

Research Article

Using Machine Learning Algorithms to Recognize Shuttlecock Movements

Wei Wang 

Department of Physical Education, Chongqing University of Technology, 400054 Chongqing, China

Correspondence should be addressed to Wei Wang; ww0206@cqut.edu.cn

Received 24 March 2021; Revised 20 April 2021; Accepted 21 May 2021; Published 2 June 2021

Academic Editor: Wenqing Wu

Copyright © 2021 Wei Wang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Shuttlecock is an excellent traditional national sport in China. Because of its simplicity, convenience, and fun, it is loved by the broad masses of people, especially teenagers and children. The development of shuttlecock sports into a confrontational event is not long, and it takes a period of research to master the tactics and strategies of shuttlecock sports. Based on this, this article proposes the use of machine learning algorithms to recognize the movement of shuttlecock movements, aiming to provide more theoretical and technical support for shuttlecock competitions by identifying features through actions with the assistance of technical algorithms. This paper uses literature research methods, model methods, comparative analysis methods, and other methods to deeply study the motion characteristics of shuttlecock motion, the key algorithms of machine learning algorithms, and other theories and construct the shuttlecock motion recognition based on multiview clustering algorithm. The model analyzes the robustness and accuracy of the machine learning algorithm and other algorithms, such as a variety of performance comparisons, and the results of the shuttlecock motion recognition image. For the key movements of shuttlecock movement, disk, stretch, hook, wipe, knock, and abduction, the algorithm proposed in this paper has a good movement recognition rate, which can reach 91.2%. Although several similar actions can be recognized well, the average recognition accuracy rate can exceed 75%, and even through continuous image capture, the number of occurrences of the action can be automatically analyzed, which is beneficial to athletes. And the coach can better analyze tactics and research strategies.

1. Introduction

Shuttlecock is developed from the ancient shuttlecock game with a history of more than 2000 years in my country. It combines scientific ability, wide publicity, excellent skills, and rich entertainment. It is a relatively new sport in modern society. The technical difficulty is medium, the exercise intensity is low, and the requirements for gender, age, location, and equipment status are low. The development of shuttlecock has played a decisive role in promoting the implementation of nationwide fitness programs. The development of shuttlecock sports provides people with good sports and entertainment methods, promotes social stability, promotes people's physical and mental health, and delays the process of social aging [1].

Computer vision and machine learning technologies are widely used in data mining, information security, remote sensing image processing, bioinformatics, intelligent transportation, intelligent security, and medical services. As one of the important branches in the field of computer vision, moving target detection technology has been widely used in real scenes. Existing moving target detection methods have problems such as long calculation time and high complexity. How to meet the real-time performance in real scene problem is becoming more and more important. With the rapid development of deep learning, the recognition accuracy of another important branch in the field of computer vision-target recognition technology has been greatly improved. However, due to the complex network structure and high computational complexity of the deep learning, how to quickly complete the training process of deep learning

networks has become an urgent problem in the field of deep learning.

It is a challenge for Lin to track players and shuttlecocks in broadcast badminton videos, especially for small-sized and fast-moving shuttlecocks. There are many situations that may cause occlusion or misjudgment. A method for tracking athletes and badminton in broadcast badminton video is proposed. They use adaptive Kalman filtering, trajectory confidence estimation, and confidence update (position similarity and relative motion relationship, RMR) to improve the accuracy of the target trajectory. Experimental results show that this method significantly improves the tracking success rate of athletes and shuttlecocks. However, this method also has a shortcoming, that is, there are too many influencing factors to be considered when the accuracy test is carried out, and there is a certain degree of difficulty in practical application [2]. Aiming at the problem of action recognition in still images, Zhichen proposed a method to arrange the features of different semantic parts in spatial order. Their method consists of three parts: (1) a semantic learning algorithm, which collects a set of partial detectors, (2) an effective detection method, which uses the same grid to divide multiple images and computes them in parallel, and (3) a top-down spatial arrangement increases the variance between classes. The proposed semantic part learning algorithm can not only capture interactive objects but also capture distinguishing gestures. Their spatial layout can be seen as a kind of adaptive pyramid, which highlights the spatial distribution of body parts in different movements and provides a more distinctive representation. Experimental results show that their method significantly outperforms existing methods on two challenging benchmarks. However, their method has limitations in that it is only for the processing of static pictures. However, in reality, more needs are the processing and application of dynamic pictures [3]. Jean et al. reviewed and commented on the past, present, and future of numerical optimization algorithms in machine learning applications. Through case studies of text classification and deep neural network training, they discussed how optimization problems in machine learning arise and what makes them challenging. A major theme of their research is that large-scale machine learning represents a unique environment in which stochastic gradient (SG) methods traditionally play a central role, while traditional gradient-based nonlinear optimization techniques usually faltering. Based on this point of view, they proposed a simple and general SG algorithm comprehensive theory, discussed its actual behavior, and emphasized the opportunity to design algorithms with improved performance. This led to the discussion of the next generation of large-scale machine learning optimization methods, including the investigation of two mainstream research directions, techniques, and methods to reduce noise in random directions. However, their algorithm cannot fundamentally solve the difficulties in the application of machine learning [4].

The innovations of this paper are (1) combine qualitative research with quantitative research and fully analyze the research data and (2) combine theoretical research with empirical research and combine shuttlecock sports on the basis of machine learning algorithm theory.

2. Using Machine Learning Algorithms to Recognize Research Methods of Shuttlecock Movements

2.1. Shuttlecock. Shuttlecock is a traditional Chinese national sports event. The institutionalized event has a history of 26 years. It has now become the official event of my country's five large-scale comprehensive sports games [5]. Shuttlecock's good project participation makes it rank in the forefront of all ethnic traditional sports in China, and it has been well promoted worldwide [6]. The World Shuttlecock Federation was formally established this year, and shuttlecock sports have been developed in many countries including Asia and Europe. The international development of shuttlecock has greatly promoted the improvement of the level of competition.

(1) The research significance of shuttlecock

Shuttlecock is an excellent national traditional sport in our country. Shuttlecock has a history of more than 2,000 years. It not only inherits the national spirit of self-improvement in traditional Chinese culture but also integrates the spirit of modern culture and sports competition [7]. Enriching people's cultural life, if it can be widely promoted, can promote the construction of socialist spiritual culture, and contribute to the construction of a harmonious society. Shuttlecock is very valuable as well as entertainment value. It has a broad collective foundation, which is not only pleasing to the eyes but also popular with the audience. Through practice, the shuttlecock can improve a great level and has a unique charm [8]. We should dig, organize, inherit, and develop. With the development of national fitness exercises, key ball sports do not require high participants, and there are not many requirements for venues, and the equipment is cheap. Therefore, many squares, parks, schools, residential areas, and other open spaces and other shuttlecock sports are everywhere.

