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Data Analysis of the Development Status of Basketball National Fitness Based on Fog Computing

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ABSTRACT

As part of the national strategy to enhance fitness, mass sports development is continuously being promoted and facilitated. As the living standards of Chinese residents continue to improve, the demand for health for people of all ages is increasing. Basketball, a widely played and popular sport, has flourished in recent years and has gained the love of people from different age groups. As a vital sport in the national fitness strategic plan, basketball has laid a strong foundation for the progress and development of the national fitness strategic plan in China. However, the active development of basketball in the context of national fitness has also raised the bar for the level of competence in basketball, particularly in terms of professional theoretical knowledge, professional skills, and physical quality training for basketball referees. Thus, this paper aims to combine the advancements in fog computing and deep learning to further enhance the training of basketball referees.

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Introduction

National fitness is not only an important reflection of the country's comprehensive strength, but also an important way and means to achieve national health, and a powerful support for building a "healthy China" and an important guarantee for building a moderately prosperous society. Health is an inevitable requirement for the comprehensive development of people, is the basic condition for economic and social development, is an important symbol of national prosperity and national wealth, is the common pursuit of the masses. Later, it was also stressed that national fitness is the basis and guarantee of a healthy life for all people, is an important connotation of building a well-off society in all aspects, is an important basis for every citizen to grow and achieve a happy life. It can be seen that health is the responsibility, fitness is the task, national fitness is to build a strong sporting country and the

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foundation of a healthy China (Ding, Qu, and Xi 2019; Gao, Li, and Wan 2020; Gao, Xue, and Wan 2020).

In the implementation of the national fitness program, to reflect the leading position and role of the government, for the people's health services. The national fitness plan mentions that all places should strengthen the organizational leadership of the national fitness cause, establish and improve the implementation of the national fitness plan of organizational leadership and coordination mechanism to ensure that the national fitness national strategy to promote in-depth.

First, the government should improve the laws related to national fitness, promote local national fitness legislation, and protect the rights of national physical fitness. Second, it should pay attention to the construction of systems and organizational structures to provide organizational and institutional guarantees for the comprehensive development of basketball. In order to meet the needs of the comprehensive development of basketball, adjust the institutional settings, implement classification management, promote synergy, strengthen the construction of rules and regulations, and improve internal management. The improvement of the organizational structure and the continuous strengthening of the system construction provide a strong organizational and institutional guarantee for the comprehensive development of basketball. Really do the government to build a good platform for all aspects of society to the platform to realize its value and reflect its value (Chen et al. 2022; Ding et al. 2020; Zhao et al. 2022).

The main role of enterprises in the development strategy of national fitness strategy for the realization of the national fitness strategy, the use of government and social capital and other financing channels, and gradually enhance the financial budget of sports facilities, the national fitness requirements into the financial system, the government to purchase services to provide security for the masses fitness. In the game operation should also adhere to the "government-led, enterprise operation, social participation, multi-party cooperation" development policy, improve the social forces involved in the development of basketball incentive system, do a good job of market development, promote industrial integration, further invigorate the market, encourage social capital investment, enhance their own blood-making function, and continue to seek more social Support attention, give full play to the role of social capital ties.

The government is the leader, and the Non-Governmental Organizations (NGO) can promote the development of national fitness to a certain extent. First, the premise of social infrastructure construction, through increased efforts and policy guidance means to comprehensively enhance the degree of participation in social basketball, fully with the help of sports social organizations to carry out a variety of mass activities to attract more people to appreciate and participate in them, to enhance the project basis of basketball;

Second, actively guide non-governmental organizations to do a good job of collaborative work, make up for the current shortage of national fitness venues, and do a good job of supporting venues. Finally, sports clubs and associations are encouraged to actively expand basketball-related activities based on enriching the amateur cultural life of the public, and to do a good job of interaction and communication to meet the basic requirements of national fitness and at the same time, enhance the friendship between the community.

The national fitness plan mentions the need to promote the reform of sports social organizations and stimulate the vitality of national fitness. In accordance with the requirements of the reform and development of social organizations, accelerate the promotion of sports social organizations to become autonomous according to law, the separation of government and society, clear powers and responsibilities of modern social organizations, guide the transformation of social sports organizations to independent legal organizations, promote their rule of law, socialization, efficient development, and improve the ability and quality of sports social organizations to undertake national fitness services (Jv, Pr, and Srk 2021).

The development model of government-led and collaborative development of all citizens is effective in promoting basketball's multi-dimensional and collaborative development, and it is also the basic guarantee for the realization of the national fitness strategy. In the national fitness development strategy mentioned talent training and employment policy, training composite sports industry talent, support for retired athletes to work in the sports industry (Rodrigues et al. 2022). The value and role of all citizens in the development of sports can be found in this opinion.

First, we rely on sports industry professionals to optimize and update the industrial model and contribute to the development of sports; second, we rely on sports researchers to explore the new model of basketball organization so as to find a way to develop in a new direction and meet the basic requirements of national fitness; third, we rely on the collaboration of all people to promote the basketball program under the perspective of the strategic deployment of national fitness. Thirdly, we rely on the synergy of all people to jointly promote the basketball program in the perspective of the strategic deployment of national fitness and benefit all local community residents. Play a good role in the main position of schools in basketball reserve talent training basketball reserve talent training should be based on youth, we should take youth as the key population to implement the national fitness program, and vigorously promote basketball in the campus to improve the physical quality of youth.

Integrate sports and education together, popularize and improve the combination of each district and county set basketball sports, traditional project schools and key institutions of higher learning echelon construction as the focus, each project should be set up in accordance with the three age levels of elementary school, junior high school, high school multiple male and female basketball teams, the planned implementation of basketball amateur training competition activities. Gradually form a complete system of talent selection, training, delivery, assessment and reward, forming a perfect talent training chain (Sri Raghavendra, Chawla, and Gill 2021).

With the rapid development of the modern basketball level, higher requirements for the level of basketball ability have been put forward. Therefore, it is necessary to use digital technology to enhance the analysis of basketball basic skills training and development methods. This paper combines the accumulation of fog computing as well as deep learning in human action recognition and explores the combination of it with basketball technical action recognition and planning to better serve the national basketball sport, so as to effectively promote the level of development of national fitness. In recent years machine learning algorithms have been gradually applied to intrusion detection and achieved better results.

