Mathematical Biosciences and Engineering

http://www.aimspress.com/journal/mbe

MBE, 20(2): 1919–1937.
DOI: 10.3934/mbe.2023088
Received: 20 September 2022
Revised: 11 October 2022
Accepted: 17 October 2022
Published: 09 November 2022

Research article

A video images-aware knowledge extraction method for intelligent healthcare management of basketball players

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Abstract: Currently, the health management for athletes has been a significant research issue in academia. Some data-driven methods have emerged in recent years for this purpose. However, numerical data cannot reflect comprehensive process status in many scenes, especially in some highly dynamic sports like basketball. To deal with such a challenge, this paper proposes a video images-aware knowledge extraction model for intelligent healthcare management of basketball players. Raw video image samples from basketball videos are first acquired for this study. They are processed using adaptive median filter to reduce noise and discrete wavelet transform to boost contrast. The preprocessed video images are separated into multiple subgroups by using a U-Net-based convolutional neural network, and basketball players' motion trajectories may be derived from segmented images. On this basis, the fuzzy KC-means clustering technique is adopted to cluster all segmented action images into several different classes, in which images inside a classes are similar and images belonging to different classes are different. The simulation results show that shooting routes of basketball players can be properly captured and characterized close to 100% accuracy using the proposed method.

Keywords: smart health management; feature extraction; fuzzy clustering; adaptive median filter

1. Introduction

Basketball is one of the most popular sports worldwide. Basketball games may be difficult to recreate using motion capture video because kinematic procedures, such as blend and distortion, which can rapidly sever the exact connection between the motion of an item and the motion of the player. Basketball video games from the NBA 2K and NBA Live series, which use motion, capture data to display very realistic action, and are immensely exciting for fans, but include artifacts. For example, the ball could seem to be glued to the player's hand or move in an impractical manner. Basketball skill animation using physics-based controls has the potential to be of excellent quality and physical realism. The complexity of the interactions between the ball and the ground, the dexterity and grace needed to complete the necessary tasks, and the interplay between locomotion control and the manipulation of the basketball's swift motion makes it difficult to develop such controls [1].

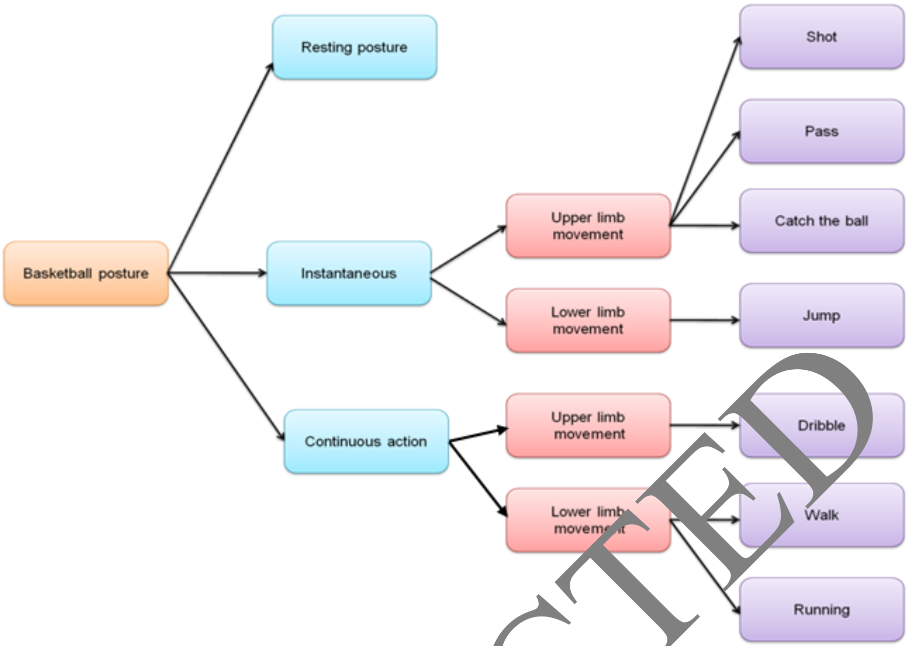

Figure 1. Classified summarization of basketball postures.

Athletes eventually become proficient in sports motions via a lot of repeating repetitions. The current approaches to educating and training athletes have a significant impact on how well athletes progress. However, video, animation, and other multimedia interactive model systems are among the most significant media in terms of how basketball is played and regulated. Currently, the NBA and other professional contests make extensive use of the multimedia interactive model system, but general physical education instruction has not used this technology [2]. Basketball is a team sport in which points are scored when the ball is passed through the goal. As a result, shooting is a crucial talent that directly affects the performance of the team. The major scoring advantages are given to a player by being capable of shooting a successful jump shot: a) accuracy, b) speed, c) security from an opponent, and d) the ability to release the ball from a variety of distances from the basket. Due to this, the jump shot has emerged as the most effective and popular shooting manoeuvre, irrespective of the player's position on the team [3].

It is believed that heart rate monitoring is inadequate for performance analysis to anticipate a player's internal stress during a game. As a result, time-motion analysis approaches are the focus of the development of a monitoring system. These techniques are often dependent on commerce, are unavailable, or are not suitable for indoor sports. The Video Manual Motion Tracker 1.0's accuracy hasn't been tested, although it was created to analyze the time-motion of indoor sports. The "cartographical approach," which included plotting a player's motion onto a court's coordinate map and then calculating the distance that was finally covered, was the first technique for time-motion analysis [4]. Figure 1 shows a representation of basketball postures.