Scientific fitness, rich entertainment, and diverse skills have a good role in promoting the physical and intellectual development of the broad masses of people. In order to promote the inheritance and development of the current shuttlecock sport in our country, the action recognition is carried out to better learn the laws of the shuttlecock sport [9]. It also provides useful enlightenment for the development of the national fitness program and provides a theoretical basis for the national traditional sports to better integrate into the mass fitness activities. Using machine learning algorithms to conduct motion recognition research on shuttlecock sports can effectively promote the development of shuttlecock sports, carefully study the characteristics of shuttlecock sports, and win impressive results on the court.

(2) The characteristics of shuttlecock

At this stage, the shuttlecock sport is an emerging national sport that integrates fitness, entertainment, mass, popularity, high skill, strict collective, fierce confrontation, technical duality, and appreciation. The reason why the

shuttlecock sport is loved by people [10] is also because the shuttlecock itself also shows the characteristics of simplicity, small size, light weight, slow speed, low difficulty, simple control, and very interesting. Shuttlecock integrates football skills, badminton courts, and volleyball rules. It is easy to learn and understand. In addition, it is not affected by various indoor and outdoor spaces, equipment, and climatic conditions and can autonomously control the amount of exercise with strong adaptability. Athletes can practice regardless of age, gender, or level [11]. Therefore, the shuttlecock can not only move the body but also has a beautiful artistic performance. It is displayed on various occasions and plays a unique role in the audience.

(3) The value and function of shuttlecock

Viewing function: The viewing function of traditional national sports is a collection of natural beauty and social beauty. The main content includes physical beauty, sports beauty, spiritual beauty, and clothing beauty. National traditional sports are a kind of comprehensive overall beauty. The perfect movement skills are fascinating and indescribable. In basic sports, not only the body is exercised, but the artistic performance is also beautiful [12]. Therefore, the shuttlecock has both the beauty of the human body and the unique sports characteristics of the country. The movement of the button ball reflects the physique of the human body and can also improve the strength, speed, endurance, and flexibility of the human body [13].

Educational function: In this way, we can take advantage of the fitness function, aesthetic value, and ideological and educational significance of the shuttlecock sport itself to carry out educational activities, which can not only promote the traditional national sports culture of our country but also enrich the people's amateur life and at the same time enhance the cultivation of people's good thinking. Moral quality lays a solid foundation for lifelong sports [14]. Carrying forward traditional national sports in the process of developing mass sports will undoubtedly have certain positive significance for carrying out extensive traditional moral education.

Economic value: Shuttlecock, as a traditional cultural carrier, carries the unique cultural knowledge of the nation, can make people deeply feel the value of national sports, guide consumers to buy related sports goods, books, audio, and video products, and create the company's products. R&D, mass production, and large-scale business conditions improve the economic benefits of society [15]. Make full use of the cultural advantages of the shuttlecock project to carry out multiform cultural industry research and development to increase publicity and attract more tourists to participate in the entertainment of the shuttlecock. National aerobics attracts tourists from all over the world with its unique style, thereby driving the local economic development. Analyzed from multiple angles, the exhibition of the shuttlecock project has a positive effect on driving the development of various industries [16].

2.2. Feature Selection and Extraction of Moving Targets. Feature extraction section selects senior stage is the body motion

recognition. It is hot and difficult to study. Human feature selection and extraction refers to selecting appropriate features from related videos or images to effectively describe the human movement.

The feature extraction link is an indispensable part of a complete motion recognition system. It is not only related to the accuracy and speed of subsequent motion recognition but also affects the performance of motion classification and discrimination [17]. There are many kinds of human body features. Among the many features, only a few are effective. Therefore, how to extract features that are unique to the target itself and have low sensitivity to environmental changes is the main task of feature extraction, and it is also the focus of human action recognition research [18].

At present, the features used in human action recognition mainly include motion features, shape features, and the fusion of the two features. The extraction based on motion features is based on the information shown by the human body's motion state, such as motion displacement, motion speed, motion direction, and angle information. Motion characteristics have the advantages of relative invariance and periodicity [19]. The extraction based on the shape feature uses the static feature of the moving human body to describe the action. Commonly used shape features mainly include contour features, perimeter, area, compactness, and circumscribed rectangle features. Compared with motion features, shape features have the advantages of distance from the camera and insensitivity to the surrounding environment. Based on the extraction of contour features of human actions from multiple perspectives, excellent recognition results are obtained [20]. Extract the width feature of the circumscribed rectangle of the moving target as a feature vector to identify human gait changes.

2.3. Machine Learning. Machine learning is a discipline dedicated to the study of how to use computational methods and use the acquired knowledge to improve the performance of the system itself. In computer systems, the so-called "experience" usually exists in the form of "data," so the content of machine learning research is to use the characteristics of the data to generate the algorithm of the model [21]. From the core perspective of machine learning, optimization and statistics are the two core supporting technologies (as shown in Figure 1).

Machine learning can not only be regarded as a method but also can be used for pattern recognition or data mining. There are four main types of problems (applications) in the field of machine learning: (1) prediction-can be solved by regression algorithm; (2) clustering-such as K -means method and hierarchical clustering algorithm; (3) classification-such as support vector machine method and decision tree algorithm; (4) dimension reduction-such as principal component analysis (PCA) [22]. At present, in many fields of computing science, including graphics and image processing, software engineering, computer vision, and natural language processing, machine learning can serve them. At the same time, machine learning is also performing well in interdisciplinary subjects, especially in the field of bioinformatics, where a large amount of data needs to be processed

