Analysis and System Construction of ALSTM-LSTM Model-based Sports Jumping Rope Movement

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***Abstract*—Computer technology's maturity has enabled intelligent and interactive sports training. Jumping rope test in secondary school faces difficulties due to bulky testing equipment and inefficient data measurement. An ALSTM-LSTM model based on visual human posture estimation is proposed for motion system analysis. Joint pose features are fused through LSTM, and the attention mechanism assigns weights to feature sequences to achieve motion recognition, considering the data's multidimensional and hierarchical nature. The model's precision value is 95.83. Its average accuracy is much higher than LSTM, ML-KNN, and RSN models. Additionally, the model has 95.2% accuracy in localizing jump rope stance movements with low data consumption. The model can improve the accuracy of the analysis of the jump rope sport's posture based on the characteristics of human movement, and inspire new technical tools for teaching instruction.**

***Keywords*—ALSTM-LSTM model; jumping rope exercise; Sports; human posture estimation algorithm; attention mechanisms**

I. Introduction

The development and maturity of computer vision and intelligent technology has provided new research tools and ideas for human motion analysis. They are also applied in pattern recognition, image processing, and interaction between real and imaginary scenes. In addition, the application of computer vision and intelligence technology to sports training makes the analysis of movement types and posture recognition possible. The estimation of human posture is achieved by using algorithms to identify and locate the position of the body's joints [1-2]. With the development of national fitness activities, strengthening the integration of artificial intelligence and the sports industry is an important direction for development. As a sport with regularity and requiring coordination and cooperation, jumping rope is crucial for the enhancement of individual fitness and the development of children's intellectual ability [3]. The bulky nature of traditional sports jumping rope monitoring equipment and the high cost of manual measurement make it difficult to train effectively and to provide normative guidance on student performance [4]. Existing human motion recognition algorithms suffer from poor accuracy due to overburdening and have less application in posture assessment [5]. Common jumping rope detection is often calculated using instruments or manual calculations, which lack stability in algorithm accuracy and effectiveness. There are few common applications for posture assessment in jumping rope, and the dynamic nature of its jumping behavior greatly reduces the accuracy of traditional posture estimation. In order to better adapt to the action analysis of students in the jumping rope scene, the research first introduced short-term memory network for in-depth learning based on the mobile visual characteristics of the action, and fused multi-level features to improve the target detection performance. The proposed algorithm is to give full play to the complementary feature of information detection in different dimensions and levels, so as to ensure that the classification data can recognize the information in dynamic and static scenes. According to the differences in the role and speed of different limb movements in jumping rope, image distortion is inevitable. Therefore, the study introduced the concept of learning weight into the network structure for different feature extraction. The study starts with the analysis and characteristics of the movements of the research object (jumping rope), and proposes continuous improvement and optimization of network structure features to achieve accuracy in motion capture and analysis. The study aims to effectively detect jumping rope movements, and construct corresponding systems to provide reference and guidance for improving the quality of physical education teaching.