Traditional machine learning methods mostly target ground wired networks and mostly use centralized learning methods to aggregate traffic data for centralized processing and analysis, and centralized intrusion detection methods based on deep neural networks and K-nearest neighbor algorithms are evaluated on public data sets with high detection accuracy. The hierarchical intrusion detection method based on extreme learning machine clusters nodes according to the functions of wireless sensor networks, which improves the intrusion detection accuracy and reduces the detection time, but the algorithm has a high false alarm rate when the percentage of attack traffic in the network is small, and the traffic categories are unbalanced. The centralized intrusion detection method based on recurrent neural network algorithm has better intrusion detection capability in the software-defined network environment.

However, the above centralized learning is a traditional method, which is difficult to be applied to wireless sensor networks. For the characteristics of channel instability in wireless sensor networks, the centralized learning mode not only brings the problems of bandwidth resource constraint and high delay and loss of network traffic data transmission, but also is prone to high communication cost and privacy leakage when collecting data. A distributed learning approach based on fog computing can better solve these problems. This approach can offload computational tasks to the fog computing nodes of the network, such as base stations, small servers and other devices, and the models are closer to the data terminals, enabling faster responses such as detection alarms (Aljawarneh 2021).

However, distributed learning is vulnerable to the threat of noisy data, data poisoning, and adversarial samples due to the inability to supervise the training behavior of participants locally. Among multiple distributed learning solutions, federated learning, which was initially used to address data silos and data privacy issues, has demonstrated great advantages in the field of intrusion detection.

The rest of the article is structured into four main sections: related work, methods, experiments and results, and conclusion. The related work section provides an overview of the existing literature on online medical diagnosis systems and highlights their strengths and limitations. The methods section describes the technical details of the proposed system, including its architecture, algorithms, and data processing techniques. The experiments and results section presents the results of the system's performance evaluation and compares its accuracy with traditional diagnostic methods. This section also discusses the system's user interface and user experience and presents user feedback and satisfaction metrics. Finally, the conclusion section summarizes the key findings of the study, discusses the system's limitations and future research directions, and highlights the practical applications of the proposed system. Overall, the article provides valuable insights into the development and evaluation of online medical diagnosis systems and their potential impact on healthcare delivery.

Related Work

The Current Situation of National Fitness Development

The promulgation and implementation of the national fitness program has greatly promoted the development of national fitness movement, the number of sports and fitness facilities and venues has increased, the number of sports instructors has increased, the number of people participating in sports and the proportion of sports population has been greatly enhanced, and the awareness of national fitness has been significantly increased, so the development prospect of national fitness movement in China is very optimistic.

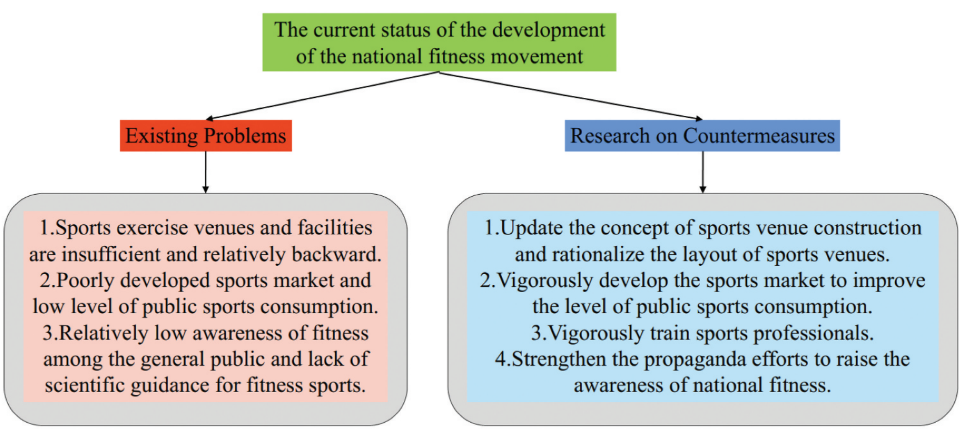

Figure 1. The current status of the development of national fitness.

The current status of the development of fitness for all is shown in Figure 1. In the process of implementing the national fitness program there are some problems that hinder the development of the national fitness movement, mainly manifested in the lagging and insufficient sports exercise facilities, the slow construction of sports venues, the poor comprehensive quality of sports instructors, and the large gap between the levels of sports consumption in different places, which restrict the sustainable development of the national fitness movement in China (Cornell et al. 2015; Peng, Shi, and Zhang 2015; Oprea and Bra 2021; Zhu, Li, and Wang 2021).

China faces several challenges in the development of national fitness sports, including insufficient venues and facilities, an underdeveloped sports market, and a lack of scientific guidance for fitness exercise. These challenges can be attributed to economic limitations, time constraints, low consumer demand, poor market sensitivity, and inadequate intermediary organizations. Furthermore, there is a lack of awareness and sportsmanship regarding national fitness, and individuals tend to spend their leisure time watching TV and browsing the Internet. The absence of proper scientific guidance for fitness exercise can result in adverse physical reactions and pose a risk to individual safety (He 2018; Vaquero and Rodero-Merino 2014; Wu 2019).

In order to advance China's national fitness movement, it is crucial to conduct research, update the construction concepts of sports venues, and strategically layout sports facilities to cater to the diverse fitness requirements of various sporting populations (Nae 2015; Loturco and Abad 2016; C. D. J, T, and B). One of the key priorities is to enhance economic growth and boost residents' income, while also expanding fitness and sports programs to increase participation and enthusiasm. Additionally, it is essential to improve the operation system of the sports market and establish a unified and transparent market system (Dawes, Marshall, and Spiteri 2016; Tomovic et al. 2016). As the demand for sports professionals continues to rise, it's crucial for colleges and universities to improve the training provided to sports professionals and social sports instructors. Additionally, government departments should utilize media to promote the significance of the national fitness movement and increase awareness about national fitness.

Current Status of Fog Computing Research

In recent years, the number of IoT devices around the world is exploding, and with it comes a huge amount of data. The traditional cloud computing model is usually deployed far away from IoT devices, and the processing of data is concentrated in the data center, so the storage and calculation of big data puts considerable pressure on cloud servers (SELF-ESTEEM 2015; Tan 2015; Yanci et al. 2015). Therefore, fog computing, as a supplement to cloud computing, is different from the high "cloud," "fog" is closer to the ground, hence the name of fog computing.