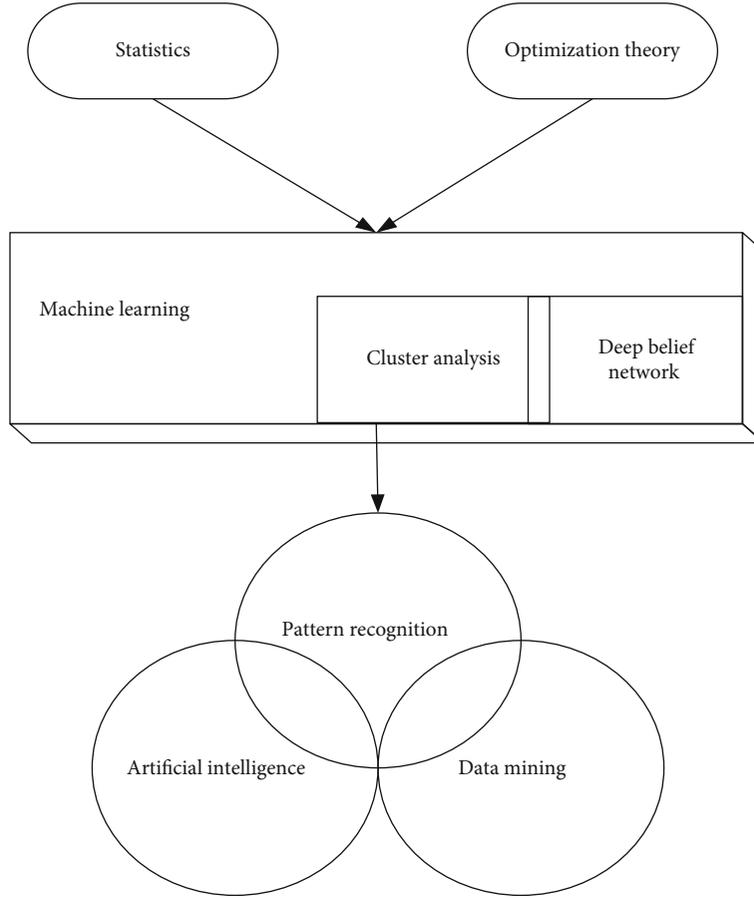


FIGURE 1: Application level of machine learning and pattern recognition.

and analyzed, and machine learning just meets its requirements.

2.4. Deep Belief Network. A deep belief network model can be regarded as the superposition of multiple RBM models, and the output of the hidden layer in each layer is used as the input of the visible layer in the next layer, so that a layered training model can be generated [23]. The training process of multiple RBM superimposed DBN. The restricted Boltzmann machine RBM is a bipartite undirected graph based on the energy model. RBM contains m visible layer nodes and n hidden layer nodes, and the connection between the visible layer and the hidden layer is obtained through the weight matrix W [24]. In addition, both the visible layer and the hidden layer contain the corresponding offset values v bias and h bias.

In a given state, the energy function of the visible layer and the hidden layer is defined as

$$R(b, l) = - \sum_{i=1}^n \sum_{j=1}^m e_{ij} l_i b_j - \sum_{j=1}^m a_j b_j - \sum_{i=1}^n c_i l_i. \quad (1)$$

This energy function indicates that in a certain state, each node of the visible layer and each node of the hidden layer

have a capability value, and then, the energy value in this state is obtained [25, 26]. According to the energy function, the joint probability of the visible layer node and the hidden layer node is defined as

$$o(b, l) = \frac{e^{-R(b, l)}}{\sum_{b, l} e^{-R(b, l)}}. \quad (2)$$

So, we get the conditional probability of the visible layer and the hidden layer, where the conditional probability of the visible layer is

$$o(b) = \sum_l o(b, l) = \frac{1}{X} \sum_l e^{-R(b, l)}. \quad (3)$$

The conditional probability of the hidden layer is

$$o(l) = \sum_b o(b, l) = \frac{1}{X} \sum_b e^{-R(b, l)}. \quad (4)$$

Among them, $X = \sum_{b, l} e^{-R(b, l)}$, the maximum likelihood is used to solve the energy function, and the corresponding parameters (including the weight matrix, the visible layer offset value, and the hidden layer offset value) are obtained to

make the RBM energy function value the lowest [27]. The solution formula is as follows:

$$\frac{\partial \ln o(b, \vartheta)}{\partial} = \frac{\partial}{\partial \vartheta} \left(\ln \sum_l e^{-R(b,l)} \right) - \frac{\partial}{\partial \vartheta} \left(\ln \sum_{b,l} e^{-R(b,l)} \right), \quad (5)$$

$$\frac{\partial \ln o(b, \vartheta)}{\partial \vartheta} = - \sum_l o(b, l) \frac{\partial R(b, l)}{\partial \vartheta} + \sum_{b,l} o(b, l) \frac{\partial R(b, l)}{\partial \vartheta}. \quad (6)$$

By solving the W in the model by maximum likelihood estimation, we can get

$$\frac{\partial \ln o(b)}{\partial w_{ij}} = p(l_i = 1 | b) b_j - \sum_b o(b) o(l_i = 1 | b) b_j. \quad (7)$$

Among them, the solution of the first term is

$$o(l_i = 1 | b) = \tau \left(\sum_{j=1}^m w_{ij} b_j + v_i \right). \quad (8)$$

Among them, $\tau(x) = 1/(1 + e^{-x})$. The solution of the second term needs to traverse all possible values. The commonly used method is based on Monte Carlo's Gibbs sampling method.

3. Using Machine Learning Algorithms to Recognize the Research Model of Shuttlecock Movements

This article mainly uses multiview clustering algorithm based on multicore learning for the shuttlecock movement recognition model, which recognizes information through the state of human movement and movement. The basic movements of the shuttlecock sport include panning, turning, knocking, jumping, and step. Through experimental research, data collection, preprocessing, and feature extraction of these actions are carried out, and the key steps are continuously improved and optimized, so as to improve the accuracy of motion recognition as a whole.

(1) Multiview clustering algorithm based on multicore learning

In many machine learning, computer vision, and image processing applications, because the data comes from different data sources and reflects the different characteristics of the data itself, the data can often have multiple views. For example, the same image can contain multiple feature representations: color, shape, and texture. Compared with the traditional single-view clustering algorithm, the multiview clustering algorithm can make full use of the complementary information from different views in the same sample, thereby ultimately improving the performance of the clustering algorithm.

The existing multiview algorithms can be divided into three main categories: multiview clustering algorithms based on collaborative training, multiview clustering algorithms based on subspace, and multiview clustering algorithms based on multicore learning. Among these algorithms, our work mainly focuses on the multiview clustering algorithm based on multicore learning. This algorithm has been widely researched and applied in recent years and has achieved the best results among the current multiview clustering algorithms. In more detail, the multiview clustering algorithm based on multicore learning can be divided into two methods: the combined kernel function method and the public kernel function method. The combined kernel function method learns a linear or nonlinear kernel function combination as the input of the final clustering algorithm. This method has received a lot of attention in recent years. However, in a real environment, we often introduce noise information when we collect data, because it does not have a mechanism to deal with noise, so the combined kernel function method may not get better performance. Another method is the public kernel function method, which learns a public kernel function from the basic kernel function composed of multiple views. Compared with the combined kernel function method, this method has great advantages in noise processing.