II. Related Works

The progressive development of society and the increase in economic have led to a greater focus on physical exercise, while the maturation of the theory of intelligent technology has provided new tools and instruments for the analysis of sports. The mathematical model based on the acceleration sensor was developed by Xu to better analyse the experimental data of the rope and hand during jumping rope. A control group and an experimental group were set up, and volunteers were selected to carry out experimental observations of exercise energy consumption. It was proved that the sensor can construct and generate a model of the multidimensional data of the subjects, and can effectively analyse the energy consumption of the experimental group. The results of this experiment can effectively provide new ideas for improving the teaching of jumping rope sports [6]. In order to ensure the fitness of jumping rope while enhancing its safety, Wang and other scholars applied the inverse mechanics model to the analysis of jumping rope movement and combined big data to analyse the changes of each joint position during the movement. The results showed that the validity of the motion analysis of fancy jump rope was better and the introduction of fancy jump rope in university physical education had high significance and value [7]. Nie proposed a hierarchical contextual refinement network for the estimation of human posture in order to reduce the problem of poor joint localization performance, i.e., to achieve the transfer detection of diffuse joints. The method effectively achieved the detection of joint points in the hierarchical state and is less affected by interference factors [8]. Cao and other scholars proposed a motion detection system based on deep learning guidance for better analysis of motion data. It was proved that it is more than 95% accurate in the evaluation of jumping rope data and its recall values were high. The wearable device under this monitoring system can effectively analyse the sports data [9]. Yu innovated the application of EMG signal acquisition to sports. Based on the actual needs of athletes, the individual differences and wavelet principal component model for sports recognition was proposed. The wavelet-based model had high accuracy and detail observation of motion recognition, and also has high theoretical value [10]. For the detection and recognition of specific motion, Cust and others used the help of inertial measurement units and computer vision for in-depth analysis. Database search results show that support vector machines and convolutional neural networks as well as long and short-term memory architectures are mostly used for data processing and target motion feature recognition [11]. Ramirez Campillo R scholars used a meta-analysis system to analyze the jumping rope training for effectively improving the physical fitness of athletes. The analysis including resting heart rate, body mass index, fat mass, cardiopulmonary endurance, and so on [12]. They analyzed the impact mechanism between enhanced jumping training (PJT) and athlete's repetitive sprint ability (RSA) [13]. Layne T scholars believed that using sports technology feedback education for jumping performance testing can effectively stimulate the potential of athletes [14].

Deep learning algorithms have good data processing and information extraction capabilities. It can provide new tools for the recognition of sports analysis and can effectively reduce the influence of objective factors and individual differences in performance on the results [15-16]. The team of Rana found that the emergence of wearable inertial sensors provided a convenient tool to carry out sports analysis, and the device could effectively provide solutions based on the characteristics of different athletes compared to the original manual analysis of athletes' data metrics [17]. The edge box method was used to refine the scale of the tracker, while a convolutional network was used under the recursive concept to implement frame video image recognition. The results show that the improved method is highly effective and efficient for the analysis of sports videos [18]. To address the difficulty of quantifying feature extraction, Mathis and Mamidanna proposed a bit-pose estimation method with deep neural networks and migrated the method to markerless applications to avoid the impact of intrusive markers on motion control. Experimental results demonstrated the high accuracy as well as versatility of the framework approach and the accuracy of its data tests was comparable to the real values [19]. Kong scholars proposed to accelerate the analysis and prediction of trajectory data under localization technology based on real-time location and long time access are the more common services. The study proposed spatio-temporal long- and short-term memory for data analysis, and the results showed that the method can link and predict historical visit information backwards and forwards, with a high fit between the real values [20]. Nadeem scholar team identified human behaviors with the help of entropy Markov model, and added contour detection and multidimensional cues to the original automatic human posture estimation method. They implemented action recognition through image preprocessing and image noise removal as part model construction. The method can detect limb movements with high recognition accuracy, and its interactive advantage has good applicability in other fields [21]. He introduced three-dimensional space technology in image processing and established a sports tracking system with the help of particle filtering to improve its accuracy. A similarity estimation method was proposed according to the characteristics of volleyball. The method has good tracking performance and its success rate exceeds 80% [22]. Jalal introduced a pseudo-2D model to the original human pose estimation method to achieve the extraction of contour features and pose point features He introduced a K-ary tree hashing algorithm to optimize the data set. The results proved that the method has an accuracy of more than 80% in key point detection in motion datasets, which is a good application in sports [23].

The aforementioned studies suggest that enhancing feature recognition in sport is a key focus for improving video data analysis and the quality of sports. Some scholars have proposed sensor design, short and long term memory networks, convolutional neural networks and entropic Markov models to achieve information recognition and data analysis. Therefore, this study will improve on the long-short memory network and apply it to the analysis of sports jumping rope to improve its posture recognition accuracy, and provide a new tool for the improvement of physical education.

