

Retraction

Retracted: Real-Time Analysis of Basketball Sports Data Based on Deep Learning

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

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

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

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

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- [1] P. Yao, "Real-Time Analysis of Basketball Sports Data Based on Deep Learning," *Complexity*, vol. 2021, Article ID 9142697, 11 pages, 2021.

Research Article

Real-Time Analysis of Basketball Sports Data Based on Deep Learning

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This paper focuses on the theme of the application of deep learning in the field of basketball sports, using research methods such as literature research, video analysis, comparative research, and mathematical statistics to explore deep learning in real-time analysis of basketball sports data. The basketball posture action recognition and analysis system proposed for basketball movement is composed of two parts serially. The first part is based on the bottom-up posture estimation method to locate the joint points and is used to extract the posture sequence of the target in the video. The second part is the analysis and research of the action recognition algorithm based on the convolution of the space-time graph. According to the extracted posture sequence, the basketball action of the set classification is recognized. In order to obtain more accurate and three-dimensional information, a multitasking target method can be used in training; that is, multiple indicators can be detected and feedback is provided at the same time to correct player errors in time; the other is an auxiliary method, which is compared with ordinary training. The method can actively correct technical movements, train players to form muscle memory, and improve their abilities. Through the research of this article, it provides a theoretical basis for promoting the application of deep learning in the field of basketball and also provides a theoretical reference for the wider application of deep learning in the field of sports. At the same time, the designed real-time analysis system of basketball data also provides more actual reference values for coaches and athletes.

1. Introduction

At present, many data of most sports competitions need to be recorded and counted manually on-site or by watching videos, such as basketball shots, points, rebounds, and assists. Using action recognition to assist manual statistics can greatly reduce the workload of individual event statisticians and provide extremely effective help to the whole competition and the technical statistics of each athlete. For the national economy, the sports industry is an essential component, and its value and function are fully reflected in accelerating the construction of a strong sports nation [1]. With the support of the development strategy of combining artificial intelligence and sports and the application of related intelligent sports products, the sunrise sports industry, which has both economic and ecological benefits, can help

the capital market explore market opportunities, make changes in business models, improve customer service experience, innovate management systems, and improve decision-making capabilities, thus realizing the high-quality development of the sports industry [2]. On this basis, it will promote the fundamental transformation of the sports industry model and enterprise form, drive the “wisdom upgrade” of the traditional sports industry, and enhance the international competitiveness of the sports industry.

In most sports events, athletes' information needs to be recorded and counted manually, such as basketball players' shots, field goal attempts, rebounds, assists, steals, and caps. These data are important for the coaching team and teammates to understand the performance of their own players and the opponent teammates on the court. Although each game will be manually marked, but it is only in terms of

data. If you want to see the scene of a certain athlete's data movement, you need to look back at the video. Watching the video replay from the beginning again is extremely time-consuming, and it is easy to miss looking back and forth in a manual way [3]. According to the general analysis, sports data is the identification and recording of one action, which is composed of one joint gesture. Therefore, the significance of this research is to propose an innovative idea to use the gesture method and combine it with action recognition to constitute a system that initially realizes semiautomatic data statistics for targets in the progress of video, replacing the tedious work of recording statistics. For the convenience of the study, this paper focuses on the analysis of basketball game videos and does not experiment with other sports [4].

The object of this paper is the application of deep learning in the field of basketball and how it can be implemented, as well as its feasibility. Specifically, we analyze the real-time data of basketball, how it affects players, teams, and the game of basketball, and whether it can be effectively implemented. Finally, conclusions are drawn and recommendations are given. The first chapter is an introduction. The research background and significance of this paper are discussed, and the main research content and organization of this paper are introduced. The second chapter discusses the current research status of real-time analysis of basketball sports data based on deep learning at home and abroad. The third chapter proposes the real-time analysis method of basketball sports data based on deep learning, constructs the relevant research model, and designs the real-time analysis system. The fourth chapter goes through the model analysis, real-time analysis of basketball sports data, and real-time analysis system analysis. It summarizes the relevant research work and innovation points of this dissertation and looks forward to the future research direction of deep learning of basketball sports real-time data.

2. Related Work

Since basketball is a complex game in terms of player's postural movements and tactics, the current research is mainly conducted using two ways of analysis; one is based on player trajectories, and the other is using postural movement analysis. Kumar and Jaiswal argued that different players and different teams have different characteristics due to their own athletic and tactical styles, and these characteristics are hidden in the trajectory of the actual game, and then according to this characteristic, convolutional neural networks with one-dimensional convolutional kernels can be used to model the trajectory characteristics of players according to the game, and these characteristics are extracted implicitly for the recognition of events [5]. Cust et al. studied basketball offensive calling tactics, using trajectory sequence data of players in two-dimensional coordinates and using traditional neural networks and recurrent neural networks in machine learning to model the training

of coordinate trajectories in these planes for the classification of basketball tactics for dynamic analysis, with good results for both the trained season and the season different from the one used for training [6]. Mohammadi et al. found that only a small fraction of multiplayer event recognition works for events. Accordingly, they used recurrent neural networks, combined with weight-learning time-varying attention mechanisms to construct a new model that can learn to detect events in videos while automatically focusing on the main characters of the event, and experimentally demonstrated the effectiveness of their model [7].