Assuming that the same input data sample has the information of n views, we use the information of n views to construct n kernel functions F_1, F_2, \dots, F_n , and we use the method of multicore learning to learn from these basic kernels from different views. The function learns an optimal common kernel function B as the input of the final clustering algorithm to classify data from different categories into their respective categories. In order to better obtain the correct structure information implicit in the data and at the same time remove the noise information that may affect the performance of the final clustering algorithm from the learned public kernel function; we consider the following aspects of the problem: (1) we that learned public kernel function has low-rank characteristics and tends to block diagonal matrix structure and has less noise information; (2) since noise may be introduced when data is obtained, we construct multiple basic kernel functions. There will be a certain amount of noise information.

Based on the above considerations, we define the model of joint optimization as follows:

$$\min_{B, R_p} \text{rank}(B) + \gamma \sum_{p=1}^n \|R_p\|_l, \quad s.t. \forall p, F_p = B + R_p. \quad (9)$$

Among them, the model or distribution of the error $\|\cdot\|_l$ is obtained a priori for the norm on the error matrix R , which γ is a parameter to weigh the two optimization items. In actual application scenarios, it $\|\cdot\|_l$ represents the noise associated with random elements. In order to solve the above optimization model more generally, we

adopt $\|\cdot\|_1$ the constraint of our error matrix R . Thus, the optimized model we retrieved is as follows:

$$\min_{B, R_p} \text{rank}(B) + \gamma \sum_{p=1}^n \|R_p\|_1, \quad s.t. \forall p, F_p = B + R_p. \quad (10)$$

The optimization problem becomes difficult to solve because the problem includes the solution of the rank function. We convert the rank function into a kernel norm to solve the problem. Since the kernel norm is a good approximation of the rank function, we can turn the problem into the following form:

$$\min_{B, R_p} \|B\|_* + \gamma \sum_{p=1}^n \|R_p\|_1, \quad s.t. \forall p, F_p = B + R_p. \quad (11)$$

We use the nondeterministic augmented Lagrangian method to solve the problem, so we can get the following form:

$$\begin{aligned} L(B, R_p, U_p, \nu) = & \|B\|_* + \gamma \sum_{p=1}^n \|R_p\|_1 + \sum_{p=1}^n \langle U_p, F_p - B - R_p \rangle \\ & + \frac{\nu}{2} \sum_{p=1}^n \|F_p - B - R_p\|_G^2. \end{aligned} \quad (12)$$

Among them ν , the convergence rate of the nondeterministic augmented Lagrangian method will be penalized, and U_p is the Lagrangian multiplier constraint of $F_p = B + R_p$. $\langle \cdot \rangle$ represented inner product operation, and $\|\cdot\|_G$ represented G-norm.

(2) Optimization algorithm

Fix other parameters, optimization B : When other parameters are fixed, the subproblem of optimization is

$$B^{(k+1)} = \arg \min_B L(B, R_p^{(k)}, U_p^{(k)}, \nu^{(k)}). \quad (13)$$

The singular value threshold method can be used to solve the problem. Among them,

$$(I, M, V) = \text{svd} \left(\frac{1}{n} \sum_{p=1}^n F_p - \frac{1}{n} \sum_{p=1}^n R_p^{(k)} + \frac{1}{n\nu^{(k)}} \sum_{p=1}^n U_p^{(k)} \right). \quad (14)$$

After solving, we can get the result of B as

$$B^{(k+1)} = ID_{1/(\nu^{(k)})}[M]V^T. \quad (15)$$

Among them, D is a shrink operation, which is defined as

$$D_\phi(x) = \begin{cases} x - \phi, & \text{if } x > \phi, \\ x + \phi, & \text{if } x < -\phi, \\ 0, & \text{otherwise.} \end{cases} \quad (16)$$

(3) Fix other parameters and optimize R

The subproblem obtained by optimizing R is

$$R_p^{(k+1)} = \arg \min_{R_p} L(B^{(k+1)}, R_p^{(k)}, U_p^{(k)}, \nu^{(k)}). \quad (17)$$

Its solution formula is

$$R_p^{k+1} = D_{\nu^{(k)}} \left[F_p - B^{(k+1)} + \frac{1}{\nu^{(k)}} U_p^{(k)} \right]. \quad (18)$$

The optimization of the Lagrange multiplier can be defined as

$$U_p^{(k+1)} = U_p^{(k)} + \nu^{(k)} (F_p - B^{(k+1)} - R_p^{(k+1)}), \quad (19)$$

where $B(k+1)$ and $R_p^{(k+1)}$ are the result of the $k+1$ iteration above.

In feature extraction before extracting the characteristics of human motion state, data preprocessing needs to segment the data. The feature data extracted from the sensor data in a short time is called a window, which contains all the features of each human motion state. The duration of each cycle of each state determines the size of the window. Smaller windows may not accurately contain all the characteristics of each human motion state, but larger windows will bring more noise and affect the actual feature extraction. Usually, the time signal is sampled in a sliding window of 2.56 seconds with a fixed width, with an overlap rate of 50% and a sampling rate of 50 Hz, for data collection of human motion status.

4. Use Machine Learning Algorithms to Recognize Shuttlecock Movements

4.1. Image Result of Shuttlecock Motion Recognition. Shown in Figure 2 is the use of machine learning algorithms to identify the effect of shuttlecock movement. Figure 2(a) is a schematic diagram of the six key actions of shuttlecock (Figure 2(a), the original picture is borrowed from Baidu Gallery: <https://wenku.baidu.com/view>), and Figure 2(b) is binarized. After the image, Figure 2(c) is the effect image after recognition. It can be clearly seen from the picture that the red box outlines the key movements demonstrated by the shuttlecock player, namely, panning, stretching, hooking, wiping, knocking, and abduction. This shows that the research algorithm in this article is very effective, it can capture the actions of shuttlecock players very well, which is



(a)



(b)

FIGURE 2: Continued.