Sports analysis makes extensive use of object tracking. Balls and players are often monitored since these interactions between players and balls most often results in major events. It demonstrates a method for locating and following balls in films that is dependent on their trajectory. To find ball participants, the ball size is first proportionately inferred from conspicuous items. The recognized basketball set type and baseball pitch assessment may both use the extracted ball trajectory. Several cameras positioned in precise locations are the foundation for several 3D trajectory reconstruction studies. In addition, emerging research topics in sports video analysis include computer-assisted umpiring and strategies inference. These, however, might be seen as sophisticated applications based on player and ball monitoring. Consequently, object tracking is a crucial and important topic in the interpretation of sports footage [5]. Image processing is a technique used to apply certain operations to a picture to produce an improved image or to draw out some relevant information from it. To preprocess the image, we use Denoising using an adaptive median filter and Contrast enhancement using discrete wavelet transform. For segmentation, we use U-Net based Fuzzy convolutional network. To reduce noise and simplify the complexity of the feature evaluations, we employ the Fuzzy KC-means Clustering method, also taking into account the many security issues that are related to them.

Main contributions of this paper can be summed up as the following three aspects:

- It is recognized that video images can be utilized for smart health management of basketball players.
- The fuzzy KC-means-based method is developed to realize this purpose, in which adaptive median filter and discrete wavelet transform is introduced for preprocessing of visual features.
- Some simulation experiments are carried out on real-world data to evaluate the proposed technical method, and results show good performance of it.

The rest of the paper is organized as follows. Section 2 makes literature review and surveys related work concerning topic of this paper. In Section 3, mathematical process of the proposed method is presented and given. The simulation experiments and results analysis are given in Section 4. And finally, we conclude this paper in Section 5.

2. Related work

The public enjoys sports videos in today's society because of their special attraction. Thus, from a commercial standpoint, analysis and examination of sports game video data are quite useful and practical. In this work, tracking elements, in a video of a basketball game, are used to identify, detect, and predict basketball players [6]. Sports movies often use interactions between athletes and the ball to create their most memorable scenes. In a sporting event with plenty of background movement, it might be difficult to identify and follow a ball or a player. Ball identification is much more challenging due to the ball's small size in comparison to the frame size [7]. Additionally, since the ball is moving at a rapid speed, the ball images are also deforming. Frequently, players will block the ball, causing the ball's image to blended with the field's lines and borders [8]. Through the addition of live video transmission, score recognition, a highlight video compilation, and internet sharing, intelligent sports video analysis may improve the functionality of intelligent arena applications [9].

Investigating sports difficulty in contests requires noninvasive methods, which are essential. This circumstance offers a chance to create an unobtrusive data gathering system that recognizes players' responsibilities in recognized basketball contests utilizing computer vision, image processing, and software teaching approaches. Sports surveillance data may be predicted using basketball principles like rebounding and video review statistics [10]. Repetition of regular empirical basketball teaching techniques may have a detrimental influence on the effectiveness of serious basketball training and the learning of fundamental technical abilities. The basketball coaching reproduction framework was developed using an augmented reality technology as a solution to this issue. The system generates a computational model of a baseball player planning their strategy. In addition to providing more focused instruction, it records the basketball player's real circumstances and compares them to the simulated trajectory [11]. Player movement patterns are actively collected and classified in the post-event video analysis for player motion tracking, which has historically utilized a variety of data gathering approaches including live observation. Research tends to concentrate solely on the limited numbers of players inside designated playing zones as personally collecting and analyzing such data requires a significant amount of work [12].

Many studies on a variety of sports video analyses and applications are motivated by the expansion of the sports fan base. More than simple highlight extraction or semantic summarizing is required by the audience, sports enthusiasts, and even pros [13]. The need for computer-assisted sports technique analysis is rising. A difficult challenge is identifying technique patterns in broadcast basketball footage because of the intricate settings, various camera movements, numerous player occlusions, etc. The action screen is a blocking technique used by offensive players in basketball games to free up a teammate for a shot, a pass, or a drive for a score by standing next to or behind the defender [14].

Many live sports broadcasts have been recorded as a result of the surge in sports fanaticism, and research has been done on automatically locating semantic occurrences in the recorded video to provide a useful video browsing tool for casual viewers. A professional athlete, or coach, on the other hand, could see high-level semantics from a different angle, such as the players' offensive or defensive strategy. The complex sceneries and variable camera motions in a broadcasted basketball film make it considerably more difficult to analyze techniques than in other sports programs [15]. The examination of the team's strategies using game footage is crucial to improving the performance of a sporting team. The most helpful indications in a sports film for technical analysis are player trajectories [16, 17]. Due to the ball being covered up by players, as well as the presence of many moving objects such as spectators, flags, twigs and tree branches, etc., ball recognition in sports videos is difficult to facilitate. The image of the ball is also distorted as a result of the ball's quick speed [18].

The development of sports movement analysis technologies using video has significant practical applications. The utilization of digital video, human-computer interaction, and other technologies may significantly increase the effectiveness of an athlete's training sessions [19]. Cao et al. [20] proposed a discriminative feature learning method via unsupervised clustering method, which can realize fast and direct classification tasks for multiple types of data. This can guide technical direction of this work. Ali et al. [21] utilized the voice features to propose an early detection method for Pakinson's disease. Ali et al. [22] also proposed an ensemble learning-based approach for early detection of the Pakinson's disease. The process of automatically creating a written description for athletic events is known as sports video captioning (basketball). In sports video, it is difficult to analyze the complex group relationship among players [23]. Ball identification is a highly challenging task in a sports film since there are so many moving things in the backdrop. Additionally, because of the ball's rapid movement, the ball images are distorted. In a sports film, it is exceedingly challenging to accurately identify and follow a ball [24].

A component of computer vision that has gained relevance in current years, movable object detection technology is becoming more and more popular [25]. Currently, moveable target detection technology is widely employed in several sectors, including intelligent transportation, healthcare, security monitoring, and military defense. Rapid and precise video image segmentation is essential to the identification, localization, and analysis of targets in moving target detection systems [26]. To improve shooting accuracy, it is essential to analyze the trajectory of a basketball player's shooting motion and separate components [27]. Basketball training uses athlete analysis to create training routines that are appropriate for each player's performance and enhance team performance. Analysis of basketball players' training-related behaviors is achievable with the use of video analysis technologies [26, 28]. Figure 2 shows the representation of our proposed method.