Fog nodes can generally be switches, routers, servers, and other devices that can be connected to the network and have a certain amount of computing power, and do not require as much computing power as cloud servers, and their smaller size makes them easier to deploy, so fog nodes can be deployed closer to the edge of the network of end devices. Because of its geographical advantage and ease of deployment, fog nodes can provide more efficient services for various latency-sensitive applications. But in fact, to overcome the drawbacks of high latency and network volatility brought by the cloud computing model, many similar computing models have been proposed one after another to provide better computing services for various latency-sensitive and computation-intensive tasks, in addition to the fog computing model (A. N. M, M, and N).

With the popularity of mobile IoT devices, mobile cloud computing has become an emerging computing model for efficient management of limited resources. Fog computing is considered as a combination of wireless networks, mobile computing, and cloud computing that can provide rich computing resources to end devices. From the user's point of view, especially when dealing with some computationally intensive applications and tasks, mobile cloud computing overcomes some limitations, such as battery life, computing power, and memory limitations. But mobile cloud computing also has several drawbacks, including low bandwidth, low security and privacy, low service availability, low network compatibility, and limited energy. Unlike fog computing, which sends task requests from end devices to nearby fog nodes for processing, mobile cloud computing computes and stores data from end devices on the cloud and does not process them locally.

Mobile edge computing is an extension of mobile cloud computing that enables cloud-based resources and services to be close to users (Gryzunov 2021). Mobile edge computing is a type of fog computing that offers virtualized computing resources to nearby mobile devices with limited resources? It's equipped with more computing power and data storage capacity, making it comparable to cloud data centers. On the other hand, fog computing is a dependable and resourceful computer or group of computers that can provide extra computing resources to end devices nearby by connecting to the internet. It has low latency and can minimize network traffic by providing an improved platform to analyze and filter data closer to the network edge.

Fog computing is highly scalable since fog nodes are typically composed of small, low-cost devices with computing power. The lifecycle of a communication network is determined by the lifecycle of communication devices, which is largely determined by their own battery capacity (Abdali et al. 2021; Samann, Zeebaree, and Askar 2021). Collaborative communication networks now have a new way to transfer energy wirelessly. This innovative paradigm enables energy-limited devices to obtain energy from wireless RF signals in their vicinity, thereby reducing reliance on the power grid. Additionally, it can be easily incorporated into fog computing networks, allowing for both data transfer and energy harvesting (Ijaz, Li, and Lin 2021; Zhu, Huang, and Gao 2021).

Methods

Model Architecture

The basketball action recognition model of fog computing is shown in Figure 2. First, the target image is collected by the low-level device, uploaded to the cloud platform by the edge computing node, and the convolutional recognition model is trained using the computing, storage and software resources of the cloud platform, and the trained convolutional recognition model is transmitted back to the edge computing node to provide real-time basketball action recognition service. The large amount of computation of the training recognition system is undertaken by the cloud computing center, while the real-time computation and equipment control are done by the edge computing, and the edge computing and the cloud computing center exchange data through the network to form a cloud-fog combination of intelligent basketball action recognition system.

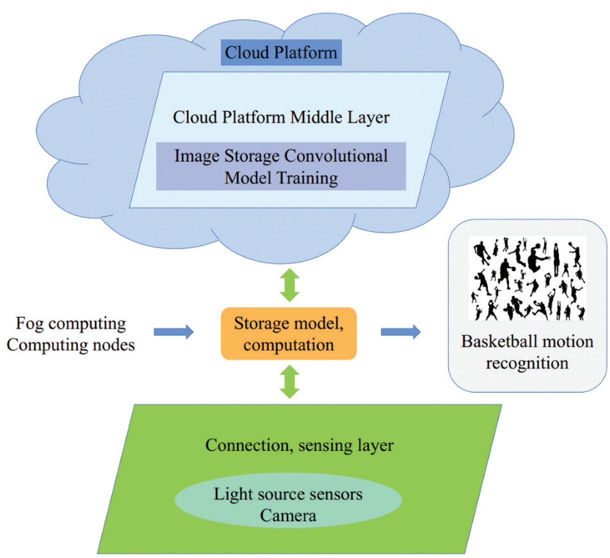

Figure 2. Model structure.

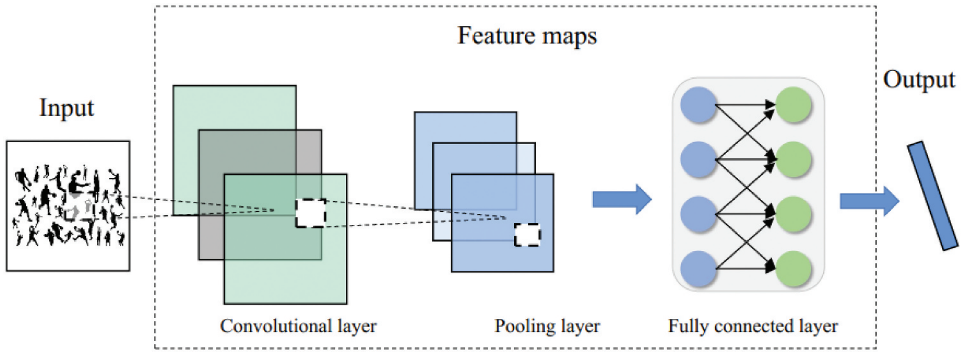

Figure 3. W-Net convolutional neural network architecture.

Recognition Algorithm

The general convolutional neural network architecture is not suitable for this kind of scenario with small number of samples and high accuracy requirements, so the paper improves on some existing convolutional neural network architecture and designs a basketball action recognition algorithm for small number of samples. The basketball action recognition algorithm includes convolutional neural network architecture design and convolutional neural network training.

In the convolutional neural network architecture design, the architecture of ALEXNET is improved: in the layer structure, the original three fully connected layers are reduced to two, and the corresponding activation and anti-fitting layers are removed to optimize the layer structure, because the parameters of the fully connected layers account for most of the parameters of the whole network after the convolutional network training is completed, especially in the case of a small number of samples (in statistics, a small sample refers to a subset of a larger population that is used to draw conclusions about the whole population. The term "small" is relative and may vary depending on the context and the specific research field).

In the case of a small number of samples, removing a fully connected layer can reduce the size of the network output model while the impact on the output results is almost negligible; in the layer parameters, the step size of the convolution and pooling layer convolution operation and the size of the convolution kernel are adjusted to increase the size of the feature map after the convolution pooling operation to better utilize the information of the input image, specific parameter adjustments will be described in the next subsection.

After the above improvements, a basketball action recognition algorithm called W(Workpiece)-Net is formed, as shown in Figure 3. The data flow between the layers is mainly in the direction of arrows in the form of

4-dimensional arrays, and the data layer has only the output of data and has label data flowing directly to the output layer, while the rest of the layers have the input and output of data.