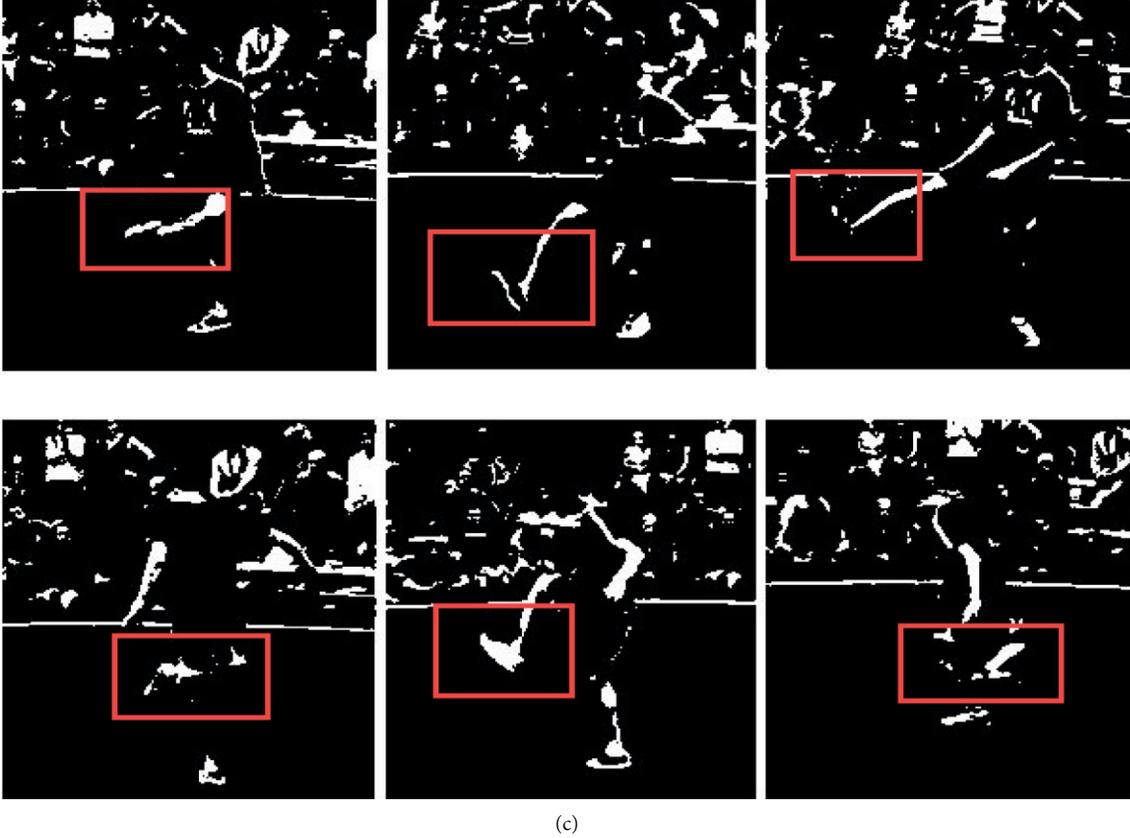


FIGURE 2: Using machine learning algorithm to recognize the effect of shuttlecock movement.

TABLE 1: Clustering algorithm confusion matrix result.

Classify	Predicted class							Recall
	WK	WU	WD	SI	ST	LY		
True class	WK	522	29	11	0	3	0	0.926
	WU	4	523	11	0	2	0	0.968
	WD	0	1	428	0	3	8	0.975
	SI	0	2	0	292	115	55	0.634
	ST	2	1	2	35	422	26	0.867
	LY	0	0	0	28	60	381	0.820
	F1	0.956	0.955	0.961	0.725	0.775	0.822	—
—	Precision	0.988	0.945	0.947	0.823	0.699	0.812	0.866

conducive to better application in shuttlecock competitions, analysis of opponents' game movements and habits, etc., and prepare for prevention in advance.

4.2. Comparison of Machine Learning Algorithm Performance.

Table 1 is the confusion matrix of the experimental classification results. The confusion matrix can be used to calculate the accuracy rate, recall rate, and the value of F . Among them, the final accuracy rate of classification is 0.866. From the specific data, the clustering algorithm has a better recognition effect on WK, WU, and WD, while the recognition effect on SI, ST, and LY is poor. The main reason is dynamic action and static state. The difference in actions and the

similarity of actions have always been the difficulty of action recognition.

It can be seen from Table 2 that the recognition efficiency is evaluated by running time. In contrast, the algorithm in this paper can effectively improve the efficiency of motion recognition, and as the time complexity increases, the feature dimension increases, and the dimensionality reduction time is extremely high. And the algorithm in this paper effectively improves the recognition efficiency of feature dimensionality reduction.

As can be seen from Figure 3, after we fine-tuned the machine learning algorithm, the GPU platform value gradually increased, but its performance speedup ratio achieved the

TABLE 2: Image dimensionality reduction time of shuttlecock motion method.

Action type	30 dimensions			60 dimensions		
	RMSC	LMKMM	Method of this article	RMSC	LMKMM	Method of this article
Plate	5.11	5.23	4.51	22.36	15.87	8.53
Stretch	5.34	5.69	3.47	24.24	16.98	8.78
Abduction	6.18	7.18	4.78	22.16	17.22	9.45
Knock	5.92	7.24	3.96	20.11	20.13	8.73
Wipe	6.64	6.68	3.04	23.75	20.16	8.92
Rear	5.13	9.18	4.57	23.13	18.22	9.91
Hook	6.21	4.58	4.34	22.98	19.23	9.38
Kick	8.89	6.32	3.32	21.56	16.29	8.22

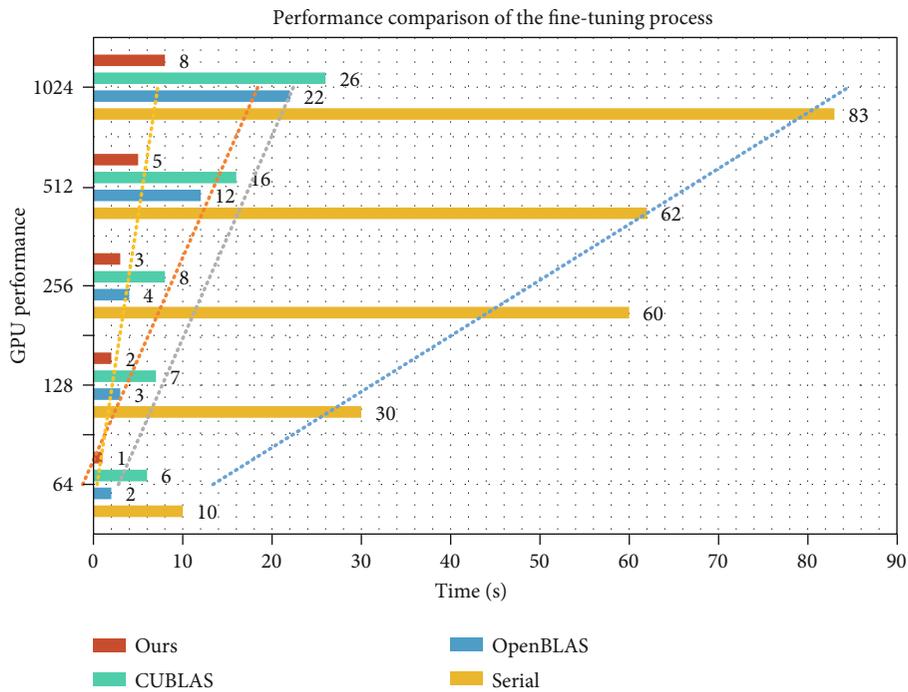


FIGURE 3: Performance comparison of the fine-tuning process.

ultimate effect. Compared with traditional algorithms, our method better verifies the effectiveness of the algorithm.

