Hindawi
Scientific Programming
Volume 2022, Article ID 9147023, 8 pages
https://doi.org/10.1155/2022/9147023

Research Article

Analysis of Children's Sports Heuristic Teaching Based on Deep Learning

Xuesheng Wang,[1] **Xipeng Zhang**,[2] **and Feng Gao**[3]

[1]*Institute of Physical Education, University Huzhou, Zhejiang 313000, China*
[2]*Qingdao Huanghai University, Qingdao, Shandong 266000, China*
[3]*Jiaxing College Sports and Military Training Department, Jiaxing University, Jiaxing, Zhejiang 314000, China*

Correspondence should be addressed to Xuesheng Wang; 02088@zjhu.edu.cn

Received 28 April 2022; Revised 19 May 2022; Accepted 10 June 2022; Published 5 July 2022

Academic Editor: Lianhui Li

The "pursuit of deep learning" is mentioned among the recent trends driving the key trends driving educational technology in schools. "Deep learning" is widely used as a term, and classroom teaching has begun to focus more and more on deep learning. The heuristic teaching method is gradually accepted and used by educators all over the world with its scientific teaching mode and novel teaching methods. In today's children's physical education classroom, the heuristic teaching method has achieved certain results and effects, but in the process of trying, there is still room for development and improvement. Based on the deep learning model, this research will improve the existing heuristic teaching methods, through the experimental research on children's physical education classroom, observe the data results obtained by the deep learning-based children's physical education heuristic teaching, and analyze according to the results, so as to achieve the effect of heuristic teaching. A multilabel classification model ALSTM-LSTM is proposed according to the algorithm adaptation method in the multi-label learning method. The experimental results obtained an accuracy of 95.1%, which is higher than other deep learning models, and also reached the best in the evaluation indicators of precision, recall, and *F*1 score.

1. Introduction

With the continuous development of science and technology and the progress of society, the future society needs talents who can create high technology and new resources. Based on such a situation, it is urgent to deepen the reform of education. In the educational reform, heuristic teaching is a key point of the reform. Heuristic teaching emphasizes the combination of educators' follow-up guidance and students' thinking expansion, so that a class should not only learn the content of knowledge but also open up a new way of thinking for students, that is, independent inquiry learning. As the main body of education, students should actively participate in the curriculum and the process of knowledge exploration, so as to achieve the purpose of integrating knowledge. Educators should also respect students, fully mobilize students' interest in the inquiry process, care for students, not criticize students' wrong answers in class, give correct guidance, and encourage students to think. It can also improve students' self-confidence in mathematics learning. The multi-label analysis of posture in rope skipping refers to the use of the constructed deep learning model to judge which limb posture meets the standard and which limb posture needs to be corrected in the process of rope skipping. In artificial intelligence science, the multi-label limb posture analysis problem in children's physical education heuristic teaching can be transformed into multi-label learning problem. Based on the principle of deep learning, through the combination of multi-label limb posture analysis in children's sports heuristic teaching, this paper designs a heuristic teaching algorithm for children's sports, so as to solve the problems in the process of children's sports heuristic teaching [1–10].

2. Related Work

With the rapid development of Internet of Things technology, the combination of sports industry and emerging industries has become closer and closer. The first extension is based on reducing the subspace and swimming style information of possible posture configuration. The researchers have developed a class of label coding with spatial redundancy, which allows the network to learn the specific filter of swimming style. This principle is applicable to any form of activity information. The second extension focuses on the time of swimming video and proposes a two-step method, in which the initial pose estimation is refined in a fixed length sequence by an independent CNN module, and the experimental results show that the LSVM has reached the best first extension based on reduction possible. The second extension focuses on the time of swimming video, which proposes a two-step method in which the initial posture estimate is refined by a separate CNN module in a fixed length sequence. The experimental results show that the method has the ability to predict and improve the posture, which clearly improves the baseline CPM architecture, which provides help to attitude analysis during the player swimming. Extract human appearance characteristics and motion characteristics by using the OpenPose network model. Use supervisory machine learning to identify four activities categories, including sitting, standing, walking, and falling. The results show that the activity recognition method based on two-dimensional bone data can obtain better matching results as compared with the method based on three-dimensional bone data. Classification of KNN classifier is found by comparing the performance of K-nearest neighbor (KNN), support vector machine, Naive Bayes, linear discriminating formula (LDA), and feedforward reverse neural network (BPNN). The effect is best, and the overall accuracy is 98%. The robustness of the method also tests in two multi-camera view scenarios, and the results show that the CNN has better classification effect than other classifiers, and the classification results are 100%. From the current development of intelligent sports in the world, it has been gradually realized. This paper realizes the principle of intelligent sports in the heuristic teaching of children's sports, which involves many contents, mainly including the collection and processing of sports data and sports characteristics, the extraction of sports network model, the research on the development of the rope skipping action analysis system, etc., and the heuristic teaching experience research based on rope skipping in sports [11–15].