Convolutional Layer and Pooling Layer

In order to learn the input image features, multiple convolution kernels are set in the convolution and pooling layers to extract the features, and the size and number of convolution and pooling operations and their output feature maps, and the three numbers below each operation layer are multiplied by $c \times h \times w$ to indicate the number of channels, height and width of the input feature map in that layer, respectively. and width, respectively. Considering the image input and output sizes, the original 256×256-pixel image is randomly cropped to 221×221-pixel image for 3-channel input, and the convolution and pooling operations are performed. To preserve the significant features of the image, the pooling layers P1, P2 and P5 are subjected to the maximum pooling operation, and the output of the pooling nodes as:

$$x_n(a,b) = max\left\{ \sum\nolimits_{\substack{i \in k_w a \\ j \in k_h b}} X_{n-1}(i,j) S_{ij} \right\} + b_n \tag{1}$$

where S_{ij} is the corresponding coordinate parameter of the pooling kernel; a is the horizontal coordinate value; b is the vertical coordinate value; and b_n is the n-th layer bias.

Local Response Normalization Layer

To normalize the local input region, mimic the lateral inhibition mechanism of the biological nervous system, create a competition mechanism for the activity of local neurons, make the relatively larger values with larger responses, and improve the generalization ability of the model, the convolutional neural network architecture is designed with two normalization layers Local Response Normalization and LRN2, which normalize the input between different channels.

The normalized output is

$$W_1 = \frac{W_0}{\left[k + \left(\frac{\alpha}{n}\right) \sum_i x_i^2\right]^{\beta}} \tag{2}$$

Where W_0, W_1 are the input and output values, respectively; α is the scaling factor; β is the exponential term coefficient; n is the local size; k is the hyperparameter; and x_i is the node output.

To achieve the final recognition and classification of basketball actions, a fully connected layer and an output layer are set. The size of the convolutional kernel of the fully connected layer is the same as the size of the input data, and the size of the output feature map after the operation is *1 × 1*, so that all the learned distributed features can be mapped to the sample tag space. The output layer includes the precision layer and the loss function layer.

The accuracy layer calculates the accuracy of the training model with test samples as an important basis for judging the merit of the model, and the loss function layer calculates the probability of each category and uses the loss function values to guide the model training.

Convolutional Neural Network Training

Each layer of the convolutional neural network consists of several neurons, and the neurons obtain their outputs from the input and activation function of the previous layer. The activation function uses the ReLu non-negative activation function. Compared with the common activation functions such as Sigmoid and Tanh, ReLu adds nonlinearity to the model to enhance the fitting ability of the model, and at the same time makes the weights of some neurons zero, which increases the sparse performance of the weights and prevents overfitting to some extent.

For the forward propagation of the whole network as:

$$\begin{gathered} a^{i,l} = \sigma\left(z^{i,l}\right) = \sigma\left(W^l \cdot a^{i,l-1} + b^{i,l}\right) \\ a^{i,l} = \sigma\left(z^{i,l}\right) = \sigma\left(W^l * a^{i,l-1} + b^{i,l}\right) \\ a^{i,l} = \mathrm{pool}\, a^{i,l-1} \\ a^{i,L} = softmax\left(z^{i,L}\right) = \frac{\mathrm{e}^{w^l a^{i,L-1} + b^{i,L}}}{\sum_j \mathrm{e}^{w^l aj,L-1 + b^{i,L}}} \end{gathered} \tag{3}$$

Where $a^{i,l}$& is the output of the ith picture sample at layer l, σ is the activation function, $z^{i,L}$ is the input of the i-th picture sample at layer l, W^l is the weight of layer l, $b^{i,L}$ is the bias of the i-th picture sample at layer l, L is the output layer; pool is the pooling operation, * is the convolution operation.

In the output layer for the error function is calculated as:

$$\begin{gathered} J = -\sum_i y^i \ln \mathrm{a}^{\mathrm{i,L}}, \mathrm{y}^{\mathrm{i}} = 0 \text{ or } 1 \\ \frac{\partial J}{\partial W^L} = \left(a^{i,L} - 1\right) a^{i,L-1} \\ \frac{\partial J}{\partial b^L} = a^{i,L} - 1 \end{gathered} \tag{4}$$

Where J is the loss function value; y^i is the sample corresponding label value; W^L is the L-th layer weight; b^L is the L-th layer bias.

Fog Calculation Structure

Suppose there are a total of M smart devices in the device layer, which are all integrated with passive power dividers inside, and the smart devices, possibly due to their limited computing resources and battery capacity, processing all tasks locally may bring problems such as high energy consumption or device power exhaustion. To alleviate these problems and improve the user experience, the smart device can migrate some pending computational tasks to nearby fog nodes for processing through the signal base stations in the fog node layer, and then transmit the computational results to the smart device *i* via Score-Based Scheduling (SBS) after the fog nodes have processed these computational tasks. The fog computing task model is shown in Figure 4.

The nearby fog nodes can provide additional computing resources for the smart device, and the smart device *i* can migrate some tasks to the fog nodes to assist in processing through SBS according to the task migration a_i to reduce its own energy consumption and optimize the user experience of the smart device. First, the uplink migration rate of smart device *i* is defined as

$$R_i = B_u \log_2\left(1 + \frac{P_i G_u^2}{n_u B_u}\right) \tag{5}$$

where P_i denotes the transmission power of smart device *i*, B_u denotes the uplink bandwidth of smart device *i*, n_u denotes the noise power spectral density of the uplink, and G_u denotes the wireless channel gain of the uplink.

Similarly, the transmission rate of the signal transmitted by the SBS to smart device *i*, i.e., the downlink rate of smart device *i*, is defined as:

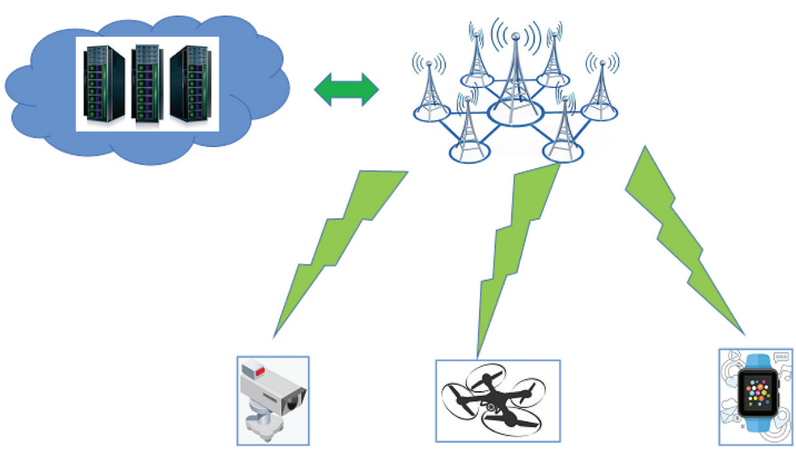

Figure 4. Fog computing task model.

$$R_d = B_d \log_2\left(1 + \frac{\beta_i P_c G_d^2}{n_d B_d}\right) \tag{6}$$

where P_c denotes the transmission power of the SBS, B_d denotes the downlink bandwidth of smart device i, n_d denotes the noise power spectral density of the downlink, G_d denotes the wireless channel gain of the downlink, and i denotes the power splitting factor of smart device i.