4.3. Experimental Results of Shuttlecock Motion Recognition Based on Machine Learning Algorithms. Figure 4 lists the experimental results of our method and other methods on the OxfordFlower17 dataset. From the table, we can see that the results obtained by all multiview-based methods optimize the experimental results of the optimal single view, thereby verifying the effectiveness of the multiview clustering algorithm; our proposed method is significantly better than the existing multiview Clustering Algorithm.

It can be seen from Figure 5 that when the proportion of damage gradually increases from 10% to 60%, the experimental results obtained by our method are better than the other two clustering performance indicators in accuracy, cross-correlation information, and purity. The multicore learning method of the public kernel function proves that

our method can deal with the noise information related to randomly generated elements. When the damage ratio is greater than 60%, the performance of the three methods is severely reduced due to the damage of the key information in the data. It is worth noting that when the proportion of damage is greater than 40%, the RMKC-SC method has been significantly reduced.

Figure 6 shows the classification accuracy obtained by the six algorithms of SVM, SPL, CSVM, CSPL, MV_SVM, and MV_SPL under the data set. It can be seen from the figure that under the same dictionary length and perspective, the classification effect of SPL is better than that of SVM. For the UTKinect-Action data set, the classification accuracy of SPL is about 6% higher than that of SVM on average. For the Florence3D-Action dataset, the classification accuracy of SPL is about 3% higher than that of SVM on average. Under the same dictionary length, the classification effect of MV_SPL is better than that of MV_SVM. For the

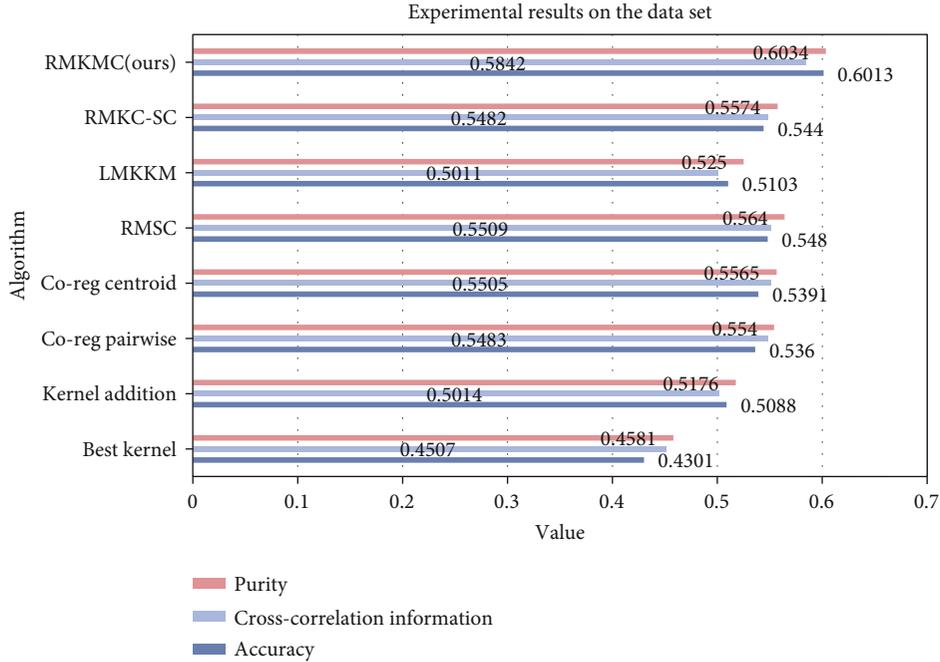


FIGURE 4: Experimental results on the data set.

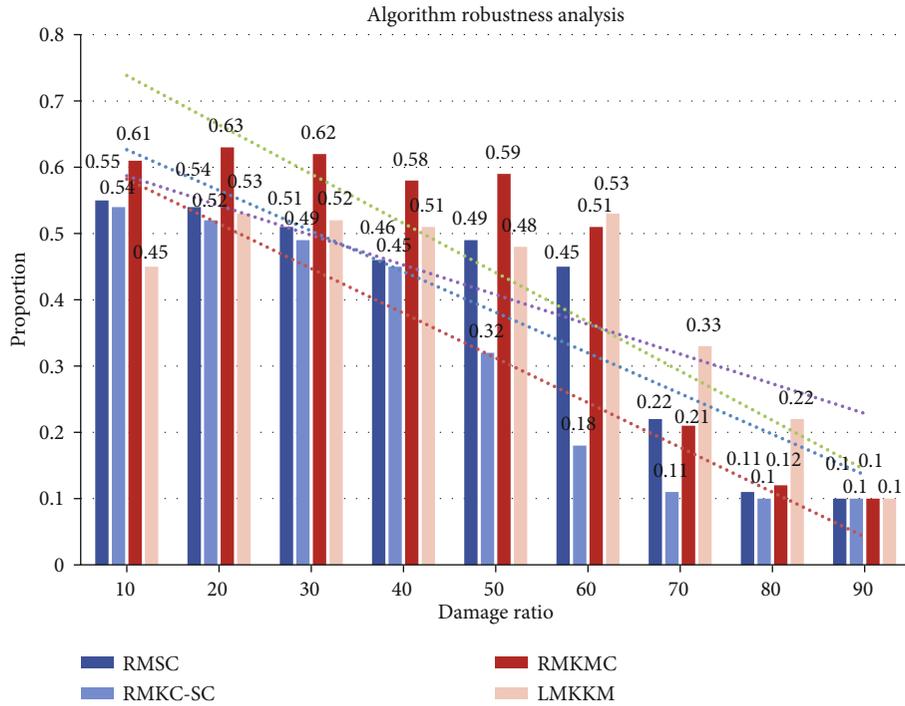


FIGURE 5: Algorithm robustness analysis.

UTKinect-Action dataset, the classification accuracy of MV_SPL is about 5.7% higher than that of MV_SVM. For the Florence3D-Action dataset, the classification accuracy of MV_SPL is 5.9% higher than that of MV_SVM on average. All of the above verify the effectiveness of the algorithm in this article.