3. Related Theoretical Methods

3.1. Circulating Neural Network Model. The time series is a series of data accumulated in the time dimension, and many applications are analyzed in time series data. Assuming $1 = \{x, \ldots, x\}$, X_n is a time series of a length N, $X = \{X^1, \ldots, X^M\}$ consists of M different single-dimensional time series, and for each $1 \leq i \leq M$, the length of the time sequence is n. On the classification problem of the time series, the format of the data is usually as follows: dataset $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$ indicating the time series and corresponding label, y_i is achieved by one-hot coding, and the length k indicates that there is K category. From a whole, in a network model based on a time series, the input is the corresponding classification probability of the continuous learning of the neural network in the middle of the time series. Because time data are complex and unstable, the depth learning method is not assumed to assume the basic mode of the data, which is more robust to noise, so the depth learning model is the preferred method in time series data analysis. Circulating neural networks are complex depth learning networks that can be remembered, so they are widely used in the processing of sequence data. The RNN unit is the backbone of the circulation network, and there are two incoming connections and two outgoing connections in the RNN. LSTM can select an input sequence area that contributes to class tags in the context vector by attention. Note that mechanisms are often used in natural language processing. In the machine translation, a set of context vectors C is conditioned in the target sequence y, and the context vector Ci depends on the annotation sequence $(h_1, \ldots, h_{Tx})$ that maps the input sequence to the encoder. In each comment, H_i contains information about the entire input sequence, and the model will focus on the part around the i-th word of the input sequence where c_i is weighted and calculated by h_i [16]:

$$c_i = \sum_{j=1}^{T_X} a_{ij} h_j. \tag{1}$$

Each comment a_{ij}'s weight hj is calculated as follows:

$$a_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}, \tag{2}$$

where $e_{ij} = a(s_{i-1}, h_j)$ is the alignment model, which scores the matching degree of the input around the j position with the output at the i position. Bahdanau et al. parameterized the alignment model as a feedforward neural network that is co-trained with all other parts of the model, computing the soft alignment directly during the computation of the alignment model [17].

3.2. Heuristic Teaching Network Structure Based on OpenPose. In preschool physical education, OpenPose, an open source library for real-time multi-person pose estimation based on deep learning, is introduced. It can accurately estimate the pose of each person in the image in physical education teaching in real time, so as to realize the extraction of face, trunk, limbs, and hand bone points. It takes into account real-time performance and accuracy and has strong robustness. The core of this method is a bottom-up human pose estimation algorithm based on part affinity fields (PAFs), that is, to detect key points before acquiring the skeleton, which avoids the long calculation time in multi-person scenarios [18].

3.2.1. OpenPose Network Structure. Figure 1 shows the multi-level prediction network structure designed by

OpenPose. The framework is based on the VGG19 network model and converts the input image into image features F, $L(p)$, and $S(p)$ by stage prediction. $L(p)$ is the affinity vector field PAFs, and $S(p)$ represents the confidence of the key points in the skeleton. The structure divides the prediction into 6 stages, the first 4 stages predict the affinity vector field, and the last 2 stages predict the confidence. At each subsequent stage, the predictions from the previous stage are concatenated with the original image features as input to generate more refined predictions. After obtaining the confidence and affinity of the key points, the Hungarian algorithm is used to optimally match the adjacent key points to obtain the skeleton information of each person. OpenPose has good real-time performance and has designed a variety of model architectures to be compatible with different hardware configurations. It uses a monocular camera for reliable key point information without the need for a dedicated depth camera like Kinect. Parts that can be estimated are eyes, ears, nose, neck, shoulders, elbows, wrists, hips, knees, and ankles [19].

