In addition, the free throw prediction module shown in Fig. 12(b) allows users to predict the shooting results of the free throw team player and record this information. These modules provide users with a complete penalty analysis and training aid. The system is further functionally tested, and the test results are shown.

As shown in Fig. 13, the performance evaluation results of the posture analysis and hit probability prediction system showed that with the continuous operation of the posture analysis and hit probability prediction system, the server CPU usage increased, and the overall trend was upward, but the fluctuation was large. When a new process joined, the CPU usage increased instantaneously, and then dropped to the normal level. The CPU usage was up to 21.7%, and the lowest CPU usage was at the beginning of the process. The CPU usage was basically kept below 20% during the whole system operation, and the proportion of server resources was within a controllable range. The CPU proportion of the system was similar to the proportion of server resources over time. The proportion of CPU was slightly higher than that of server resources, with the highest CPU proportion of 27.6% in the whole system running time, the lowest CPU usage at the beginning of the process, and the CPU usage basically remaining below 30% during the system running time. Considering the requirements of the posture analysis and hit probability prediction system, the CPU proportion of the system should be controlled below 40%. The test results should be in line with the system design. The response speed test results for video files of different sizes are shown in Fig. 14.

Fig. 14 shows the response speed test results of different sizes of video files. The video file files are set to 5MB, 10MB, and 15MB. As the size of the model file changed, the system response speed also changed, and the system transaction processing efficiency was basically the same. When the video file was 5 MB, the overall Transaction per Second (TPS) changed smoothly and remained at a low level over time, when the video file was 10 MB, the TPS fluctuation was more severe than that when the video file was 5 MB, but it was still flat. When the video file was 15 MB, the TPS fluctuation was larger, but the system still maintained good system stability and had a good user experience while the system processed the video, which met the actual use requirements.

TABLE II. DEGREE OF INFLUENCE OF DIFFERENT FEATURES ON THE PREDICTION RESULTS

Diagnostic property	Predictive accuracy	Accuracy impact
Thigh-calf angle	78%	8%
major arm-torso angle	81%	5%
The angle between the big and small arms of the shooting hand	79%	7%
Calf foot pinch angle	86%	<1%
Carapace thigh angle	83%	3%
Auxiliary hand large arm small arm angle	80%	6%
Arm acceleration	86%	<1%



(a) Penalty shot prediction system (b) Projected results

Fig. 12. Functional demonstration of attitude analysis and hit probability prediction system.

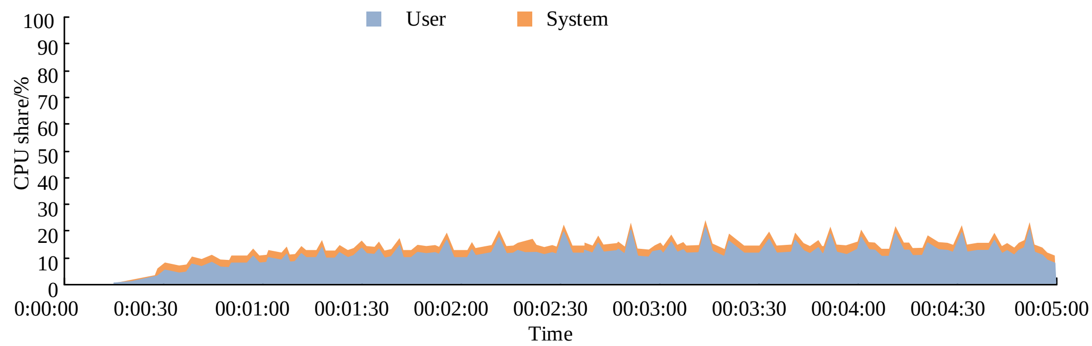


Fig. 13. Performance evaluation results.

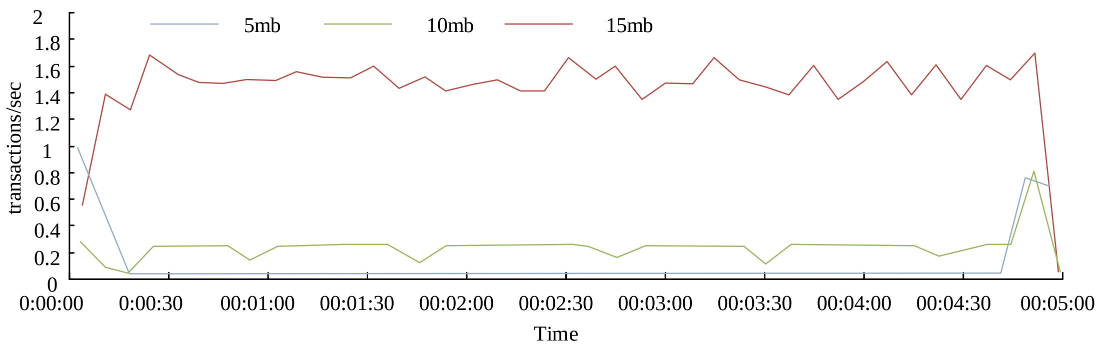


Fig. 14. Response speed test results.

V. Conclusion

Basketball education, as popular physical education curriculum content around the world, puts forward comprehensive requirements for students' physical fitness, skills and teamwork ability. The constantly evolving teaching of skills and tactics requires educators to update their teaching methods and cultivate high-quality athletes who can adapt to the development of modern basketball. Free throws are an important scoring method for students in basketball teaching practice. The hitting rate directly affects students' sports scores. In order to automatically predict the probability of free throw hit and reduce manual fatigue, a basketball free throw posture analysis and hit probability prediction system was constructed based on YOLOv5 network and OpenPose algorithm. The performance test results showed that when the free throw key frame limb angle was used as the feature, the goal prediction accuracy was 71% internally and 89% externally. The recall rate was 86% and 77%, respectively. The improved model was characterized by the combination of the relative position gap and the angle of the joint points. The accuracy was significantly improved to 80% internally and 95% externally. The recall rate was also increased to 96% and 75%. Experimental results show that the functional modules of basketball free throw posture analysis and hit probability prediction system basically meet the expectations, which proves that the basketball free throw posture analysis and hit probability prediction system based on deep learning can meet the practical teaching application needs. However, there are still some shortcomings in the research. The application of video human posture estimation in physical education teaching has broad prospects. Although the study has achieved results in the detection, tracking and prediction of free throw players, the accuracy of identification and prediction in complex scenarios still needs to be improved. The future research directions mainly include expanding training datasets to improve model generalization, especially in complex scenarios, optimizing feature extraction and machine learning algorithms to enhance prediction accuracy, and enhancing the real-time processing capability of the system to ensure its ability to quickly respond to actual competition demands. In addition, the user interface will be improved to enhance the user experience, and potential applications of the system in basketball tactical analysis and athlete performance evaluation will be explored. It also includes conducting long-term tracking tests to evaluate system performance and the long-term impact on athlete training effectiveness, with the ultimate goal of improving the technological support in basketball training and matches.

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