The task completion time is composed of the uplink transmission time of smart device i, the computation time of the fog node, and the downlink transmission time of smart device i to receive the SBS return information. Define the uplink transmission time of smart device i as:

$$T_i^{tra} = \frac{a_i w_i}{R_i} \tag{7}$$

Experiments and Results

Experimental Setup

Our Basketball dataset is composed of multiple live videos of basketball games. The total duration of these videos is about 8 hours. These videos are shot from different angles to capture the various actions of the players during the basketball game. Since the basketball arena is extremely spacious and has many spectators and various obstacles, the obtained videos often contain many extraneous things. In the annotation process, we first selected three coarse-grained movements, namely dribbling, passing and shooting, for classification. Then, we further subdivided them into 26 fine-grained actions. Finally, our dataset consists of a total of 3399 annotations, with an average of about 130 samples per action class. For each action example, we have labeled the start time and end time as well as its label.

In order to verify the performance of the proposed method in this paper and compare it with the current mainstream alignment methods, the evaluation metric used in this paper is the average precision mean. Firstly, the following metrics are introduced: 1) True Positive (TP): positive class samples are predicted as positive classes; 2) True Negative (TN): negative class samples are predicted as negative classes; 3) False Positive (FP): negative class samples are predicted as positive classes; 4) False Negative (False Negative, FN): positive class samples are predicted to be negative class. The training process performance enhancement and loss convergence are shown in Figures 5 and 6.

The schematic diagram of the training process is an important aspect of machine learning and deep learning algorithms. It illustrates the process of training a model using a dataset and optimizing it to achieve better performance on a given task. The diagram typically includes the input data, the

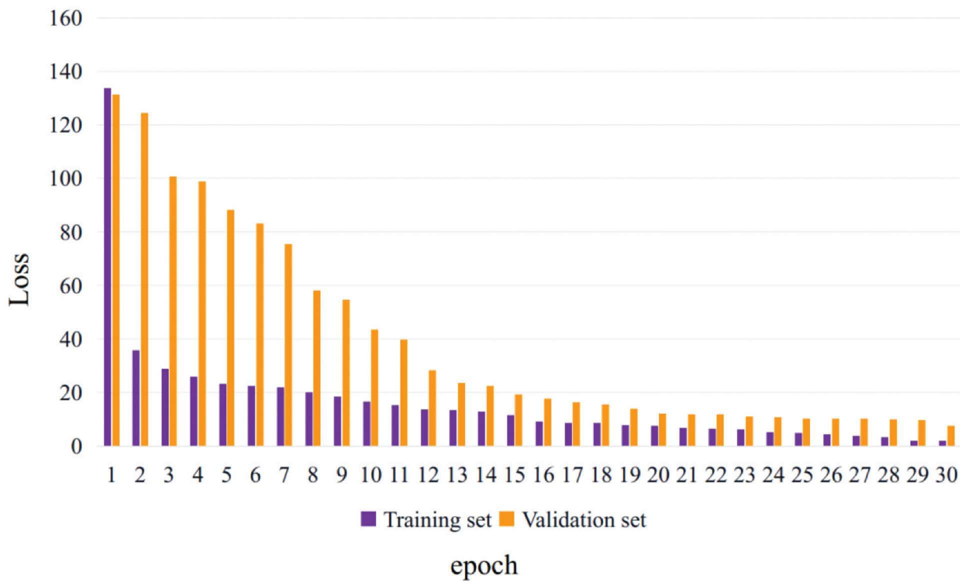

Figure 5. Schematic diagram of training process performance improvement.

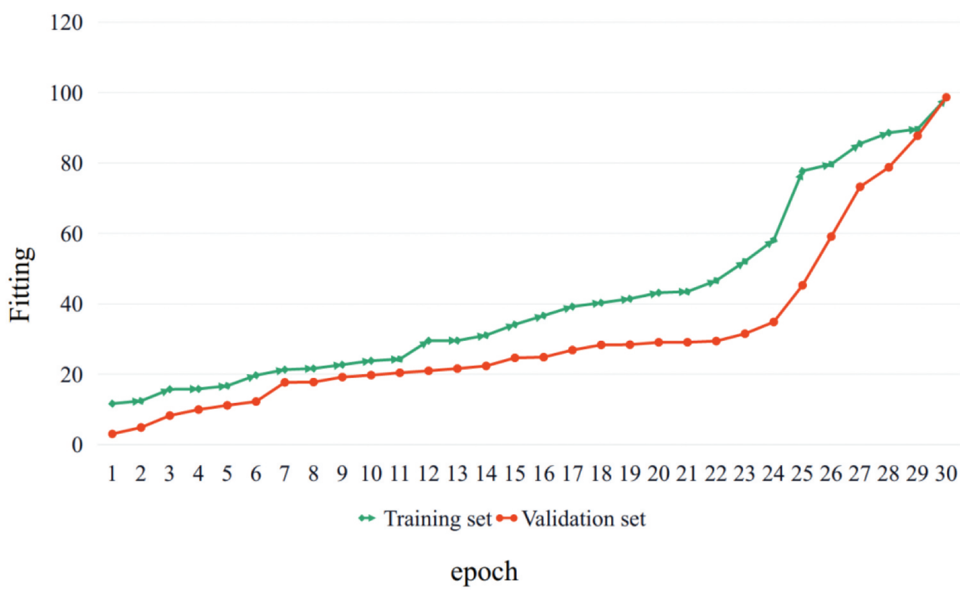

Figure 6. The training process loss convergence schematic.

model architecture, the loss function, the optimization algorithm, and the output or predicted values.

One way to improve performance in the training process is by optimizing the hyperparameters of the model, such as the learning rate, batch size, and regularization parameters. These hyperparameters can greatly affect the performance of the model, and finding the optimal values for them can lead to significant improvements.