3.2.2. Confidence Map. In the human body pose estimation based on OpenPose, in order to obtain the coordinate information of the key points of the human body, the Gaussian modeling method is used to obtain the confidence map of the position of the key points, and the confidence map is used to represent the key points, wherein the value in the confidence map is expressed as a certain probability of key point locations. The confidence map of key point locations can be expressed as [20]

$$\begin{aligned} c_{j,k} &= \exp\left(-\frac{\left\|p - x_{j,k}\right\|_2^2}{\delta^2}\right), \\ c_j(p) &= \max S_k^{j,k}(P), \end{aligned} \tag{3}$$

where j represents the joint point of the human body, k represents the kth target person in the image.

4. Action Analysis Algorithm in Heuristic Teaching Sports Scenario

Computer vision-based motion analysis during exercise is a complex problem, especially when analyzing vigorous sports. In order to achieve a detailed description of the body movements during the movement process, this paper uses deep learning to build a model of the network.

4.1. Problem Definition. The content of this paper is an implementation method of intelligent sports in the rope skipping motion analysis system, which involves many fields, including data collection and processing, feature extraction, data transmission, network model design, system implementation, etc. According to the flowchart, it can be clearly seen that the analysis of the swaying and jumping action mainly includes two modules: one module is used to obtain the key point information of the human body, and the other module is used to mathematically model the obtained key point information and build a multi-label classification network model [21].

The problem can be defined as given m groups of rope skipping records, preprocess m groups of sequence data to obtain a data sequence $D = (r1,\ r2,\ldots,rm)$, where rj, $i = 1,\ldots,m$ represent m sequence data, where the label set $L = (l1,\ l2,\ldots,ln)$, lj, $j = 1,\ldots,n$ represent the limb labels during the rope skipping process, and each record in D is associated with multiple labels in L. Multi-label pose analysis can be represented by a tuple (r_i, Y_i), where Y_i is contained in L. Our goal is to design and implement a label classification model that judges the limb labels Y_i during rope skipping based on the new pose dataset ri' [22–24].

4.2. Network Framework Design

4.2.1. MobileNetV2 Framework. Convolutional neural networks have made breakthroughs one after another in the field of computer vision, but the application of deep learning models on the mobile terminal is not wide enough. At present, the recognition effect of the lightweight network on the ImageNet dataset is based on top-1, which is improved compared with ResNet-34 and VGG19, and its accuracy is slightly lower than that of ResNet-50, which is lightweight. The high-level network model has a certain balance in real-time performance and accuracy. In order to train and apply the model in an environment with few resources and low hardware support, a lightweight network model is more needed in real scenarios. When obtaining the human body pose, the OpenPose network model first sends the image frame to VGG19 to obtain the set of image feature maps $F = (F1, F2,\ldots,Fx)$, where x represents the number of feature maps. However, VGG19 consumes more computing resources and will generate a lot of parameters during the training process, which will take up more memory. In view of the high performance and efficiency of MobileNetV2, this paper modified the original OpenPose method when extracting image feature maps.

The MobileNetV2 network is an improved version based on the MobileNet network. Its innovation is that an inverted residual structure is added to MobileNetV2. The inverted residual structure is different from the original residual structure.