Zhu et al. put big data into use in basketball games. Freed full-angle replay technology brings fans a stronger visual experience, and the application of big data can improve the quality of training, measure the value of players, and ensure the fairness of the game, among others. However, it is ultimately an auxiliary tool that ultimately relies on referees to make decisions, so it is important to combine big data with experience to make the most reasonable calls [8]. Shan et al. mentioned that big data can be used to collect and analyze players' height, bouncing, sprinting explosive power, and so on during the draft, to evaluate players' comprehensive ability and predict their ranking, and the fact is that most of the predicted high ranking players will also become successful. Relatively speaking, the domestic league is not enough for data collection, accurate, and too favorable to big players. Basketball and data should be effectively combined to establish a complete data analysis system to achieve the purpose of high-quality player selection [9]. Liu G et al. concluded by studying deep learning in real-time analysis of basketball sports data that, in today's big data era, a team's completeness, accuracy, and systematization of data collection in basketball games and the results of its analysis will not only make the management mode of basketball data change, but also indirectly affect the level to which basketball games will develop in the future [10]. Therefore, the current basketball tournament should first establish the awareness of information technology data management, apply relevant data collection and analysis software, and perfect a data query platform to provide new momentum for the development of basketball [11].

Because basketball is more complicated in the player's posture and tactics, the current research mainly uses two methods for analysis; one is to analyze the player's trajectory, and the other is to use posture and movement analysis. Nevertheless, the research of real-time analysis of basketball sports data still has many problems to overcome, and now many domestic intelligent monitoring devices are still from foreign countries, performance and security still have great problems, and there is inconvenience in the later maintenance [12]. For the current deep learning technology used in sports professional competition or examination is extremely little, sports professional examination on the fixed-point shooting is even less; the main reason is that the external environment is complex, and image processing is difficult

[13]. The sports market is in great demand at present, especially for some items in sports professional exams, which is the work we urgently want to study [14].

3. Research on Real-Time Analysis of Basketball Sports Data Based on Deep Learning

3.1. Basketball Sports Data Extraction. Data analysis of basketball games based on big data is a huge and complex project, but its application is promising. It mainly relies on analyzing the movement habits of players to analyze and predict their subsequent actions to make corresponding defensive strategies. Analyze the opponent's tactics by analyzing the opponent's players' standings on the court, behavioral changes, and then develop corresponding defensive strategies; analyze the big data of a single opponent's players for multiple games to improve our defines. The application of big data in the actual professional league and the talent selection based on player data is crucial for the team, through the draft, to obtain potential players who can change the fate of a team, so before players participate in the draft, they are subject to a series of physical fitness tests. This includes a full range of stats such as bounce, sprint burst, and height [15]. These data are then analyzed with the player's previous lower league data to predict a player's draft position and future ceiling. Therefore, high draft picks naturally become the hot spot for everyone, and their success rate is so high that the significance of picking the top pick for a team is huge.

The evaluation of players has also been linked to big data, such as the metric of Player Efficiency Value, or PER for short, which is one of the most widely used scoring methods today. It is designed to present a player's contribution concretely and statistically using a specific and rational mathematical formula that can be used to evaluate a player's overall performance and is considered a standard quantitative indicator of a player's value. Its base data are specific parameters such as the number of rebounds, points scored, and assists, during a player's game, and these data are weighted to obtain a player's efficiency value. It allows horizontal comparison of players during the season, as well as vertical comparison of the whole season, and provides a more objective evaluation of the overall value of a player.

The data mining system at the level of basketball sports mainly relies on data mining theory to categorize and integrate basketball event data, team data, individual data, and business data, build a basketball-related data warehouse, and extract the effective information and knowledge data implied in it at any time [16]. The event data is mainly the basic event data such as game time, location, and number of teams; team data is mainly the basic situation data of the team in the competition, team scores and points, and team offense and defines related data; individual data is mainly shooting, basketball boards, assists, turnovers, steals, and personal physiological data; commercial data is mainly about sponsorship, ratings, and competition-related service products. The accumulation of data can provide scientific and effective data support for basketball tournaments, team development, and player development. The basketball data

level mining system is mainly from the perspective of academic and data analysis of basketball-related knowledge, providing relevant technical analysis, data analysis, and tactical analysis, case study resources, using resources, and building a resource platform for basketball academic analysis. Figure 1 shows the mining system of basketball sports data level.

3.2. Deep Learning Real-Time Analysis Model. For the method of basketball action recognition, this subject design system imitates the process of human action recognition by first recognizing the posture of each person at each moment and then analyzing the continuous sequence of postures to identify the action. The basketball sports data real-time analysis method used in this model is based on the network structure designed by the deep learning method, and the data real-time analysis method is based on the graph convolutional neural network design; they are both based on the convolutional neural network design [17]. Besides, to quickly apply it to basketball sports data real-time analysis, this paper uses the migration learning method, which can achieve good results even under the condition that the amount of data is not particularly sufficient.