Another way to improve performance is by using more advanced model architectures, such as deep neural networks with multiple layers and more complex connections between nodes. These models can learn more intricate patterns and relationships in the data, leading to better performance on the task. Data augmentation techniques can also be used to improve performance by increasing the amount and variety of training data. This can help prevent overfitting and improve the generalization of the model to new data. Finally, the optimization algorithm used in the training process can also greatly affect performance.

Overall, the schematic diagram of the training process is a crucial aspect of machine learning and deep learning algorithms, and optimizing various aspects of this process can lead to significant improvements in performance.

The loss function is a measure of the difference between the predicted and actual outputs, and the goal of the training process is to minimize this loss function. The convergence of the loss function during training is an important indicator of the model's performance. A rapidly decreasing loss function suggests that the model is learning quickly, while a slowly decreasing loss function may indicate that the model is struggling to learn the underlying patterns in the data.

A convergence schematic would likely show how the loss function changes over the course of the training process. Ideally, the loss function will steadily decrease over time until it reaches a plateau or reaches a predetermined threshold. This indicates that the model has learned the patterns in the data and can accurately make predictions on new, unseen data.

However, if the loss function does not converge or plateaus at a high value, it suggests that the model may not be learning the underlying patterns in the data or that the data may be too noisy or complex for the model to accurately learn from. In these cases, additional adjustments to the model architecture or training process may be necessary to improve performance.

Experimental Results and Analysis

We use several common 2D network models (including Long short-term memory (LSTM), two-stream network, etc.) as benchmark models to evaluate our proposed network structure. The network is pre-trained on the ImageNet dataset and then fine-tuned to our Basketball dataset. In that experiment, 2364 instances were used for training and 1035 instances were used for testing. First, we trained and tested the three major categories (dribbling, passing, and shooting) at coarse-grained level first. "Dribbling, passing, and shooting" are three major categories in basketball that describe different technical skills.

(1) Dribbling is the skill of bouncing the ball continuously while moving or standing still. It is one of the fundamental skills in basketball and is used to move the ball around the court and to get past defenders. There are many different types of dribbles, such as crossover, between-the-legs, and behind-the-back.
(2) Passing is the skill of moving the ball from one player to another using a variety of different techniques, such as chest passes, bounce passes, and overhead passes. Passing is used to create scoring opportunities and to keep possession of the ball.
(3) Shooting is the skill of throwing the ball into the hoop, either from a distance or close range. There are different types of shots, such as layups, jump shots, and three-pointers, and different shooting techniques, such as the one-hand shot or the two-hand set shot. Scoring is the ultimate goal of basketball, and shooting is one of the most important skills for achieving this goal.

These three categories represent the foundation of basketball skills. Mastering them requires a lot of practice and dedication, and they are essential for any player looking to excel on the court.

The experimental results of the basketball dataset 26 subcategories and three major categories are shown in Figures 7 and 8. The Figure 7 shows the (mean Average Precision) mAP values of the three major classes, and the middle column shows the mAP values of the 26 subclasses. The mAP is a commonly used evaluation metric in object detection and computer

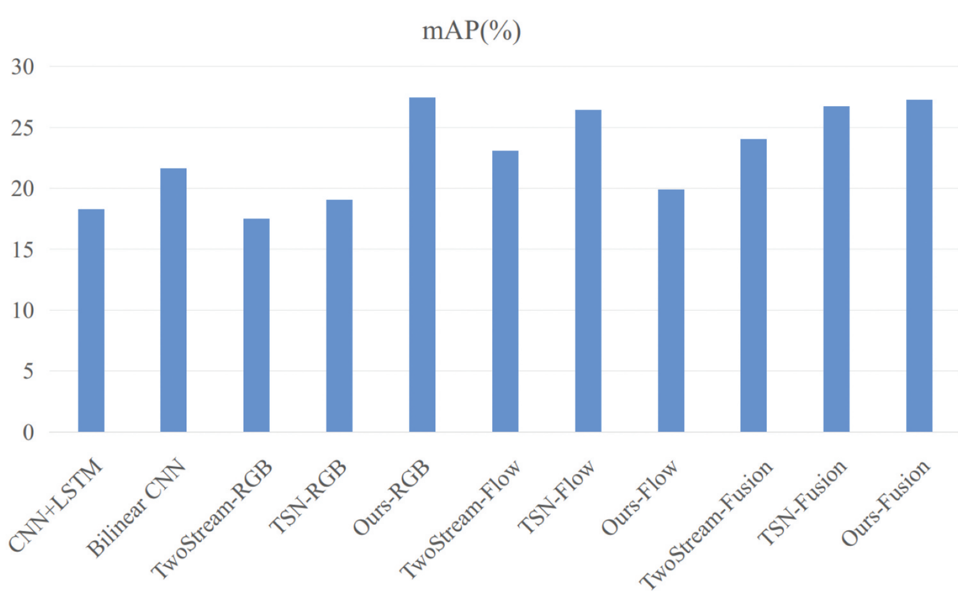

Figure 7. Experimental results for subclass 26 of the basketball data set.

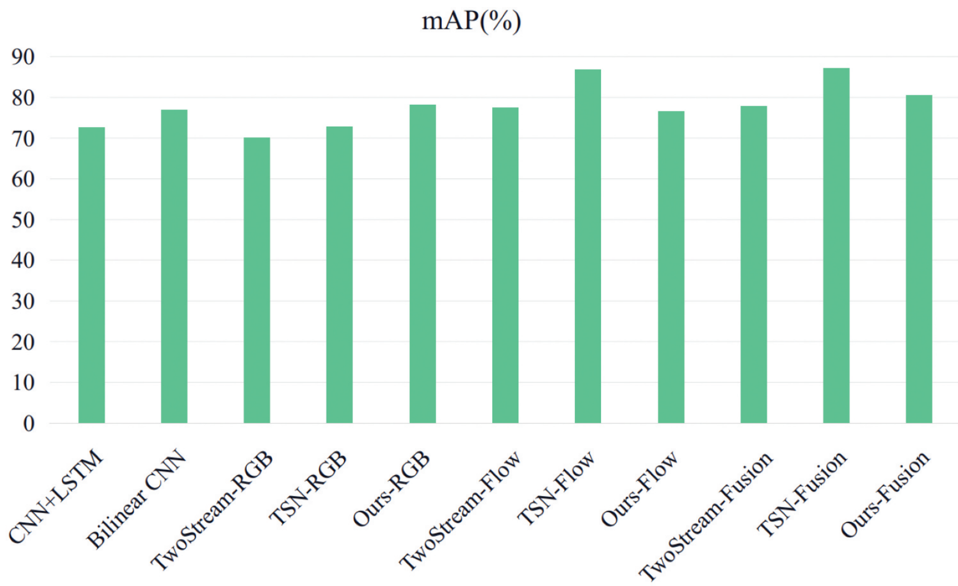

Figure 8. Basketball data set three major categories of experimental results.

vision tasks. It measures the accuracy of a model by calculating the precision and recall of the model's predictions. mAP is the average of AP (Average Precision) values across multiple classes. AP is the area under the precision-recall curve, and it represents the trade-off between precision and recall at different thresholds. In the context of the article, the mAP values refer to the accuracy of the proposed system in detecting and classifying basketball technical actions based on the three categories (dribbling, passing, and shooting).