4.2.2. ALSTM-LSTM Network Framework. In this paper, the human posture analysis problem in rope skipping obtained in physical education teaching is transformed into a multi-label classification problem according to the time order relationship. Because LSTM can play a role in global processing and storage unit, it can maintain good performance in time series. Attention mechanism is a global approach to processing. Applying attention mechanism to LSTM can improve the performance of LSTM. Therefore, inspired by LSTM and attention mechanism, this paper creatively proposes a method of applying attention mechanism in LSTM and combining a single LSTM for multi-label

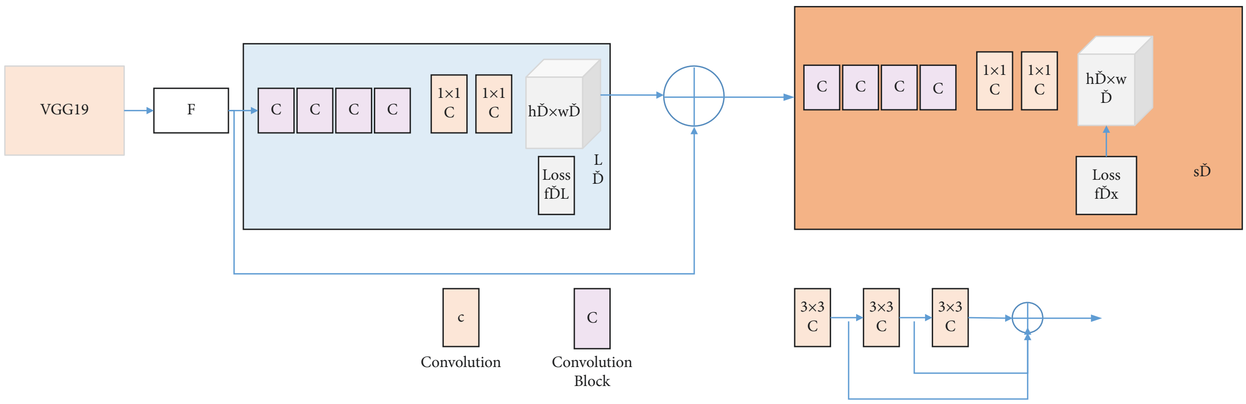

Figure 1: OpenPose network structure diagram.

classification. The network framework of ALSTM-LSTM is shown in Figure 2.

The most typical example in the breakthrough of the algorithm is the proposed batch normalization (BatchNorm) method. BatchNorm smoothes the solution space of related optimization problems, thereby ensuring more predictable gradients, which in turn allows the use of a wider range of learning rates for faster network convergence. This study demonstrates that adding a BatchNorm layer to a deep learning network model greatly improves the Lipschitzness of the loss function and gradient in the model. So, this article adds a BatchNormalization layer before using the LSTM and ALSTM layers. In addition, since this paper studies a multi-label classification problem, according to the multi-label algorithm transformation method, the activation function of the ALSTM-LSTM model in the last layer is set to the sigmoid activation function, and the loss function selects the binary cross-entropy loss function.

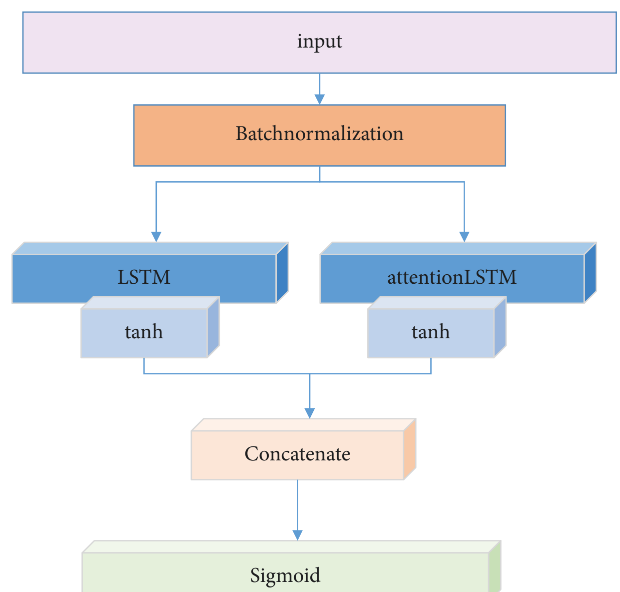

Figure 2: ALSTM-LSTM network framework.