Convolutional neural networks mainly consist of a stacked combination of multiple convolutional layers, activation functions, and pooling layers in modules, adding fully connected layers at the end or mapping the features using 2×2 convolution to adapt them to the task. In signal processing, if $g(u)$ and $G(x)$ are bounded and predictable, then define

$$\begin{aligned} h1(x) &= \int g(\mu)G(x-\mu)d\mu * \sum_{i=0}^{\infty} f(i), \\ h2(x) &= \int g(\mu)G(\mu-x)d\mu * \sum_{i=0}^{\infty} f(i). \end{aligned} \quad (1)$$

In fact, in terms of operation, convolution is extremely similar to autocorrelation, except that the convolution kernel has changed. In the field of machine vision, the convolution layer operation is the same as the convolution operation in the field of communication. Then, the general two-dimensional convolution can be expressed as

$$g(x, y) = f(x, y) * W(x, y) = \iint_{\infty} f(\xi, \eta)Wx + (\xi, y + \eta)d\xi d\eta. \quad (2)$$

And digital images are all discrete, so take the discrete representation of the two-dimensional convolution in image processing.

$$\begin{aligned} g(x, y) &= f(x, y) * W(x, y) \\ &= \sum_{s=-a}^a \sum_{t=b}^b f(s, t)W(x+s, y+t), \end{aligned} \quad (3)$$

where $g(x, y)$ is the feature map obtained after convolution, $f(x, y)$ denotes the original map, $W(x, y)$ denotes the convolution kernel, the $\{s, t | -a \leq s \leq a, -b \leq t \leq b\}$ are the

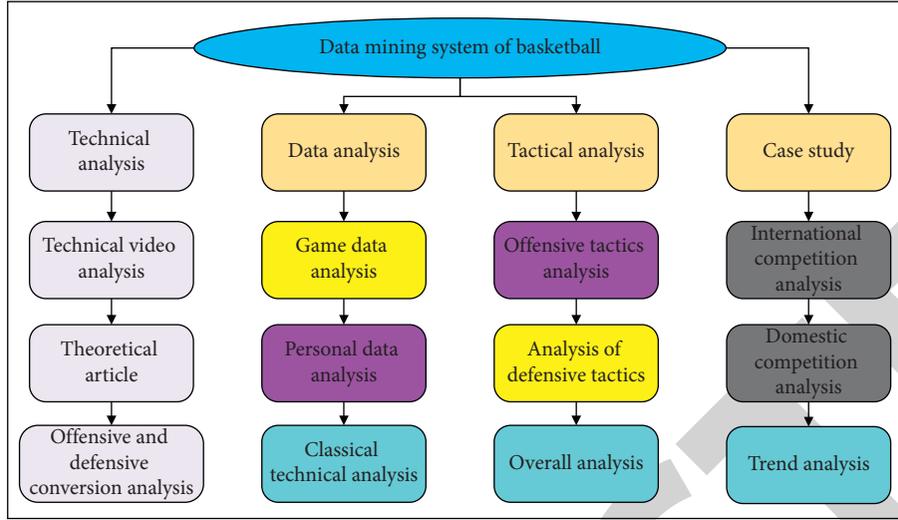


FIGURE 1: The mining system of basketball sports data level.

coordinates on the convolution kernel, x and y are the original map upper coordinates, and $2a$, $2b$ are the convolution kernel sizes [18]. Also, when the actual code is written to implement the convolution operation, for the sake of simplicity, the convolution kernel is not rotated, directly weighted superposition, and the operation is equivalent to the correlation in the signal field. The correlation operation and the convolution operation can be converted to each other by rotating the convolution kernel by 180° , so the actual final representation takes the form of

$$\begin{aligned}
 g(x, y) &= f(x, y) * W(x, y) \\
 &= \sum_{s=-a}^a \sum_{t=b}^b f(s - y, t - b)W(x + s, y + t). \quad (4)
 \end{aligned}$$

Pooling is a discrete sampling operation that aims to downsample the input representation (image, feature map, etc.), reduce its dimensionality, party different positional features, and obtain the corresponding abstract statistical information. Using abstract features for classification or recognition will be helpful in reducing overfitting. Also, dimensionality reduction will reduce the number of parameters to be learned, thus reducing the computational cost. At present, the more commonly used pooling operations are maximum pooling and average pooling. In practice, it is found that maximum pooling is often better than average pooling, and the maximum pooling operation is mostly used in research. The pooling layer uses a kernel size of 2 and a step size of 2 to perform feature aggregation, resulting in an output volume of $112 \times 112 \times 64$. The length and width are reduced by half, and the depth remains the same.

All neural networks require nonlinear layers, and convolutional neural networks are no exception. Without nonlinear layers, no matter how many layers there are, it is still equivalent to having only one layer of neural network. The commonly used activation functions are sigmoid, where

blue is the function curve, and orange is the corresponding derivative curve.