From the analysis, it can be obtained that among the following methods used for action recognition, Time-Sensitive Networking (TSN) obtains the best results in both time stream network and fusion network, while our local feature-based network structure can obtain better results on RGB images.

Overall, these methods have high recognition accuracy for all three broad categories of coarse-grained basketball actions, with an average mAP of about 80%. Next, we focus on how the action recognition results of each method in the 26 fine-grained classes. As can be seen in Figure 8, our region-based filtering method achieves a significant improvement on RGB images compared to other networks, and a nearly 9% improvement in map compared to the highest TSN in the benchmark (27.40% vs. 19.06%). However, it is still TSN that performs better on optical flow. Combining the above coarse-grained and fine-grained recognition results, it can be found that the local feature-based approach has better recognition performance on RGB images, which may be since RGB images can retain more effective region information compared to optical flow images.

Table 1. Comparison of the results of the improved converged network.

Methods	mAP(%)
TSN-RGB	19.06
TSN-Flow	26.39
TSN-Fusion	26.70
proposed method-RGB	27.40
proposed method-Flow	19.89
proposed method-Fusion	27.23
proposed method-RGB+TSN-Flow	29.78

We use linear weighted average method to calculate the results of the network. We set the weights of the spatial flow network and the temporal flow network to 0.4 and 0.6, respectively, and Table 1 below shows the comparison of our results with the results of the two original methods. As can be seen from the table, the fusion method obtained performance improvements on both datasets, with the mAP value of the Basketball dataset increasing from 27.40% to 29.78%.

However, from the overall results, the accuracy of the fine-grained video action recognition method is still very low. For the Basketball dataset, its 26 fine-grained action recognition results are much worse compared to the coarse-grained action recognition of the three major categories, which indicates that fine-grained action recognition is still a very challenging task. The fifth column of Table 2 shows the APs of each category after the fine-grained action recognition of the Basketball dataset using the above fusion network, and the analysis in the table shows that the APs belonging to different subcategories of the same broad category have large differences.

For example, in the shooting major category, the AP for free throws reached 97.14%, while the AP for jump shots was only 18.52%. The last column of the table lists the most confusing subcategories in the identification process for each subcategory. Most of the fine-grained subcategories will be confused with other subcategories of the same general category. As stated earlier, this is because for fine-grained actions, the differences between classes are small. So how to effectively extract representative features from the complex background becomes an essential task to distinguish similar actions.

Table 2. Experimental results for basketball datasets in spatial and channel domains.

Methods	mAP(%)
Spatial Domain-RGB	28.89
Spatial Domain-Flow	21.03
Spatial Domain-Fusion	29.01
Channel domain-RGB	29.64
Channel-Flow	22.60
Channel-Fusion	29.98

After combining the methods of spatial domain and channel domain attention mechanisms with dual-stream networks, respectively, we conducted experiments on two datasets. From Table 2, we can find that on RGB images, the mAP values of these two methods reach 28.89% and 29.64%, respectively, which are higher than the region-based filtering methods in Chapter 3 by 1.49% and 2.24%. On the optical streams, both are also better than the region-screening-based method, although the results are worse compared with RGB.

Moreover, after dual-stream fusion, the channel-domain attention mechanism-based method achieves the highest performance so far with an mAP of 29.98%, which is 0.2% higher than the optimal result in Chapter 3. The method based on the spatial domain attention mechanism also obtained good results after fusion, with a mAP of 29.01%.

Conclusion

Since the launch of China's national fitness program, there has been a significant increase in the number of people engaging in physical exercise, as well as the proportion of the population involved in sports. This has been accompanied by improvements in fitness venues and facilities, and a heightened awareness of the importance of physical fitness. In this context, basketball has emerged as a flourishing sport, with an enriched population involved in the game. Across all age groups, basketball has proven to be an effective tool for promoting physical health and regulating mental health levels. However, as with any sport, there are challenges to its development. It is therefore essential to continuously strengthen learning and progress in order to ensure that basketball plays a positive role in the construction of national fitness.

In this research paper, fog computing and deep learning are integrated to recognize human actions in basketball. The focus is on enhancing the basic skills of basketball referees, improving their psychological quality, developing training plans, perfecting evaluation mechanisms, enriching practice, and promoting their overall ability development.

The fog calculation, also known as edge computing, brought a novel way of processing data in real-time at the edge of the network, rather than sending it to a centralized cloud server. This approach has several advantages, including reduced latency, improved reliability, and better privacy and security of sensitive data. Fog computing also enables distributed processing of data, allowing for better scalability and flexibility in managing and analyzing large amounts of data generated by IoT devices. Additionally, fog computing allows for more efficient use of network bandwidth by reducing the amount of data that needs to be transmitted to the cloud, which can be particularly beneficial in low-bandwidth or high-latency environments. Overall, fog computing has brought significant advancements to the field of IoT and has opened up new possibilities for real-time data processing and analysis in a range of applications and industries.

One limitation of this paper is that it focuses mainly on the development of basketball within the context of national fitness in China and may not be applicable to other countries or sports. Additionally, the paper does not address the potential challenges and limitations of using fog computing and deep learning in basketball referee training.

In future studies, it would be beneficial to expand the scope of the research to other sports and countries to provide a more comprehensive understanding of how fog computing and deep learning can be applied to sports training and development. Furthermore, the paper could delve deeper into the potential challenges and limitations of using these technologies in basketball referee training and provide possible solutions or alternative approaches. Additionally, future studies could explore the potential of incorporating other emerging technologies, such as augmented reality or virtual reality, into basketball training and development.

Disclosure Statement

No potential conflict of interest was reported by the authors.