4.3. Attitude Estimation Optimization Algorithm. In the two branches of OpenPose, one branch is used to predict the confidence map (S) of the key point, that is, the probability value of this key point, and the other branch is used to predict the affinity field PAFs between the two key points (L).

$$\begin{aligned} f_s^t &= \sum_{j=1}^{j} \sum_{p} w(p) . \left\| S_j^t(p) - S_j^*(p) \right\|_2^2, \\ f_L^t &= \sum_{j=1}^{C} \sum_{p} w(p) . \left\| L_j^t(p) - L_j^*(p) \right\|_2^2. \end{aligned} \tag{4}$$

The overall loss is the loss sum of each stage:

$$f = \sum_{t=1}^{T} \sum_{p} \left(f_s^t + f_L^t \right). \tag{5}$$

In order to further improve the generalization ability of the pose estimation algorithm and improve the accuracy of the algorithm, this paper introduces two weights and a penalty term into the total loss function:

$$f = \sum_{t=1}^{T} \left(\alpha f_s^t + \beta f_L^t + \theta \right). \tag{6}$$

By introducing weights, we analyze how much the losses in the two branches affect the results.

5. Design and Implementation of Heuristic Physical Education Teaching System

5.1. Overall Design of the System. The overall design of children's physical education teaching system determines which functions the system should realize according to the analysis of children's physical education teaching needs and generally explains how the system is realized. The overall design of children's physical education teaching is to introduce the functions of each module and the relationship between each other. The overall design of children's physical education teaching system includes the design of system function module and database table.

5.1.1. Functional Module Design. The function module design is to divide the smart rope skipping teaching system into several subsystems and then divide the subsystems into different modules according to their functions. The division of project modules can help developers simplify complex problems. The design of functional modules is a further refinement of the requirements. The appropriate division of functional modules can provide a detailed understanding of each function of the system, reduce the time for developers in the development process, and enhance the maintainability of the system. In this design, the Android-based smart rope skipping teaching system APP is implemented on the server side using the SSM framework and MySQL database. The SSM framework is a combination of three frameworks, namely, Spring Framework, SpringMVC, and MyBatis. At present, the SSM framework has been widely used in the development of websites and has become more and more popular in the development of commercial software. The APP client of this system adopts the basic mode of the current popular MVP (model view presenter), which is mainly composed of three major components: view, model, and presenter. The view is responsible for displaying the page, the model is responsible for providing data support for business processing, and the presenter is responsible for processing business logic. The entire system architecture is shown in Figure 3. The user transmits data through the mobile phone camera, the MySql database is responsible for storing the data, and the server accepts the user's data request, processes, and feeds the result back to the user.

5.1.2. Database Table Design. The design of infant physical education teaching database table further describes the infant physical education teaching data by relying on the conceptual structure design of infant physical education teaching database. The early childhood physical education teaching system includes four basic tables: personnel basic information table person, video information table video, information message table news, and rope skipping analysis results. The database table is established according to the relational schema as follows:

(1) User table: the user table is used to store the basic information of the user, including the user's id, user name, user's password, and user's authority. According to the user's authority, users can be divided into administrators and ordinary users. The structure of the user table is shown in Table 1.

(2) User video table: the user video table is used to store the id of the video uploaded by the user and the storage path of the video. The structure of the user video table is shown in Table 2.

(3) Message table: the message table is used to store the information and consultation related to the rope skipping test issued by the administrator, as well as some rope skipping skills. The message table contains the id of the message, the title of the message, and the content of the message. The structure of the message table is shown in Table 3.

(4) Analysis result table: analysis result table mainly stores the contents of the results of the analysis and analysis results. The analysis result surface structure is shown in Table 4.

5.2. Detailed Design and Implementation of the System

5.2.1. Environment Introduction. The development of the APP is carried out on the Android Studio platform. It is an Android integrated development environment that only supports Android development. It is a plug-in focused on Android development that Google excludes other functions from the IntelliJ IDEA Community Edition. It is equivalent to a weakened version of the IntelliJ IDEA which is different however. Before using Android Studio, you need to download Java JDK first. During use, Android Studio's prompt tool supports ProGuard and application signature. Android Studio's powerful layout editor can directly drag UI controls and preview the effect. There is also an Android emulator on Android Studio, which makes it easy to debug during the development of the APP. During the development of the software, the Android emulator was used and several models of mobile phones were used in the testing phase. On the server side, we use HUAWEI CLOUD server as data storage and model invocation and build the deep learning model on HUAWEI CLOUD server. The training process of deep learning is implemented through Python language, and SpringMVC is used to realize the controller layer of the server side. At the same time, it also realizes the communication interface between the server and the APP. Table 5 describes the environment used for the development of this system.