III. Analysis of Sport Jumping Rope Movement and System Construction Based on ALSTM-LSTM Model

A. ALSTM-LSTM Model based on Human Posture Recognition

Human pose recognition is a key problem in human behaviour analysis and is currently a hot topic of research. It is widely used in robot training, motion tracking, film production and sports analysis. The OpenPose pose estimation open source library extracts information from the human bone nodes with good real-time performance and accuracy [24-25]. The architecture is shown in Fig. 1.

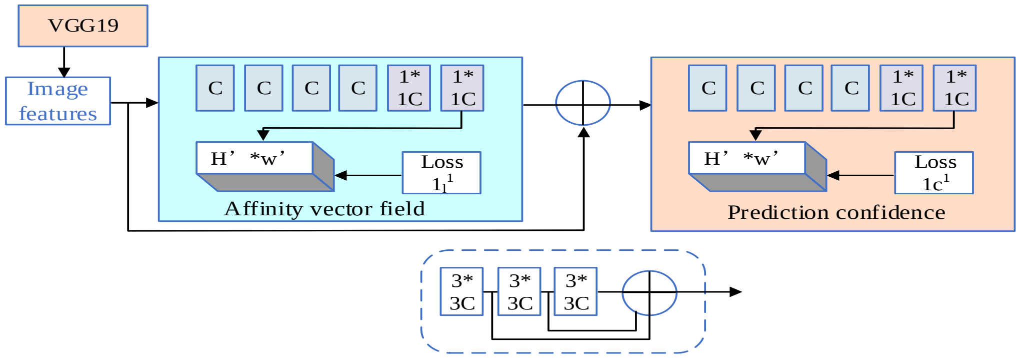


Fig. 1. OpenPose network structure diagram.

The confidence map expression formula for the location of key points in motion recognition is equation (1).

$$\begin{cases} C_{j,k} = \exp\left(\frac{\left\| p - X_{j,k} \right\|_2^2}{\delta^2}\right) \\ C_j(p) = \max_k S_{j,k}(p) \end{cases} \tag{1}$$

In equation (1), j denotes the joint point of the human body, k is the target person in the image, p is the predicted coordinates of the person, $X_{j,k}$ is the specific coordinate position, and δ denotes the minimal value. The length of the limb between two joint points can be expressed as $l_{c,k} = \left\| X_{j2,k} - X_{j1,k} \right\|_2$. The study introduces weight values and penalty terms in the loss function of the model to reduce the impact of branching losses on the accuracy results, and the mathematical expression is shown in equation (2).

$$f = \sum_l^T (\alpha f_S^l + \beta f_L^l + \theta) \tag{2}$$

In equation (2), $f = \sum_l^T (\alpha f_S^l + \beta f_L^l + \theta)$ denotes the confidence and affinity domain of the predicted key points, $f = \sum_l^T (\alpha f_S^l + \beta f_L^l + \theta)$ is the corresponding weight value and $f = \sum_l^T (\alpha f_S^l + \beta f_L^l + \theta)$ denotes the penalty term. In the jumping rope movement analysis, the movement involves the head, shoulders, wrist tin cream, ankles and other limbs of the human posture parts. This real-time movement and limb movement quality assessment can be affected by a variety of factors, so the research is based on the characteristics of mobile vision for movement analysis, and introduces the Long Short-Term Memory (LSTM) models. The LSTM network algorithm can effectively process long time sequences of data and information, and selectively forget new information and accumulated information by introducing a gating mechanism. By using memory units to transfer information cyclically, the model can effectively avoid the problem of gradient disappearance during the training process. Fig. 2 shows the structure of the recurrent unit of the LSTM network.