Figure 7 shows the comparison of the recognition performance of the two classifiers. From the data in the table, it can be seen that in the case of the same dictionary length, the recognition performance of the shuttlecock action, taking the 500 dictionary length as an example, the recognition performance of SVM is generally worse than that of SPL, but under

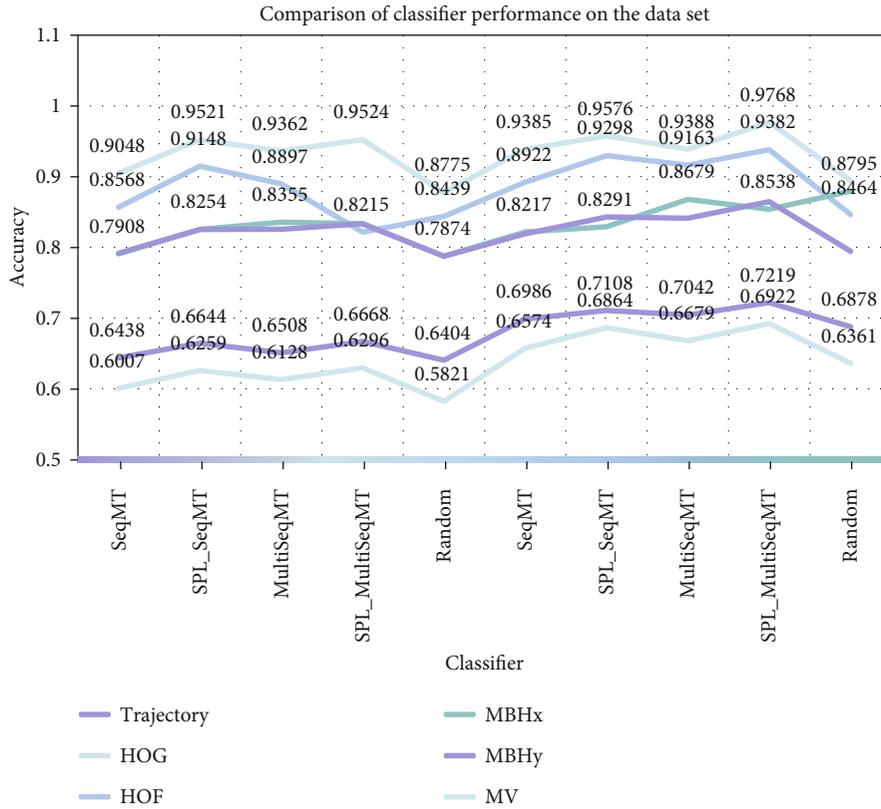


FIGURE 6: Comparison of classifier performance on the data set.

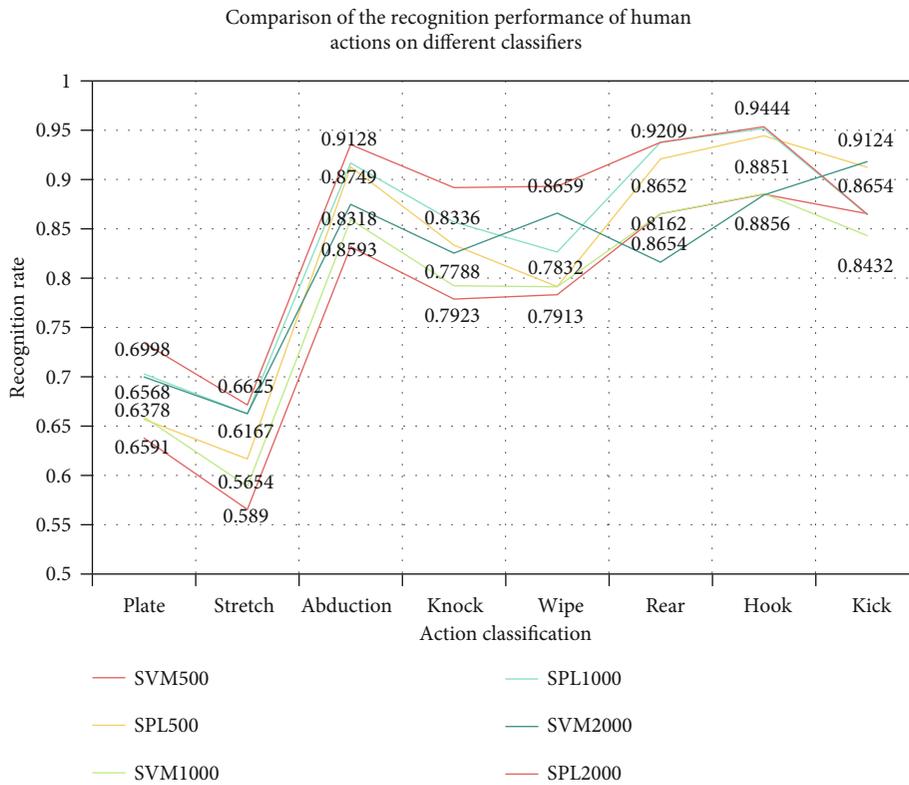


FIGURE 7: Comparison of the recognition performance of human actions on different classifiers.

TABLE 3: Experimental results of recognition of shuttlecock movements.

Action classification	Number of actions	Recall rate	Accuracy	Recognition rate
Plate	41	87.6	85.3	87.6
Stretch	156	85.3	91.4	91.2
Abduction	158	89.4	92.5	84.2
Knock	255	87.4	89.7	75.9
Wipe	136	57.3	62.5	76.3
Rear	170	64.8	75.1	72.3
Hook	224	59.6	66.8	75.4
Kick	207	58.4	68.9	71.8

the fusion algorithm, the multiview fusion algorithm is more effective. Especially in the two actions of hook and kick, SPL's action recognition rate exceeds 95%.

Table 3 shows the number of actions that occurred in a shuttlecock match, as well as the recall rate, precision rate and accuracy, and other indicators. For the shuttlecock game, the algorithm proposed in this paper has a good action recognition rate, up to 91.2%. Although several similar actions can be recognized well, the average recognition accuracy rate can exceed 75%, and even through continuous image capture, the number of occurrences of the action can be automatically analyzed, which is beneficial to athletes. And the coach can better analyze tactics and research strategies.