5.2.2. System Function Test. The goal of functional testing is to test each functional module of the system, determine whether each functional module is optimal, and make subsequent improvements based on the test results. According to demand analysis, the system is mainly divided into seven modules: system login registration module, model upload module, user management module, message release module, data upload module, and analysis report viewing module. According to the test, you can check whether each function can be carried out smoothly and optimize the interface according to the user experience. Test for each functional module is shown in Table 6. The purpose of the system registration login module test is to detect whether the user can jump normally when logging in, and whether the registered information is encrypted in the database.

The purpose of the model upload function test is to check whether the administrator can upload the newly trained model to the location specified by the server and ensure that the model can be called correctly, as shown in Table 7.

The purpose of the analysis report viewing function module test is to detect whether the server can return the results normally after the user uploads the one-minute rope skipping dataset to the server and correctly display it on the mobile phone page, as shown in Table 8.

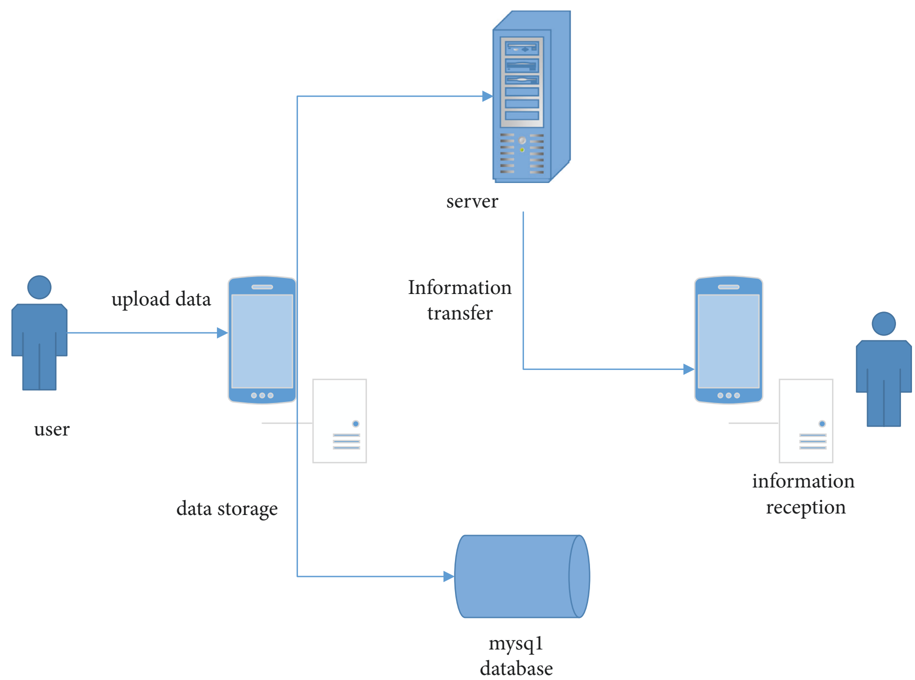

Figure 3: System architecture diagram.

Table 1: User information table.

Field name	Field type	Width	Primary key	Description
Person_id	Int	25	Yes	User unique ID, primary key
Person_name	Varchar	16		Username
Person_password	Varchar	16		User password
Person_power	Int	2		User rights

Table 2: User video table.

Field name	Field type	Width	Primary key	Description
Video_id	Int	25	Yes	Video unique identifier, primary key
Video_address	Varchar	100		Video address

Table 3: Message table.

Field name	Field type	Width	Primary key	Description
News_id	Int	25	Yes	Message unique identifier, primary key
News_title	Varchar	50		Message name
News_content	Varchar	500		Message content

Table 4: Result analysis table.