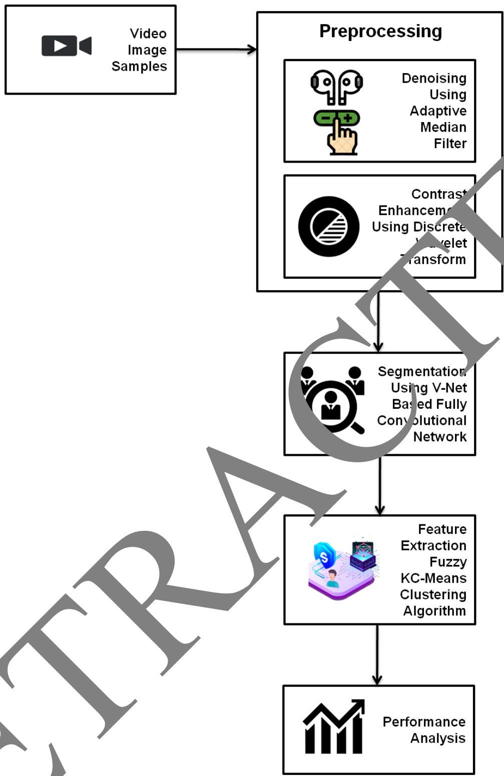

Figure 2. Illustration for main structure of the proposed methodology.

3. Proposed work

3.1. Overview

Pictures that are improperly exposed and are either too bright or too dark are common in digital photography. The camera exposure mechanism scanning the backdrop and making adjustments is typically what causes this issue. Noise from picture sensors or image transmission has an impact on digital images. To get rid of the noise in the photos, denoising is utilized. It is suggested to use trajectory-based ball recognition and a method with trajectory interpolation to locate lost balls in basketball game videos. An effective background removal approach based on the three-frame difference technique is utilized to deal with the issue of ball deformation caused by the high-speed motion of the ball and the movement of the camera. When compared to other approaches, this one is effective since it can be used to extract moving things from the front even when there are many moving objects in the background.

As one of the most watched sports in the world, basketball attracts a sizable following. While casual viewers prefer to watch only a few crucial moments rather than the whole game, technical experts are more interested in the tactical analysis of the film since it will assist them to comprehend the team's strategy and the players' performances. A probability-based play model based on the player trajectory is used to break the game down into several stages, and the game is then examined by identifying the crucial components of a basketball play.

3.2. Video pre-processing

3.2.1. Data samples

In the course of our implementation, we assemble 30 NBA games with frame rates ranging from 15 to 30 fps. Every video in the dataset has a consistent format and is made to be the same size throughout the processing stage. The motion recognition dataset for basketball players is described in Table 1. Based on CUDA 9.0 and Caffe, the experimental environment consists of an i7 CPU and GTX 1080 ti GPU. As the training set, we randomly choose 20 movies, the validation set, 5 videos, and the remaining 5 videos as the testing set. The videos omit the pause and the commercial break. The hand-written labels for the motions in the videos.

Table 1. A description of the motion recognition dataset for basketball players.

Movement Type	Shoot	Pass	Dribble	Foul
Training set	924	1038	711	649
Valid set	208	227	191	147
Testing set	2[illegible]4	261	172	153

The characteristics of the dataset are first pre-processed using LSN. By normalizing the dataset's properties, the problem of a large number range being dominant is avoided, allowing the algorithm to provide accurate predictions. An hourly resolution was used to gather data on energy use. A pre-processing technique was developed to convert hourly cost information into the greatest linear-scaling transformation. For the length of the investigation, the observable data points are normalized into values between 0 and 1. The average daily energy usage is then shown using the scaled hourly data.

$$m_a = \frac{m_a - m_{\min}}{m_{\max} - m_{\min}} \tag{3.1}$$

where m_a is the normalized value scaled to the range [0, 1], m_{max} and m_{min} are the maximum and minimum values of the characteristics, respectively. The preprocessed data is used to construct training and testing datasets.

3.2.2. Denoising using the adaptive median filter

Denoising is a phrase used to describe the intermediate step of eliminating and reducing noise from a picture, and it often occurs during the preprocessing stage. The fast development of digital image processing technology has led to the emergence of the two primary types of image denoising techniques: mean filtering and median filtering. The mean image filtering technique works directly on the source picture that has to be processed. This technique of operation divides mean filtering denoising into direct operations on each pixel in the picture and direct processes on the pixel's surrounding region.

When an image has been tainted or accompanied by noise, it may be removed and suppressed via a process called picture denoising. Denoised images often go through preprocessing, which directly affects how an image is processed after that. The performance of the camera's internal parts is influenced by a variety of objective elements, such as the thermal noise of the camera, the jitter noise brought on by the camera's mechanical motion, and other internal noises. Additive noise, salt and pepper noise, quantization noise, and multiplicative noise are a few of the more prevalent noise types.

3.2.3. Contrast enhancement using discrete wavelet transform

Wavelets are being employed in image processing and are often used for picture super-resolution, face recognition, compression, and feature extraction. By dividing pictures into different frequency ranges, it is possible to separate into separate sub bands the frequency components brought about by "intrinsic deformations" or "extrinsic influences." This method isolates minute picture changes, primarily in high frequency, sub-band images. As a result, the discrete wavelet transform (DWT) is a useful method for developing classification algorithms.

2-D wavelet decomposition of the image is carried out by first applying 1-D DWT along the picture's rows and then decomposing the outcomes along the picture's columns. Four deconstructed sub-band images—known as low-low (LL), low-high (LH), high-low (HL), and high-high—are created as a consequence of this technique (HH).

3.3. Segmentation using U-Net-based fuzzy convolutional network

As is shown in Figure 3, the expanding route and the contracting path are two components of the U-Net network's u-shape topology. The expanding route is utilized for accurate placement, while the contracting path is used to acquire background data. Figure 3 represents Model A's U-Net network architecture for contour detection.