The expression and derivative of the sigmoid function are defined as

$$f(x) = \frac{e^{-x}}{1 + e^{-x}}, \quad (5)$$

$$f'(x) = f(x)(1 + f(x)).$$

The parameters of the previous low-level layers are fixed during training or learned using a lower learning rate, and the high-level feature abstraction layers are mainly optimized, which reduces the number of parameters that need to be fine-tuned while reusing features from the lower layers [19]. In the image domain, lower-level features are likely to be similar, and the model can combine low-level features into new higher-level feature representations depending on the specific problem. When only a few images are available, in most cases, training the model directly can easily lead to overfitting, and the parameters to be tuned are too small compared to the number of images available for training. In this case, it is better to use a large pretrained network directly and then fine-tune the optimization only for the last one or two layers of the network.

3.3. Basketball Sports Data Real-Time Analysis System Design.

The specific structure block diagram is shown in Figure 2. The first thing is to input the video of the competition for the system, because it is still single-person data statistics, so we need to specify the target object to be counted. The video interception is performed according to the method described before, the position of the tracking frame is obtained, and the center point is selected as the position of the target, which is sent to the pose estimation network for estimation, and the nodal point data is output. For the later graph convolution action recognition, it is known from the

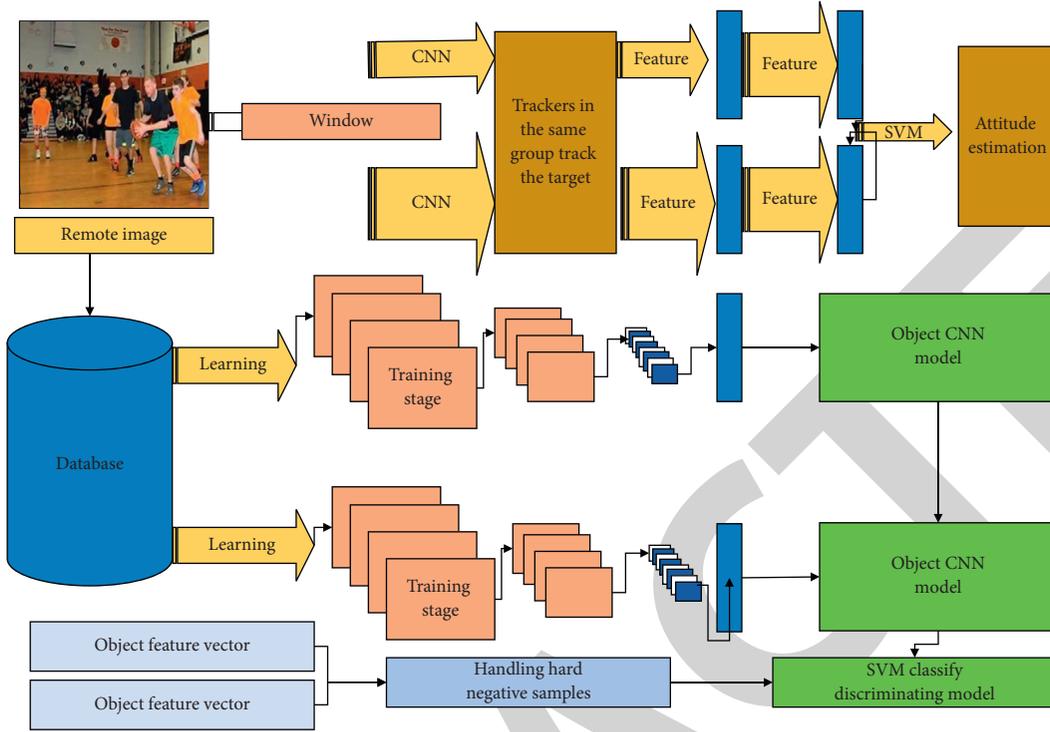


FIGURE 2: Basketball sports data real-time analysis system structure diagram.

experiments in Chapter 4 that the network needs consecutive frames as input, and 190 frames are the better input frame length, so let the pose estimation network run 190 frames first, and feed the nodal results into the loop array (the loop array length is the space required for 190 frames) [20–23]. When the loop array is detected to be full of 190 frames, the system takes out 190 frames of data from the latest video frames of the loop array and puts the video frames into the input cache of the network in reverse order, the graph convolutional network is started, and the action category is finally inferred by the graph convolutional neural network [24–26]. The new video frame overwrites the oldest frame in the loop array, then 190 frames are taken forward from the latest video, and then the video frames are reverse-ordered and fed into the graph convolutional network for inference, and so on until the video ends or tracking fails.

The tracker's tracking algorithm loses the target when there are commercials and playback shots in the game video, and then it is necessary to manually perform a new target selection again, waiting for 190 frames again. Based on the action recognition result, the corresponding timestamp, action category, and action pose information are output.