References

Abdali, T. N., R. Hassan, A. M. Aman, Q. N. Nguyen, and A. S. Al-Khaleefa. 2021. Hyper-angle exploitative searching for enabling multi-objective optimization of fog computing. *Sensors* 21 (2):558. doi:10.3390/s21020558.

Aljawarneh, N. M., M. M. Taamneh, N. Alhndawi, K. A. A. Alomari, and F. Masa'd. 2021. Fog computing-based logistic supply chain management and organizational agility: The mediating role of user satisfaction. *Uncertain Supply Chain Management* 9 (3):767–78. doi:10.5267/j.uscm.2021.4.001.

SELF-ESTEEM,Andonova, T. 2015. Perceived physical fitness and perceived physical appearance in early adolescent basketball players. *Research in Kinesiology* 43 (2):185–188.

Chen, C., J. Jiang, Y. Zhou, N. Lv, X. Liang, and S. Wan. 2022. An edge intelligence empowered flooding process prediction using internet of things in smart city. *Journal of Parallel and Distributed Computing* 165:66–78. doi:10.1016/j.jpdc.2022.03.010.

Cornell, D. J., K. T. Ebersole, and B. B. Meyer. 2015. Relationships between extraversion and measures of counter movement jump performance.*International Journal of Sports Science* 5 (2):73–79.

Dawes, J. J., M. Marshall, and T. Spiteri. 2016. Relationship between pre-season testing performance and playing time among NCAA DII basketball players. *Sports and Exercise Medicine - Open Journal* 2 (2):47–54. doi:10.17140/SEMOJ-2-138.

Ding, S., S. Qu, and Y. Xi. 2019. A long video caption generation algorithm for big video data retrieval. *Future Generation Computer Systems* 93:583–95.

Ding, S., S. Qu, Y. Xi, and S. Wan. 2020. Stimulus-Driven and Concept-Driven Analysis for Image Caption Generation. *Neurocomputing* 398:520–30. doi:10.1016/j.neucom.2019.04.095.

Gao, Z., Y. Li, and S. Wan. 2020. Exploring deep learning for view-based 3D model retrieval. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)* 16 (1):1–21. doi:10.1145/3377876.

Gao, Z., H. Xue, and S. Wan. 2020. Multiple discrimination and Pairwise CNN for view-based 3D Object Retrieval. *Neural Networks* 125:290–302. doi:10.1016/j.neunet.2020.02.017.

Gryzunov, V. V. 2021. *Fist geoinformation system model using fog computing in destabilization*, vol. 48. Russia, Moscow: Herald of Dagestan State Technical University Technical Sciences.

He, J. 2018. The value and significance of table tennis in the national fitness. *DEStech Transactions on Social Science, Education and Human Science*. doi:10.12783/dtssehs/emss2018/24098.

Ijaz, M., G. Li, and L. Lin. 2021. Integration and applications of fog computing and cloud computing based on the internet of things for provision of healthcare services at home. *Multidisciplinary Digital Publishing Institute* 10 (9):1077.

Jv, A., B. Pr, and C. Srk. 2021. Fog computing based secured mobile cloud for cumulative integrity in smart environment and internet of things. *Materials Today* (2):176–181.

Loturco, I., and C. Abad. 2016. Differences in fitness characteristics between Brazilian world championship and South-American championship national basketball teams. *The Journal of Sports Medicine and Physical Fitness* 56 (11):1428–9

Nae, I. C. 2015. Basketball trends and perspective on a national and international scale. *Marathon* 7 (2):202–6.

Oprea, S. V., and A. Bra. 2021. Edge and fog computing using IoT for direct load optimization and control with flexibility services for citizen energy communities.*Knowledge-Based Systems* 228: 107293.

Peng, M., Y. Shi, and K. Zhang. 2015. Fog computing based radio access networks: Issues and challenges. *IEEE Network* 30 (4):46–53. doi:10.1109/MNET.2016.7513863.

Rodrigues, L., J. Rodrigues, A. Serra, and F. A. Silva. 2022. A queueing-based model performance evaluation for internet of people supported by fog computing. *Future Internet* 14 (1):23. doi:10.3390/fi14010023.

Samann, F., S. Zeebaree, and S. Askar. 2021. IoT provisioning QoS based on cloud and fog computing. *Journal of Applied Science and Technology Trends* 2 (1):29–40. doi:10.38094/jastt20190.

Sri Raghavendra, M., P. Chawla, and S. S. D. Gill. 2021. DEEDSP: Deadline-aware and energy-efficient dynamic service placement in integrated internet of things and fog computing environments. *Transactions on Emerging Telecommunications Technologies* 32 (12). doi:10.1002/ett.4368.

Tan, T.-C. 2015. The transformation of china's national fitness policy: From a major sports country to a world sports power. *International Journal of the History of Sport* 32 (8):1–14.

Tomovic, M., D. Batinic, S. D. Saranovic, and M. Antic. 2016. P-91 anthropometric features of elite male basketball players regarding their playing position. can a high bmi be a health risk for this group of athletes? *British Journal of Sports Medicine* 50 (Suppl 1):A82.1–A82. doi:10.1136/bjsports-2016-097120.144.

Vaquero, L. M., and L. Rodero-Merino. 2014. Finding your way in the fog: Towards a comprehensive definition of fog computing. *Computer Communication Review* 44 (5):27–32. doi:10.1145/2677046.2677052.

Wu, J. 2019. The influence of internet + Sports on the development of national fitness in China. *Bulletin of Sport Science & Technology* 11:134–135.

Yanci, J., C. Granados, M. Otero, A. Badiola, J. Olasagasti, I. Bidaurrazaga-Letona, A. Iturricastillo, and S. Gil. 2015. Sprint, agility, strength and endurance capacity in wheelchair basketball players. *Biology of Sport* 32 (1):71–78. doi:10.5604/20831862.1127285.

Zhao, M., C. Chen, L. Liu, D. Lan, and S. Wan. 2022. Orbital collaborative learning in 6G space-air-ground integrated networks. *Neurocomputing* 497:94–109. doi:10.1016/j.neucom.2022.04.098.

Zhu, J., X. Huang, and X. Gao. 2021. Multi-interface channel allocation in fog computing systems using thompson sampling. *IEEE Internet of Things Journal* 99:13542–13554.

Zhu, R., S. Li, and P. Wang. 2021. Energy-efficient deep reinforced traffic grooming in elastic optical networks for cloud–fog computing. *IEEE Internet of Things Journal* 8 (15):12410–12421.