Figure 3 shows the contracting path, which is comprised of a repeating 3×3 convolution kernel and a 2×2 maximum pooling layer, on the left. The activation function uses ReLu, and after every sample, the number of characteristic channels doubles. The increasing route in the image is shown on the right side, where each step of deconvolution results in a halving of the number of characteristic channels. The matching contraction route feature graph and the deconvolution result are then combined. The spliced feature network is then convolved twice by 33 after that. Each 2-bit eigenvector is moved to the network's output layer using the 11 convolution kernels at the last layer of the expanding route. A U-Net network with 23 convolution layers is used to train the contour detection model A as well as the contour optimization model B. Figure 4 shows Model B's contour optimization network structure.

As illustrated in Figure 3 and Figure 4, for contour detection model A, the input image resolution is 4848, while it is 480×480 for contour optimization model B. Image resolution is found in the bottom left corner of the multi-channel feature graph shown by the blue box in the structural diagram. The cloned feature graph is represented by a white box, and the top of the box lists the number of channels. The activation function and cost functions for the neurons in the network are, respectively, the sigmoid function and cross-entropy. This might accelerate the updating of weights and, as a result, substantially speed up training.

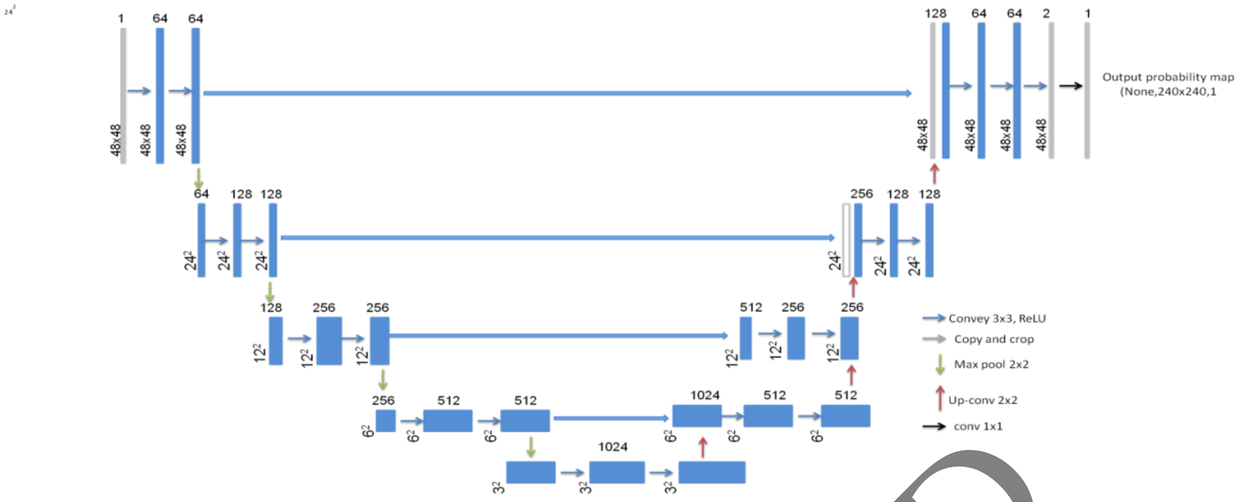

Figure 3. Model A's U-Net network architecture for contour detection.

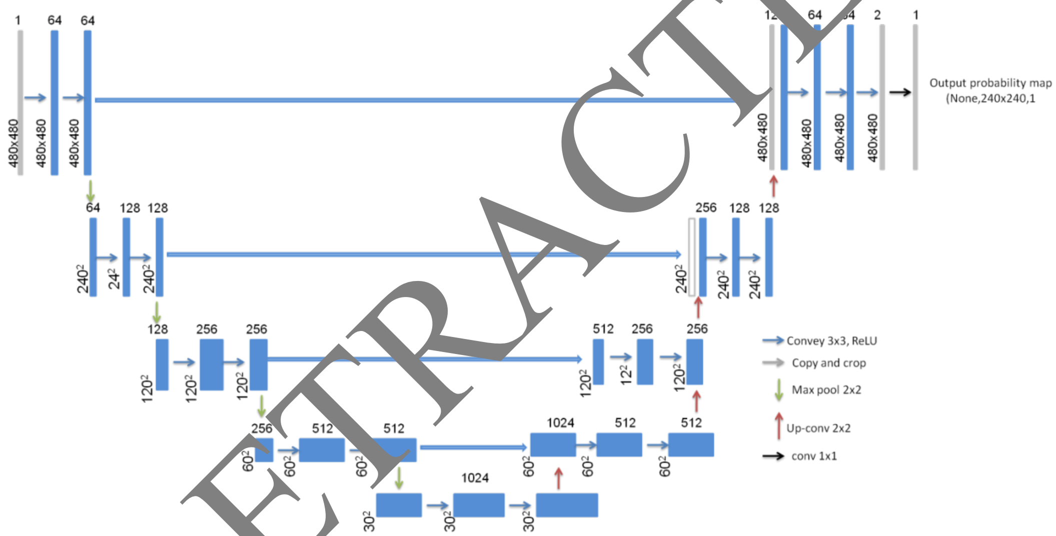

Figure 4. Model B's contour optimization network structure.