Field name	Field type	Width	Primary key	Description
Results_id	Int	25	Yes	Analysis result unique identification, primary key
Results_content	Varchar	500		The content of the analysis results

Table 5: System environment introduction.

Client	Android
Service terminal	Java
Deep learning model	Python 3.5
Database	MySql

Table 6: System registration and login function test case table.

Test module name	System registration login		
Condition	The user registers and logs in after the registration is successful. The password and account must meet the requirements.		
Serial number	Results required for needs analysis	Actual effect	Whether it is expected
1	RegisterLoginJump	Able to realize the jump of registration and login	Yes
2	The registration password needs to be encrypted	The registration password is encrypted in the database	Yes

Table 7: Model upload function test case table.

Test module name	Model upload		
Condition	Upload and train the new network model		
Serial number	Results required for needs analysis	Actual effect	Does it meet expectations
1	Upload the locally trained model to the server	Ability to upload and apply models	Yes

Table 8: Analysis report view functional test case table.

Test module name	Analysis report view		
Condition	The user uploads the rope skipping video to view the rope skipping analysis results		
Serial number	Results required for needs analysis	Actual effect	Does it meet expectations
1	User clicks the query report button query report	Correctly return query results and generate reports	Yes

Table 9: System performance test cases.

Serial number	Test performance name	Start event	End event	Time consumption (s)
1	Model upload	Click the model upload button	Model uploaded successfully	20.23
2	Analysis report query	Video upload	Analysis report query	75.23

5.2.3. System Performance Test. The performance of the system can directly affect the user's experience. In order to upload the model, the system performance is tested during the analysis report generation process. Its test is shown in Table 9.

6. Conclusion

Traditional teaching methods can play a certain role and effect in imparting knowledge and skills. It has the advantage of being able to popularize educational knowledge quickly, imparting knowledge to students under the circumstance of limited teaching environment, single teaching method, and tight teaching time. Combined with the literature, we can see that traditional teaching is derived from class-based teaching under specific social conditions. However, in the classroom of traditional teaching method, the shortcomings of this teaching method can be clearly found, including the lack of subjective initiative of students in learning, low learning interest, less interaction between teachers and students, and depressed classroom atmosphere. With the development of the times, predecessors have conducted more research on heuristic teaching, which has laid a solid foundation for the popularization of heuristic teaching in primary and secondary schools. Teaching research is rarely involved, and a set of elementary school basketball heuristic teaching experimental program has not been formed. Therefore, heuristic teaching is a new type of teaching method at present, which can be improved according to the inner development and actual needs of young children and is in line with the development needs of the current new era. In view of the current research hotspots for human behavior detection and recognition, this paper seldom studies the recognition of continuous actions in actual scenes, focusing on the improvement of the recognition rate and accuracy of motion actions, and is committed to solving traditional sports training equipment to realize the scientific, standardized, and unified management of children's sports training.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This paper is the research result of the scientific research project "Experimental research on the impact of skill sports on children's attention level (no. kx25064)" of Huzhou Normal University.

References

[1] B. L. M. Hernandez, D. Gober, D. Boatwright, and G. Strickland, "Jump rope skills for fun and fitness in grades K-12," *Journal of Physical Education, Recreation and Dance*, vol. 80, no. 7, pp. 15–41, 2009.

[2] Y. Wang, Yi Wang, and Z. Zhang, "Multi-label classification method of human behavior in rope skipping scene based on complexity graph," *Security and Communication Networks*, vol. 2022, Article ID 8202383, 7 pages, 2022.

[3] A. S. Ha, C. Lonsdale, J. Y. Y. Ng, and D. R. Lubans, "A school-based rope skipping program for adolescents: results of a randomized trial," *Preventive Medicine*, vol. 101, pp. 188–194, 2017.

[4] A. Subasi, D. H. Dammas, R. D. Alghamdi et al., "Sensor based human activity recognition using adaboost ensemble classifier," *Procedia Computer Science*, vol. 140, pp. 104–111, 2018.

[5] M. M. Hassan, M. Z. Uddin, A. Mohamed, and A. Almogren, "A robust human activity recognition system using smartphone sensors and deep learning," *Future Generation Computer Systems*, vol. 81, pp. 307–313, 2018.