Based on the LSTM input human action data, the formulae for input gate i_t, forgetting gate f_t and output gate o_t at moment t are shown in equation (3).

$$\begin{cases} f_t = \sigma(M_f \cdot [h_{t-1}, x_t] + b_f \\ i_t = \sigma(M_i \cdot [h_{t-1}, x_t] + b_i \\ o_t = \sigma(M_o \cdot [h_{t-1}, x_t] + b_o \end{cases} \tag{3}$$

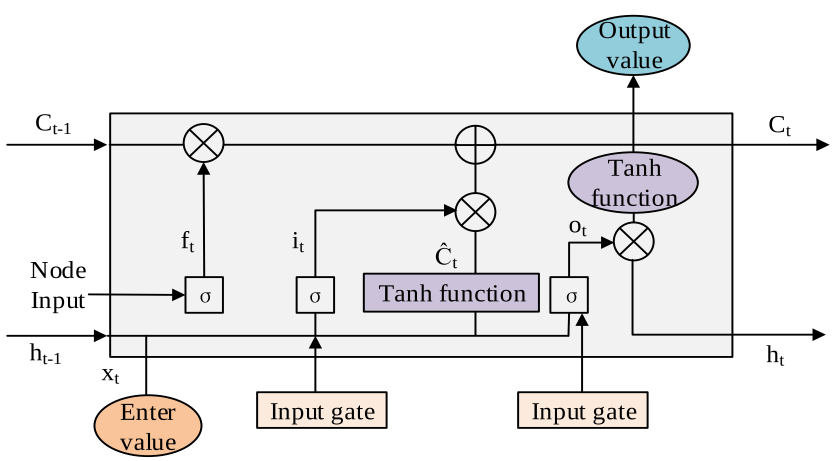


Fig. 2. Schematic diagram of network cycle unit structure.

In equation (3), h_{t-1} is the output of the previous layer and the information of the structure, h_t is the output, σ is the gate activation function, x_t is the input value and M, b denote the weight matrix and the deviation value. The long-term memory state at moment t can be expressed as equation (4).

$$c_t = f_t \circ c_{t-1} + i_t \tanh(W_c * [h_{t-1}, x_t] + b_c) \tag{4}$$

In equation (4), W_c, b_c denote the weight value and bias of the input gate, and $\circ$ denotes multiplication by element. The LSTM network fuses static and dynamic features when classifying action recognition. Changes in different nodes can have an impact on action pose recognition, and degree discrimination of node importance can effectively highlight the information data of valid actions, so the study introduces an attention mechanism for weighting [26-28]. The attention mechanism assigns different weight values to different input feature sequences to show the difference in their attention, which can effectively improve the LSTM network to treat different feature states the same, ignoring the multi-dimensionality and hierarchy of features. The study represents the degree of correlation between information features and output values with the help of a one-layer perceptron, the mathematical expression of which is shown in equation (5).

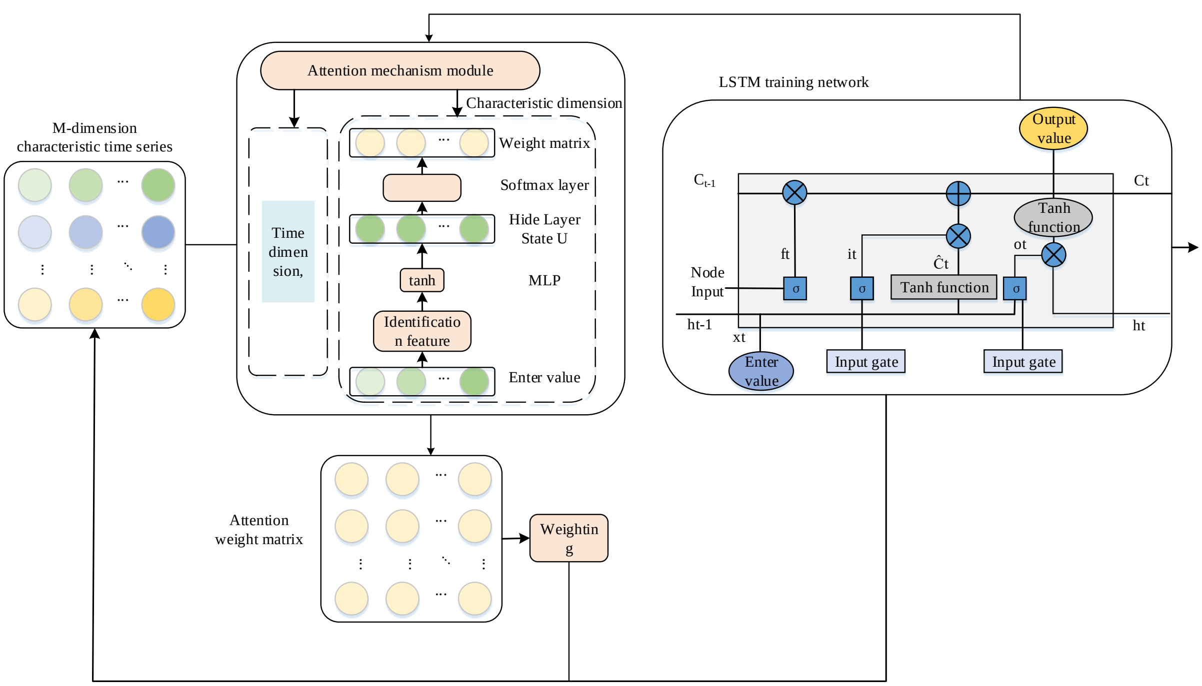
$$s_i = MLP(h_i^{'}, \tilde{y}) = v^T \tanh(W_1 h_i + W_2 \tilde{y}) \tag{5}$$