For basketball, this article sets up the statistics of shots, hits, percentage, assists, and dribble time. If we just look at the action, we cannot judge whether the score and assist are scored or not. Therefore, we need to convert the action information. In this paper, we get the score change of the two teams in the current video to determine whether a shot is scored or not. When a shot or a layup occurs, we obtain the scoring position of the yellow target's team, propose a picture of the corresponding position, convert it to grayscale,

and perform banalization, using the normalized squared difference template matching method.

$$R = \frac{\sum_{x,y} (T(x,y)^2 + I(x,y)^2)^2}{\sqrt{\sum_{x,y} (T(x,y)^2 * \sum_{x,y} (T(x,y)^2 * I(x,y)^2)^2 I(x,y)^2)}} \quad (6)$$

The system interface is implemented using the python version of QT5 combined with OpenCV. QT is responsible for the interface display, and OpenCV is responsible for the video playback and processing. The statistics interface uses the Tablelike class inside pyqt5, which is a good way to display data in a table format and can also be inherited to read and write custom data format types. Since we are currently in the testing phase, we do not use the database yet, so this article uses a custom way to read, write, and update data. The system can display the statistical results by pressing the statistics button at the bottom of the statistics panel at the location, where the data is needed to view the statistical results. When the data of more than one person is collected, the statistics of the whole team can be obtained by viewing the whole team page.

4. Analysis of Results

4.1. Real-Time Analysis of Basketball Sports Data. Real-time refers to the ability to analyze and deal with a matter in a timely and correct manner, and there is a length of time to deal with a matter, and the shorter the time is taken to deal with it, the better the real-time is, and the

longer the time is taken to deal with it, the worse the real-time is. We want to be able to process the basketball scoring event in real-time, and we want to be able to process it in as short time as possible. An image with a frame rate of not less than 25fps is called a real-time image and can meet the system's real-time requirements. To verify the rapidity of the algorithm in this paper, the time of running the algorithm is recorded, and the average value is taken as the time of running the algorithm 20 times continuously, and the results are shown in Figure 3. From the data in Figure 4, the average time of the algorithm running is calculated as $20.2\text{ ms} < 30\text{ ms}$, which satisfies the real-time requirements of basketball sports.

In the process of real-time analysis of basketball sports data, the players participating in the experiment were grouped before and after the experiment for 20 minutes of full-court games, recorded games, and the statistics of technical and tactical frequency indexes after the game are shown in Figure 4. It can be seen from Figure 4 that the indexes after the experiment are higher than those before the experiment, thus indicating using the results of the real-time analysis for the cultivation of players' shooting techniques at each position and improving the basic cooperation of players and other aspects. The results of the real-time analysis have a significant effect on the development of players' shooting techniques at each position and the improvement of players' basic coordination, such as rationality, standardization, and flexibility.

After capturing sports information, calculating, and refining sports indicators to finally form training recommendations, the deep learning sports coaching system will further break down the training, and during the training process, the intelligence can continuously track and observe multiple specific training indicators. In the actual training, the real-time comparison of tracking indicators provides real-time feedback as soon as the athlete deviates from the training goal, which will help basketball sports players maintain the set training goals as much as possible, thus achieving effective and efficient training and improving the skill level of basketball.

4.2. Deep Learning Model Analysis. The technical and tactical analysis methods differ from sport to sport, but the basic steps are similar: first collecting raw data, then extracting valid information, and then performing a deep analysis of the data. In most official competitions, athletes are not allowed to wear additional equipment, so we want to get information about the athletes in the game, mainly based on deep learning methods. The system takes a bunch of seemingly confusing and seemingly chaotic game information and turns it into a collection of data that can be explored further and is easy to read and understand and then uses machine learning methods to help team data analysts and coaches better understand the inner workings of their teams. This change, once considered a strategic gamble, has brought amazing results to the team, surprising everyone.

The results of the deep learning model analysis are shown in Figure 5. In Figure 5, we can see that the intelligent

data analysis system provides another novel way of understanding the game that challenges, and to some extent replaces, traditional methods of team data analysis. The system can track each player's movement on the court, knowing that this is something that traditional data analysis would have struggled to do anyway. The improved access to information brings with it an enormous amount of data processing.

In the whole game, players spend more time running or standing than dribbling, throwing, and passing, so if too many frames are used for smoothing, there will be excessive smoothing, and the system will not detect such actions as throwing or passing. Experiments found that the effects of using 5 and 6 frames are similar, but this paper prefers using 5 frames to get a higher check rate and get all the actions of each player as much as possible so that they can be deleted manually later, but if they are missed, the system will need to find the missing position again, and the system will lose its meaning. After improving the system, the following test results (Figure 6) were obtained by using the system and manually for the other teammates of the same team in this section one by one.

Through the analysis, it can be found that although multiframe voting can suppress individual jumps well, continuous jumps and sequential jumps at intervals are not well suppressed, so there is still a large impact on the system. This is mainly because the current amount of data acquired is still relatively small, and the recognition of basketball actions is still relatively general, and further expansion of data collection and labelling is needed in the future. Also, further subdivision of the action can make the network improve the accuracy of action recognition.

4.3. Real-Time Analysis System Analysis. By testing 30 sets of data, 10 sets of data each for left, middle, and right, the test results are shown in Figure 7. In the left, middle, and right shooting, respectively, ten groups of data, it was found that the left and right shooting data did not have the phenomenon of false detection or omission, and the third and ninth groups of data of middle shooting data had the phenomenon of omission. This article resets the basketball and system configuration parameters after the basketball enters the basket after a proper delay to solve the case of false detection. The basketball thrown from the middle position is thrown directly into the basket (hollow ball) and moves along the direction of the basket and the rim, which will lead to the phenomenon of missed detection. This phenomenon is a further work to be investigated in the future.