[6] T. Li, D. Liu, and Y. Yang, "Phylogenetic supertree reveals detailed evolution of sars-cov-2," *Scientific reports*, vol. 10, no. 1, pp. 1–9, 2020.

[7] M. Kimura and T. Ohta, "On the stochastic model for estimation of mutational distance between homologous proteins," *Journal of Molecular Evolution*, vol. 2, no. 1, pp. 87–90, 1972.

[8] L. R. Foulds and R. L. Graham, "The steiner problem in phylogeny is NP-complete," *Advances in Applied Mathematics*, vol. 3, no. 1, pp. 43–49, 1982.

[9] L. L. Cavalli-Sforza and A. W. Edwards, "Phylogenetic analysis. Models and estimation procedures," *The American Journal of Human Genetics*, vol. 19, no. 3, pp. 233–257, 1967.

[10] R. Desper and O. Gascuel, "The minimum evolution distance-based approach of phylogenetic inference," *Mathematics of Evolution and Phylogeny*, Oxford University Press, Oxford, UK, 2007.

[11] N. Saitou and M. Nei, "The neighbor-joining method: a new method for reconstructing phylogenetic trees," *Molecular Biology and Evolution*, vol. 4, no. 4, pp. 406–425, 1987.

[12] P. H. Sneath and R. R. Sokal, "Unweighted Pair Group Method with Arithmetic mean," *Nu-merical Taxonomy*, vol. 1, pp. 230–234, 1973.

[13] M. N. Price, P. S. Dehal, and A. P. Arkin, "FastTree 2 - approximately maximum-likelihood trees for large alignments," *PLoS One*, vol. 5, no. 3, Article ID e9490, 2010.

[14] S. Guindon and O. Gascuel, "A simple, fast, and accurate algorithm to estimate large phylogenies by maximum likelihood," *Systematic Biology*, vol. 52, no. 5, pp. 696–704, 2003.

[15] A. Stamatakis, "RAxML version 8: a tool for phylogenetic analysis and post-analysis of large phylogenies," *Bioinformatics*, vol. 30, no. 9, pp. 1312-1313, 2014.

[16] R. Bouckaert, J. Heled, D. Kühnert et al., "Beast 2: a software platform for bayesian evolutionary analysis," *PLoS Computational Biology*, vol. 10, no. 4, Article ID e1003537, 2014.

[17] F. Ronquist, M. Teslenko, P. Van Der Mark et al., "MrBayes 3.2: efficient bayesian phylogenetic inference and model choice across a large model space," *Systematic Biology*, vol. 61, no. 3, pp. 539–542, 2012.

[18] J. Felsenstein, "Evolutionary trees from DNA sequences: a maximum likelihood approach," *Journal of Molecular Evolution*, vol. 17, no. 6, pp. 368–376, 1981.

[19] J. Felsenstein and J. Felenstein, *Inferring phylogenies*, Vol. 2, Sinauer associates Sunderland, MA, USA, 2004.

[20] Z. Yang, *Molecular Evolution: A Statistical approach*, Oxford University Press, Oxford, UK, 2014.

[21] B. Rannala and Z. Yang, "Probability distribution of molecular evolutionary trees: a new method of phylogenetic inference," *Journal of Molecular Evolution*, vol. 43, no. 3, pp. 304–311, 1996.

[22] B. Larget and D. L. Simon, "Markov chasin Monte Carlo algorithms for the bayesian analysis of phylogenetic trees," *Molecular Biology and Evolution*, vol. 16, no. 6, pp. 750–759, 1999.

[23] K. K. Kidd and L. A. Sgaramella-Zonta, "Phylogenetic analysis: concepts and methods," *The American Journal of Human Genetics*, vol. 23, no. 3, pp. 235–252, 1971.

[24] Y. Wang, Y. Zhang, L. J. Shen, and S. M. Wang, "Analysis and research on human movement in sports scene," *Hindawi Computational Intelligence and Neuroscience*, vol. 2021, Article ID 2376601, 12 pages.