5. Conclusion

This paper mainly uses machine learning algorithms to recognize the shuttlecock movement. Through the multiview clustering algorithm and deep belief network algorithm, the shuttlecock movement is recognized and processed, and the shuttlecock movement recognition model is constructed, and various data sets are used. Perform performance testing. The algorithm in this paper can greatly improve the efficiency of motion recognition in shuttlecock motion and shows good performance in human motion detection, motion feature selection, and extraction. The innovation of this paper is to strengthen the accuracy and precision of action recognition through the application of machine learning algorithms and improve the application efficiency of the algorithm. The disadvantage of this article is that the research model of this article is not perfect, and it needs more experimental research data support. In the future, the algorithm in this article will be more widely used in motion recognition, but there are still more difficulties, and we need more in-depth research.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

- [1] C. Yang and Z. Lv, "Gender based face aging with cycle-consistent adversarial networks," *Image and Vision Computing*, vol. 100, article 103945, 2020.
- [2] Y. J. Lin and S. K. Weng, "Trajectory estimation of the players and shuttlecock for the broadcast badminton videos," *IEICE Transactions on Fundamentals of Electronics Communications and Computer Sciences*, vol. E101.A, no. 10, pp. 1730–1734, 2018.
- [3] Z. Zhao, H. Ma, and X. Chen, "Semantic parts based top-down pyramid for action recognition," *Pattern Recognition Letters*, vol. 84, no. Dec.1, pp. 134–141, 2016.
- [4] N. Jean, M. Burke, M. Xie, W. M. Davis, D. B. Lobell, and S. Ermon, "Combining satellite imagery and machine learning to predict poverty," *Science*, vol. 353, no. 6301, pp. 790–794, 2016.
- [5] C. J. Hammerlind, "Patent eligibility used as the Federal Circuit's shuttlecock in weekly badminton match," *Intellectual Property & Technology Law Journal*, vol. 31, no. 6, pp. 8–13, 2019.
- [6] S. Dagleish, L. Reissig, Y. Shuku, C. Gourlaouen, S. Vela, and K. Awaga, "Controlling the crystallinity and crystalline orientation of "shuttlecock" naphthalocyanine films for near-infrared optoelectronic applications," *Journal of Materials Chemistry C*, vol. 6, no. 8, pp. 1959–1970, 2018.
- [7] W. Chen, T. Liao, Z. Li et al., "Using FTOC to track shuttlecock for the badminton robot," *Neurocomputing*, vol. 334, no. MAR.21, pp. 182–196, 2019.
- [8] C. Dally, S. Haddow, and E. Kershaw, "A shuttlecock for the visually impaired," *Electronics Education*, vol. 1996, no. 1, pp. 28–30, 2017.
- [9] A. Abdulmunem, Y.-K. Lai, and X. Sun, "Saliency guided local and global descriptors for effective action recognition," *Computational Visual Media*, vol. 2, no. 1, pp. 97–106, 2016.
- [10] P. Wang, W. Li, Z. Gao, J. Zhang, C. Tang, and P. O. Ogunbona, "Action recognition from depth maps using deep convolutional neural networks," *IEEE Transactions on Human-Machine Systems*, vol. 46, no. 4, pp. 498–509, 2016.
- [11] M. Yu, L. Li, and S. Ling, "Structure-preserving binary representations for RGB-D action recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 8, pp. 1651–1664, 2016.
- [12] W. Du, Y. Wang, and Q. Yu, "Recurrent spatial-temporal attention network for action recognition in videos," *IEEE Transactions on Image Processing*, vol. 27, no. 99, pp. 1347–1360, 2017.
- [13] D. Stephan, E. Mina, and H. H. Bülthoff, "Action recognition and movement direction discrimination tasks are associated with different adaptation patterns," *Frontiers in Human Neuroscience*, vol. 10, no. 752, pp. 1–6, 2016.
- [14] M. Buonamente, H. Dindo, and M. Johnsson, "Hierarchies of self-organizing maps for action recognition," *Cognitive Systems Research*, vol. 39, pp. 33–41, 2016.
- [15] J. Wang, H. Zheng, J. Gao, and J. Cen, "Cross-view action recognition based on a statistical translation framework," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 26, no. 8, pp. 1461–1475, 2016.
- [16] C. Jia, M. Shao, S. Li, H. Zhao, and Y. Fu, "Stacked denoising tensor auto-encoder for action recognition with spatiotemporal

- corruptions,” *IEEE Transactions on Image Processing*, vol. 27, no. 4, pp. 1878–1887, 2018.
- [17] S. Lv, Y. Lu, M. Dong, X. Wang, Y. Dou, and W. Zhuang, “Qualitative action recognition by wireless radio signals in human-machine systems,” *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 6, pp. 789–800, 2017.
- [18] T. V. Nguyen and B. Mirza, “Dual-layer kernel extreme learning machine for action recognition,” *Neurocomputing*, vol. 260, pp. 123–130, 2017.
- [19] Z. Gao, S. H. Li, Y. J. Zhu, C. Wang, and H. Zhang, “Collaborative sparse representation learning model for RGBD action recognition,” *Journal of Visual Communication and Image Representation*, vol. 48, pp. 442–452, 2017.
- [20] S. Yu, Y. Cheng, L. Xie, and S. Z. Li, “Fully convolutional networks for action recognition,” *IET Computer Vision*, vol. 11, no. 8, pp. 744–749, 2017.
- [21] S. Wilson and C. K. Mohan, “Coherent and noncoherent dictionaries for action recognition,” *IEEE Signal Processing Letters*, vol. 24, no. 5, pp. 698–702, 2017.
- [22] N. D. Sidiropoulos, L. De Lathauwer, X. Fu, K. Huang, E. E. Papalexakis, and C. Faloutsos, “Tensor decomposition for signal processing and machine learning,” *IEEE Transactions on Signal Processing*, vol. 65, no. 13, pp. 3551–3582, 2017.
- [23] C. Helma, T. Cramer, S. Kramer, and L. De Raedt, “Data mining and machine learning techniques for the identification of mutagenicity inducing substructures and structure activity relationships of noncongeneric compounds,” *Journal of Chemical Information and Computer Sciences*, vol. 44, no. 4, pp. 1402–1411, 2004.
- [24] Z. Obermeyer and E. J. Emanuel, “Predicting the future—big data, machine learning, and clinical medicine,” *The New England Journal of Medicine*, vol. 375, no. 13, pp. 1216–1219, 2016.
- [25] S. Ying, P. Babu, and D. P. Palomar, “Majorization-minimization algorithms in signal processing, communications, and machine learning,” *IEEE Transactions on Signal Processing*, vol. 65, no. 3, pp. 794–816, 2016.
- [26] M. Wang, Y. Cui, X. Wang, S. Xiao, and J. Jiang, “Machine learning for networking: workflow, advances and opportunities,” *IEEE Network*, vol. 32, pp. 92–99, 2018.
- [27] D. Assouline, N. Mohajeri, and J. L. Scartezzini, “Quantifying rooftop photovoltaic solar energy potential: a machine learning approach,” *Solar Energy*, vol. 141, pp. 278–296, 2017.