By comparing the execution efficiency of the traditional analysis system and the analysis system in this paper, we verify the correctness of building the system based on the deep learning method as the underlying framework of the system. Observe the execution efficiency of the two solutions when processing the same algorithm or processing the same amount of data, constantly adjust the size of the data to find out the fluctuation change pattern of the computational efficiency of these two with the increase of the processing data, and prove that the operating performance of the system

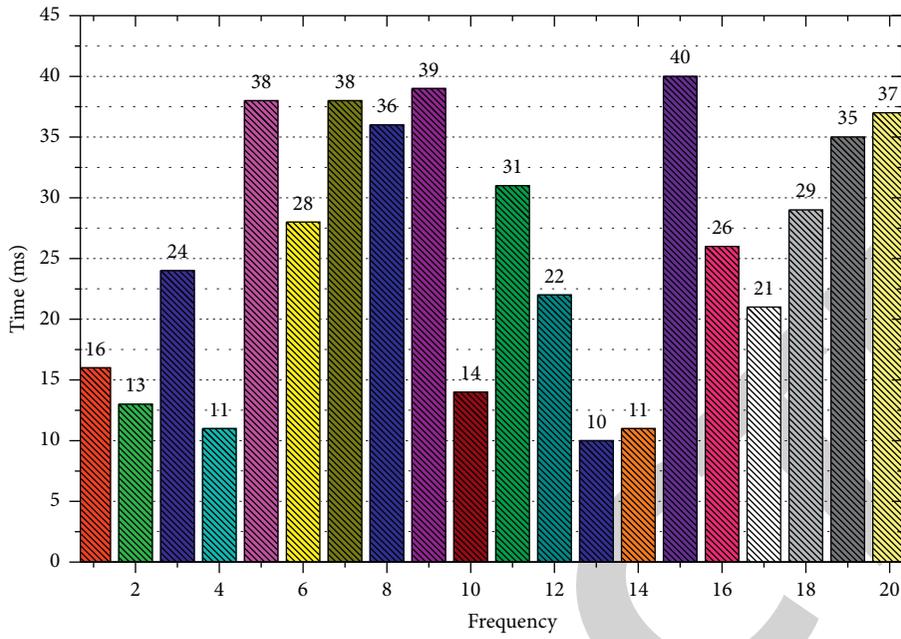


FIGURE 3: Running time.

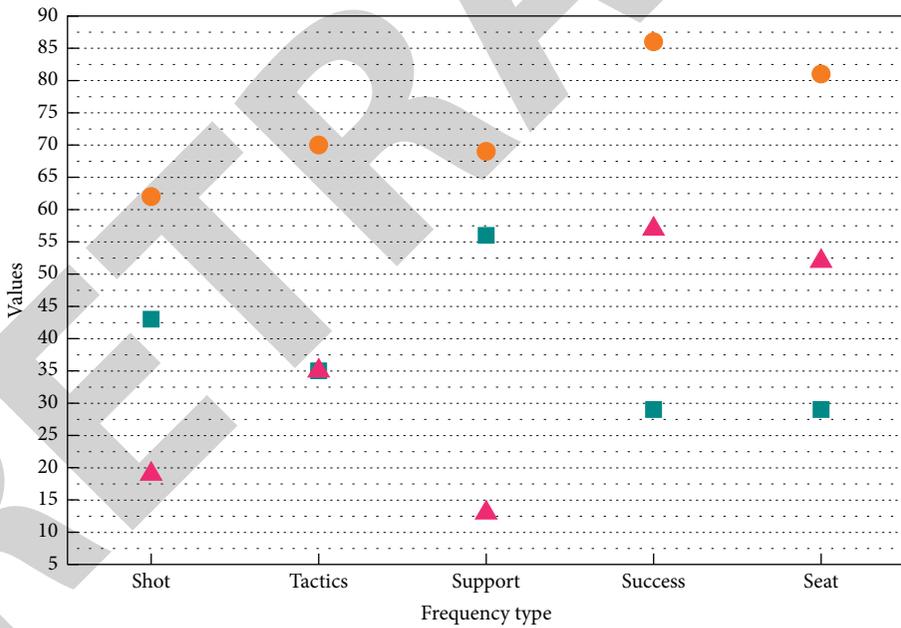


FIGURE 4: Statistical results of real-time analysis before and after the experiment.

is better than the traditional one. Test description: the data set is manually divided into 1G, 2G, 4G, 6G, 8G, and 10G files to be used separately. After uploading the data to HDFS, the deep learning algorithm is executed using the same size dataset, and the total time consumed is recorded. Next, an algorithm is written to extract the query words from the

“query” field of the dataset and write them in the text and then run the classical Word Count algorithm on them to count the frequency of words, as shown in Figure 8.