3.4. Feature extraction using Fuzzy KC-means clustering algorithm

The FCM algorithm uses fuzzy memberships to allocate pixels to each class. Let $L = \{l_1, l_2, \cdots, l_P\}$ indicate an image with P pixels that will be divided into $s\,(2 \leq s \leq P)$ classes (clusters). The most often utilized feature is the gray-level value, where l_d is the features value of pixel d and d ranges from 1 to P. The technique is an iterative optimization that aims to minimize the objective function given below:

$$\alpha = \sum_{b=1}^{s} \sum_{d=1}^{P} w_{b_d}^{q} \|l_d - X_b\|^2 \tag{3.2}$$

where variables like b and d satisfy the following conditions:

$$\forall d \in \{1, 2, \cdots, P\} \tag{3.3}$$

$$\forall b \in \{1, 2, \cdots, s\} \tag{3.4}$$

$$\sum_{b=1}^{s} w_{b_d} = 1 \tag{3.5}$$

$$0 \leq w_{b_i} \leq 1 \tag{3.6}$$

$$\sum_{d=1}^{P} w_{b_d} > 0 \tag{3.7}$$

where X_b is the center of the k-th cluster, w_{b_i} is indicating the membership of pixel l_d in that cluster, and signifies the Euclidean distance. The resultant partition's degree of fuzziness is controlled by the parameter $q\,(q > 1)$. Equations (3.3)–(3.7) update the cluster centers and the membership functions, respectively. Among, w_{b_d} and X_b can be represented as:

$$w_{b_i} = \frac{1}{\sum_{o=1}^{d} \left(\frac{l_d - x_b}{l_d - x_o}\right)^{\frac{2}{q-1}}} \tag{3.8}$$

$$X_b = \frac{\sum_{d=1}^{P} w_{b_d}^{q} l_d}{\sum_{d=1}^{P} w_{b_d}^{q}} \tag{3.9}$$

Algorithm 1: Fuzzy KC-means clustering algorithm

Input: an original picture L
Output: Membership matrix W

Initialize s, q, $itermax$
Create the cluster centers X_b randomly, where $b = 1, 2, \cdots, s$
for $g = 1 \rightarrow itermax$ **do**
  for $b = 1 \rightarrow s$ **do**
    for $d = 1 \rightarrow P$ **do**
      Update membership function according to Eqs (3.3)–(3.5)
    end
    Calculate the cluster nodes X_b according to Eqs (3.6) and (3.7)
  end
  Calculate the objective function according to Eq (3.1)
  if $\left|A^{(g)} - A^{(g+1)}\right| < \varepsilon$ **then**
    Break
  end
end

4. Results and analysis

This part examines the movement patterns of basketball players using a video image sequence, and compares the effectiveness of our suggested methodology, FKC-MC, to that of other methods already in use. The currently used techniques include the Background Difference Method (BDM) [29], Radial Basis Function Neural Network (RBFNN) [30], Grab Cut Algorithm (GCA) [31], and K-means Clustering Algorithm (KMCA) [32].

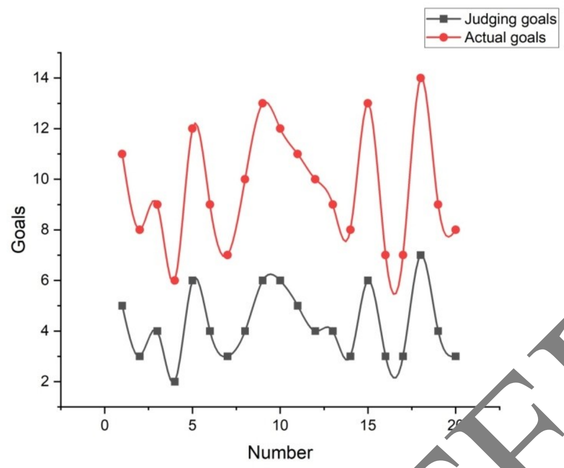

Figure 5. Output of basketball shots.

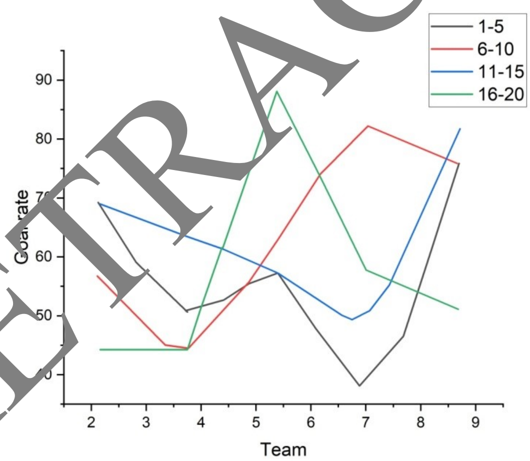

Figure 6. Output of basketball players' shooting accuracy.

As seen in Figure 5, the data from the table is transformed into a graph to more effectively illustrate the trial results. Divide the 20 athletes into four groups of five each, as shown in Figure 6, and construct a line graph of their percentages of made baskets. Figure 5 shows the basketball shots. According to the data acquired by the basketball shot recognition model produced in this article, just one of the 20 basketball players has a shooting accuracy of more than 90%, and the shooting accuracy is between 80% and 90%. Four athletes have shooting accuracies between 70% and 80%, six have accuracies in the range of 60–70%, and seven have accuracies below 60%. Figure 6 represents the Output of Basketball players' shooting accuracy.

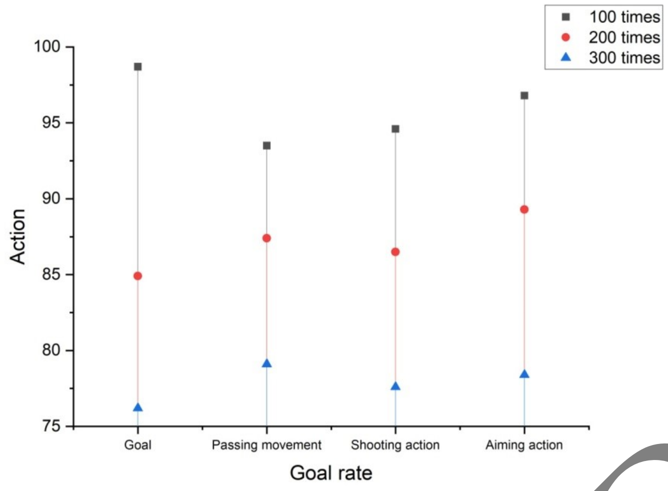

Figure 7. Result of proposed method's accuracy.