Through the above analysis, this system is feasible as a support system for real-time processing applications. The development progress of computer vision as the eye of

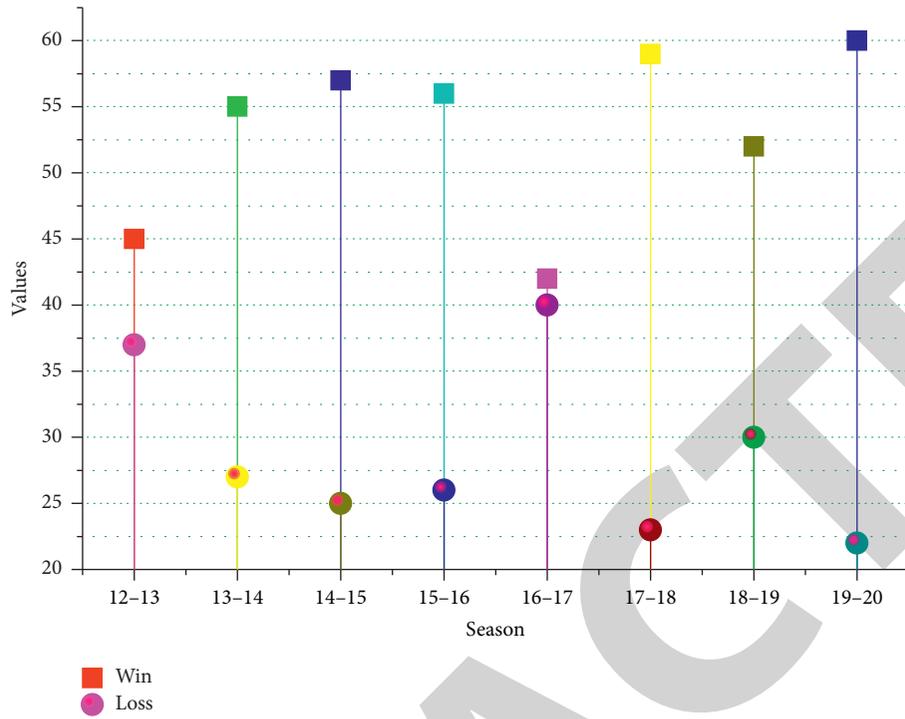


FIGURE 5: Deep learning model analysis results.

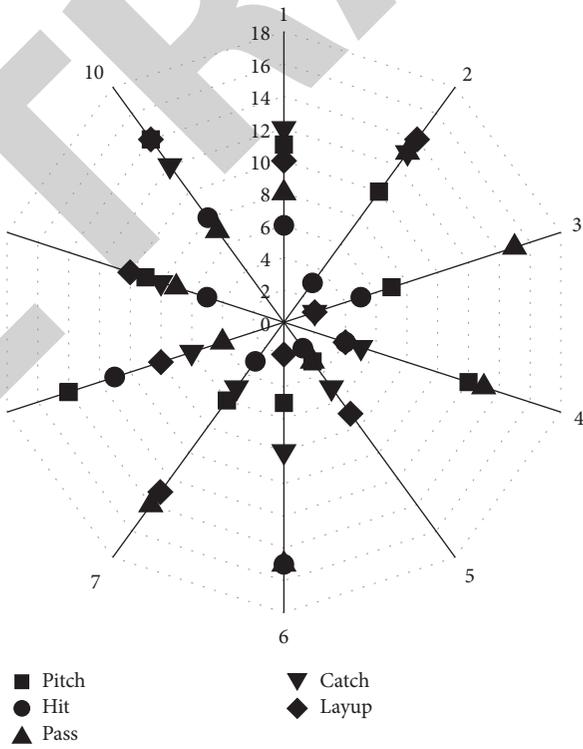


FIGURE 6: System statistics and manual statistics results.