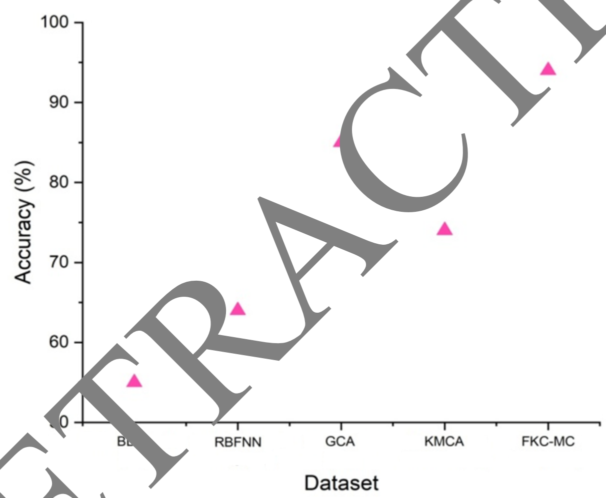

Figure 8. Comparative analysis of recognition accuracy.

The potential number of an action is affected by whether two histograms are different, which is determined by the distance threshold. Study the effects of this parameter using the "shooting" experiment. The "shooting" was picked because it is likely to be segmented hypothetically, is brief and variable, and is somewhat changeable. It turns out that the assumed number is still large and unaffected when the distance barrier is less than 0.4. On the other hand, the hypothesis number quickly drops as the distance barrier rises over 0.4. Therefore, depending on the desired degree of granularity, the distance threshold must be between 0.4 and 0.8. This value is set at 0.4 for all experiments in this article to preserve the majority of the intra-class variance. Figure 7 shows the result of the proposed method's accuracy. Test the data obtained using the aforementioned techniques based on the proposed model for action recognition, and graph the test results as illustrated in Figure 7. Through mathematical translation and computation, image processing under known circumstances may provide a model of the internal and exterior camera parameters. There are two types of camera self-adjustment techniques: Basic matrix and automated matrix calibration methods, as well as automated camera calibration technologies.

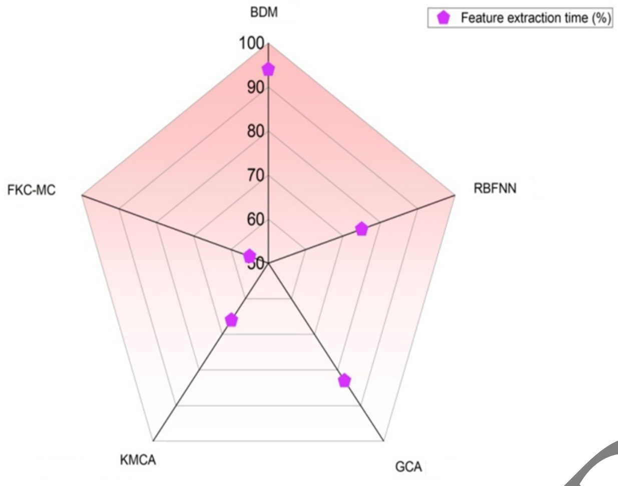

Figure 9. Comparative analysis of feature extraction time.

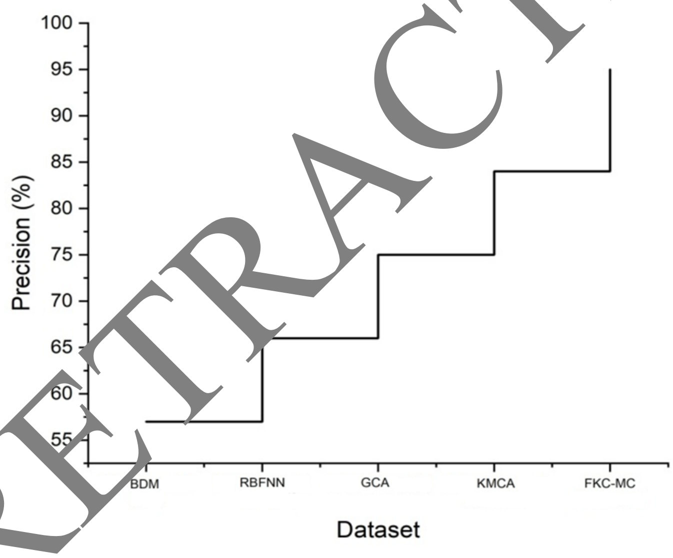

Figure 10. Comparative analysis of precision.

The degree in which a measurement, computation, or specification's outcome complies with an appropriate value or a standard is known as accuracy. According to experimental results of 100 tests, the average overall accuracy of motion tracking outcomes for feature extraction of basketball player recognition using the Gaussian mixture method is 82.9%, while the average accuracy rate of motion capture results for feature extraction of basketball player recognition using the support vector machine model is 95.9%. Figure 8 represents the comparative analysis of Recognition accuracy. The suggested system achieved 94%, followed by the BDM's 55%, the RBFNN's 64%, the GCA's 85%, and the KMCA's 74%. This indicates that the suggested system is more effective. As a result, support vector machine models have a high-accuracy rate when used to visually recognize and record basketball shooting actions. It may be used for the training of basketball players and coaches. It is easier to more properly record shooting-related activities and provide targeted photos, enabling coaches and athletes to see movement flaws and fix them to increase training effectiveness. Figure 9 displays the comparative analysis of feature extraction time. The BDM scored 94%, the RBFNN scored 75%, the GCA scored 83%, the KMCA scored 66%, and the suggested system scored 55%. It indicates lower performance for the proposed system.

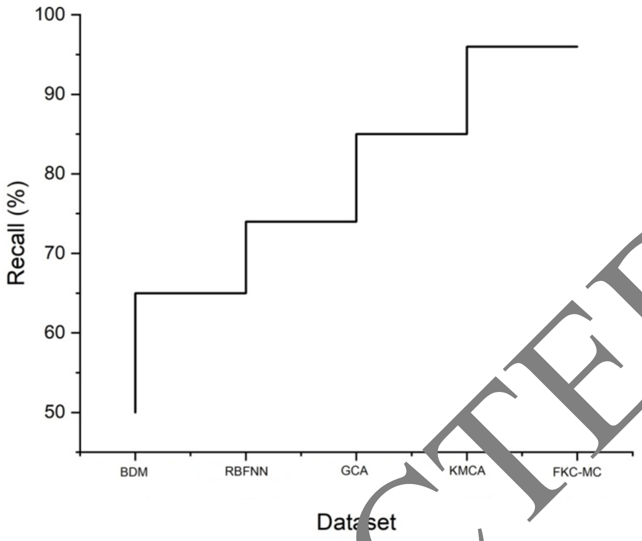

Figure 11. Comparative analysis of recall.

With feature extraction, which is a sort of dimensionality reduction, a significant portion of the image's pixels are properly represented, allowing for the effective capture of the image's relevant details. You may spot trends and get more accurate predictions by researching a series' previous behavior. Figure 10 represents a comparative analysis of precision. The BDM scored 57%, the RBFNN scored 66%, the GCA scored 75%, the KMCA scored 84%, and the suggested system scored 95%. These results indicate that the suggested system is more effective. The accuracy of a material is defined as the degree to which two or more measurements agree with one another. Precision is not the same as accuracy; it relates to the value in decimal places following the entire integer. The degree to which a measuring system is free from random mistakes is referred to as precision. Thus, if the same amount is measured repeatedly, a high-precision measuring device will only provide a limited range of values. Figure 11 represents a comparative analysis of recall. The BDM scored 50%, the RBFNN scored 65%, the GCA scored 74%, the KMCA scored 85%, and the suggested system scored 96%. It indicates that the suggested system is more effective.

The process of recalling facts or events from the past without the use of a particular prompting. The proportion of real positives that a model accurately detected is determined by recall (True Positive) for feature extraction of a basketball player. Recall should be used when the cost of a false negative remains substantial. The recall formula is as follows: the number of true positives or the number of positives the model properly detected makes up the numerator. Figure 12 represents a comparative analysis of the F score. The BDM scored 50%, the RBFNN scored 60%, the GCA scored 73%, the KMCA scored 86%, and the suggested system scored 94%. This indicates that the suggested system is more effective.

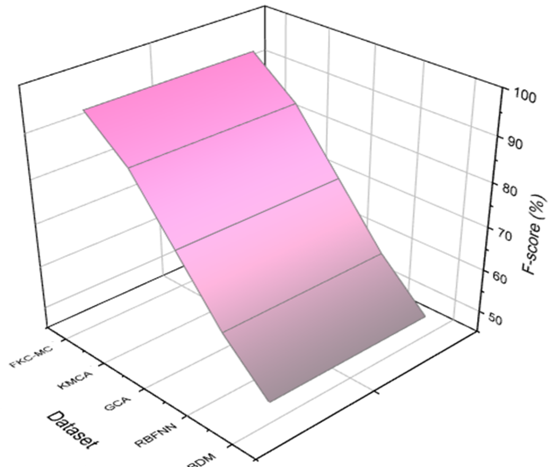

Figure 12. Comparative analysis of F-score.

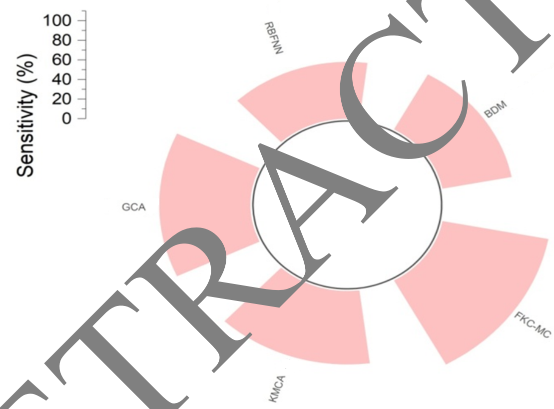

Figure 13. Comparative analysis of sensitivity.

Each feature's ability to discriminate on its own from other features is shown by the F-score. For the first feature, a score is generated, and for the second feature, a different score is obtained for basketball players. However, it says nothing about how the two elements work together (mutual information). The weighted mean of precision and recall is known as the F1 Score. As a consequence, both false positives and false negatives are included when calculating the score. F1 is not as intuitively clear to understand as accuracy, even though it is often more important than accuracy, especially if you have an unequal class distribution. Figure 13 represents a comparative analysis of sensitivity. The BDM scored 64%, the RBFNN scored 58%, the GCA scored 83%, the KMCA scored 75%, and the suggested system scored 98%. These results indicate that the suggested system is more effective. The true positive rate (TPR), often known as a test's sensitivity is the percentage of really positive samples that produce positive test results. To ascertain how much change is observed in the input values for a certain variable impact on those outcomes, the results of a mathematical model's sensitivity analysis are employed. Sensitivity analysis helps determine the optimum data to be gathered for the motion of trajectory of basketball players. Figure 14 represents a comparative analysis of specificity. The BDM scored 58%, the RBFNN scored 64%, the GCA scored 77%, the KMCA scored 88%, and the suggested system scored 97%. This indicates that the suggested system is more effective.

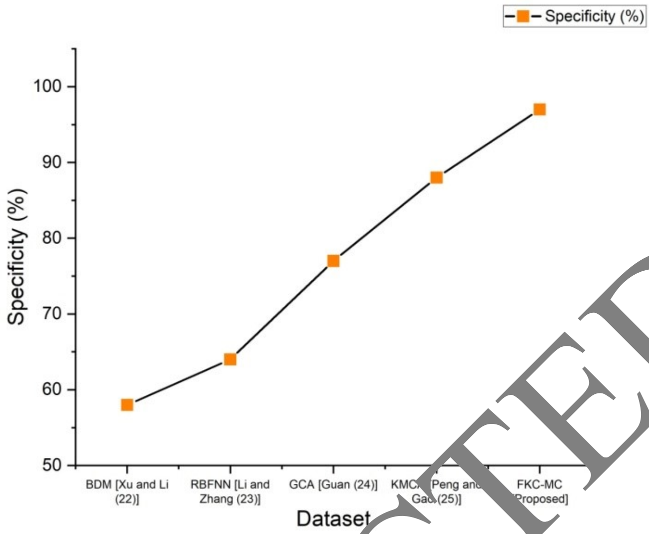

Figure 14. Comparative analysis of specificity.