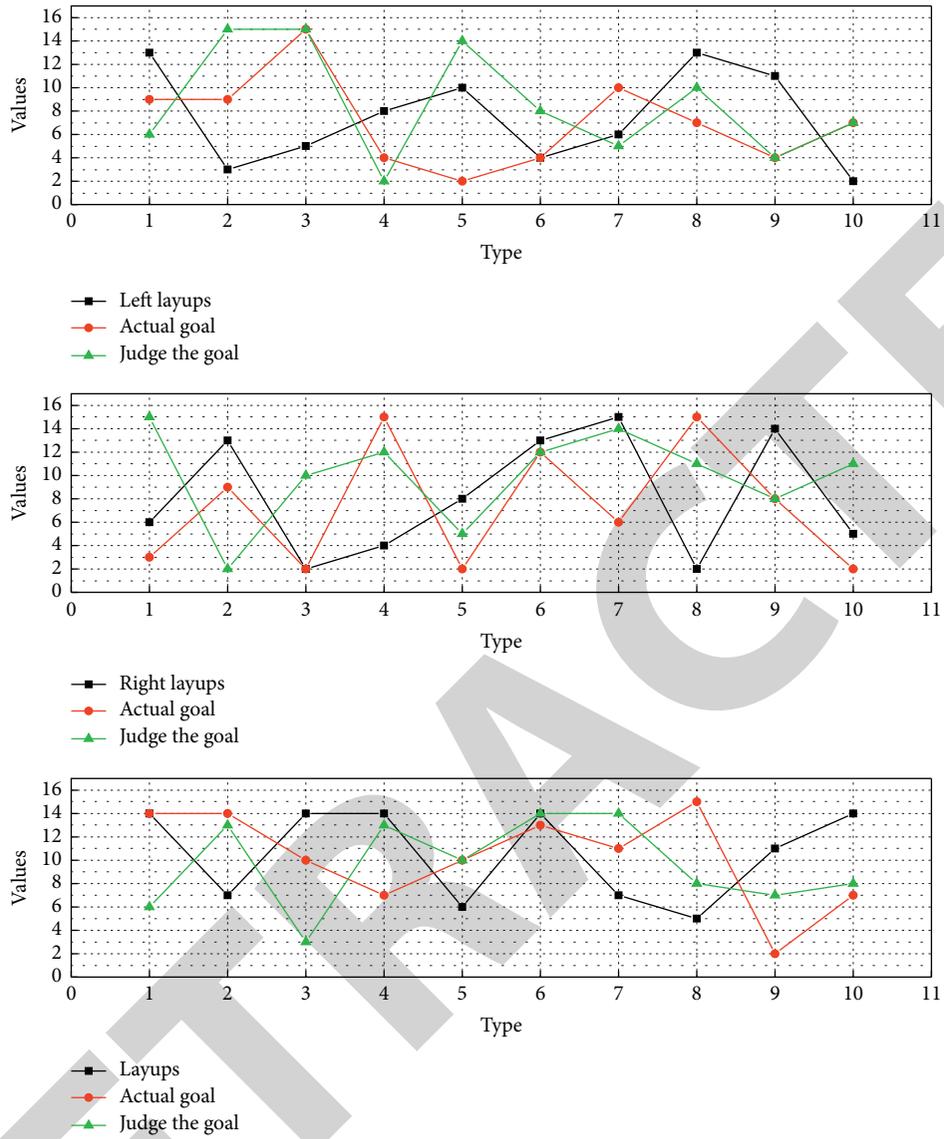


FIGURE 7: Results of left, center, and right shot statistics.

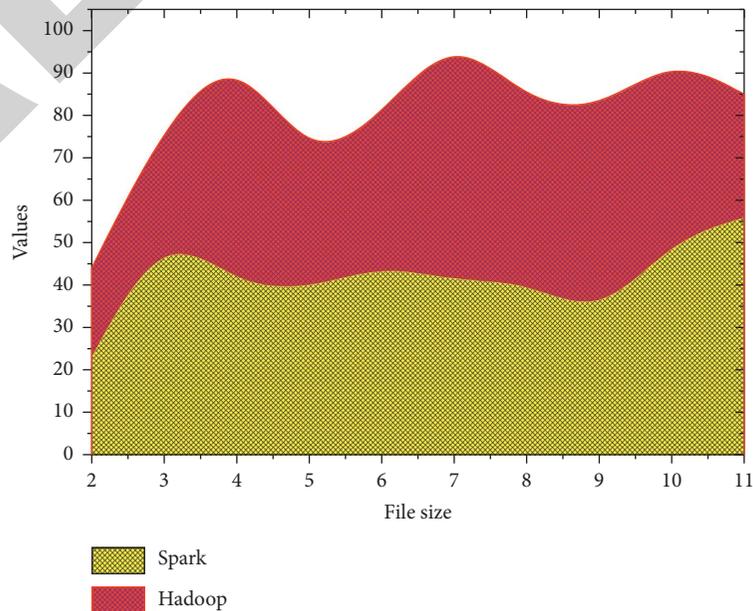


FIGURE 8: System deep learning runtime comparison.

artificial intelligence to deliver information makes human-machine interaction possible, with human and machine cooperating and the machine better serving the human with technical support from the human. The tracking and detection of motion targets, as a core component of computer vision technology, is becoming increasingly important and is widely used in military guidance, medical diagnosis, human-machine interaction, and traffic security. In this paper, we mainly analyze and study the motion target tracking and detection technology for the demand of real-time basketball data analysis project and propose an improved algorithm for the shortage of traditional algorithm, and the experimental results show that the improved algorithm can meet the demand of accuracy and rapidity of real-time basketball data analysis.

5. Conclusion

In the field of basketball, after the application of big data, through big data analysis of the behavior trajectory of the opponent and its players, the corresponding one-on-one strategy can be formulated, which can effectively improve the intensity of individual players' offense and defines it; analyze the offensive or defensive efficiency of the cooperation between different players and the tactical style of the opposing team, and formulate the corresponding tactics at the level of the whole team, which can find the most suitable tactics and player configuration for the team; analyze the data of individual players on the court, such as rebounding, passing, and holding the ball, to find the most suitable position of players. For a team, it is possible to figure out a variety of offensive or defensive tactics with high efficiency, so both individuals and teams will be able to improve their overall performance after applying big data analysis. The HD camera captures the basketball's trajectory and records the player's shot status and then combines the statistics of three-point shooting rate, mid-range shooting rate, and free throw shooting rate to find the rules to improve the shooting rate. The HD camera is supplemented with intelligent analysis system. This method is based on the information captured by the HD camera, and then the information is processed by the intelligent analysis system to derive deep information. From the analysis, deep learning techniques are more mature and have achieved significant results in the technical and tactical analysis of professional games. However, more is still in the research stage in terms of helping improve training.

Data Availability

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

Conflicts of Interest

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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