A test's specificity is measured by its capacity to label as negative someone who doesn't have a condition. A highly specialized test will provide minimal false positive outcomes. The proportion of those who do not have the ailment who have a negative test result is known as specificity. A very precise test is effective in excluding the majority of individual basketball players. A good outcome on a very precise test may be used to definitively rule in the movement of trajectory for a specific person. Table 2 shows the comparative analysis.

Table 2. Comparison of different parameters for both existing and suggested approaches.

	BDM	RBFNN	GCA	KMCA	FKC-MC (Proposal)
Accuracy (%)	55	64	85	74	94
Feature Extraction (%)	94	75	83	66	55
Precision (%)	57	66	75	84	95
Recall (%)	50	65	74	85	96
F-score (%)	50	60	73	86	94
Sensitivity (%)	64	58	83	75	98
Specificity (%)	58	64	77	88	97

The BDM is based on the various images and utilizes the same detection principle, however, rather than differentiating between two adjacent image frames, the background difference method creates a background reference model and uses the background reference model to identify differences between two adjacent images frames. The feed-forward neural network RBFNN is very effective. The process of forecasting how accurately basketball players would shoot includes a fair amount of complexity, which makes it challenging to develop mathematical models for behavior prediction. GCA is a graph-cut-based technique for segmenting images. The algorithm estimates the color distribution of the target object and the background using a Gaussian mixture model, starting with a user-specified bounding box around the object to be segmented. The segmentation can't be optimalx if the objects are highly similar and the backdrop is complicated. On the other hand, the algorithm's use is severely constrained by its poor speed and complex iterative procedure. KMCA when you have unlabeled data, you may utilize clustering, a sort of unsupervised learning. The number of groups denoted by the variable K represents the number of groups that this algorithm is looking for in the data. The fuzzy KC - method of clustering is that it enables data points to gradually join the clusters being assessed. This enables the flexible expression that data points might be a part of many clusters. Thus, it is more effective than the other available techniques. Typically, the outcomes of the various clustering techniques are highly diverse. This happens as a result of the various criteria for merging clusters. You should carefully examine the best strategy for the subject you want to learn.

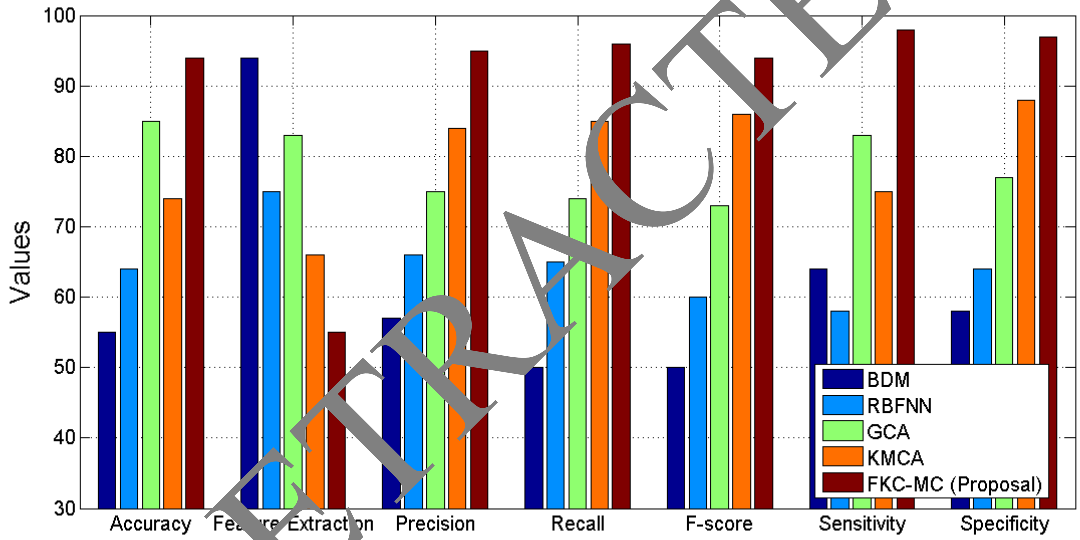

Figure 15. Comparative analysis of specificity.

5. Conclusions

Basketball action recognition is a kind of human body gesture recognition that uses the background difference technique, optical flow method, and frame difference approach. The optical flow technique has the advantage of using computing to support the camera's movement status and more comprehensively extract data from the location of moving objects in image sequences. The background difference approach, which has the distinguishing characteristics of precise detection, a straightforward algorithm, and simple implementation, is appropriate when the camera is mounted in a steady location. The automated recognition and tracking of a basketball during a long-shot sequence in a basketball sports film is the contribution of the suggested framework. The results demonstrate that the strategy described in this study has a high rate of accuracy in forecasting basketball players' shooting accuracy and requires less running time. FKC-MC is unsuitable for identifying clusters with non-convex forms and cannot manage noisy data or outliers. A video image sequence aims to capture a series of photographs continuously over a predetermined amount of time. Image denoising is a multi-step procedure that eliminates and reduces image noise. A future study might modify the procedure to extract discriminative characteristics using a multi-class classifier to meaningfully segregate the ischemia and other secondary lesions for the evaluation of object trajectory movement. In the future, to promote team collaboration, we will further investigate the behavior prediction of team members via the prediction of shooting accuracy. Through the shooting prediction, the trajectories of basketball players' shots are examined to increase their accuracy.

Conflict of interest

The author declares there is no conflict of interest.

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