In equation (5), $h_i^{'}$ is the intermediate layer state after LSTM recognition, $\tilde{y}$ is the target intent and v, W_1, W_2 are the learning parameters. The normalisation is performed to obtain the attention weights of the features, see equation (6).

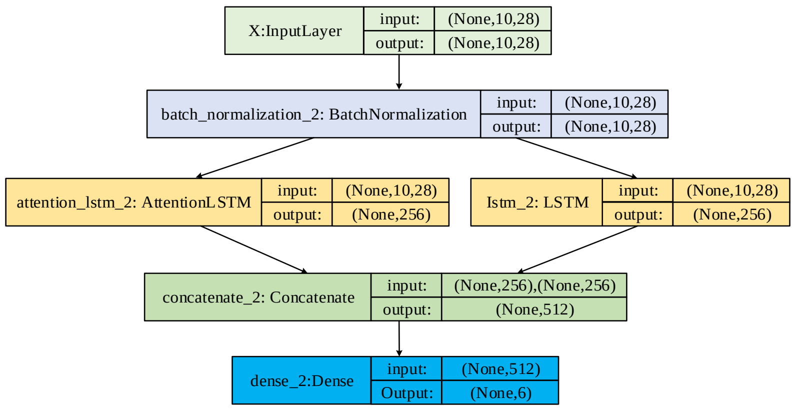
$$Att_i = soft\max(s_i) = \frac{\exp(s_i)}{\sum_{j=1}^{m} \exp(s_j)} \tag{6}$$

In equation (6), s_i is the learning degree of the feature and m denotes the number of features. Fig. 3 shows the network architecture of the introduced attention mechanism.

The analysis of human posture during jumping rope can be regarded as a label classification problem with temporal and sequential characteristics, and the body movements involved in it can also have an impact on the continuity and integrity of jumping rope when deviations and movements occur. The study incorporates an attention mechanism into the LSTM model, as shown in Fig. 3(b). The ALSTM-LSTM model consists of five aspects: the input layer, the batch normalisation layer, the ALSTM-LSTM layer, the connection layer and the sigmoid layer. The data is normalized by BatchNorm to ensure predictability of the data gradient and to reduce the data fluctuation problem of the problem solution, allowing the algorithm performance to achieve high convergence within the learning rate range. Traditional jump rope physical education is taught through demonstration by the physical education teacher as well as explanation of the movements, followed by the students exercising on their own [29-30]. Since there is a large variability among individual students, their mastery of the ability varies. Therefore, the study introduced an attention mechanism into the LSTM model to make the extraction of effective movement information more effective. Fig. 4 is the schematic diagram of the analysis model for jumping rope movements.



(a) LSTM network architecture based on attention mechanism



(b) Model diagram of ALSTM-LSTM

Fig. 3. Network architecture of introducing attention mechanism.

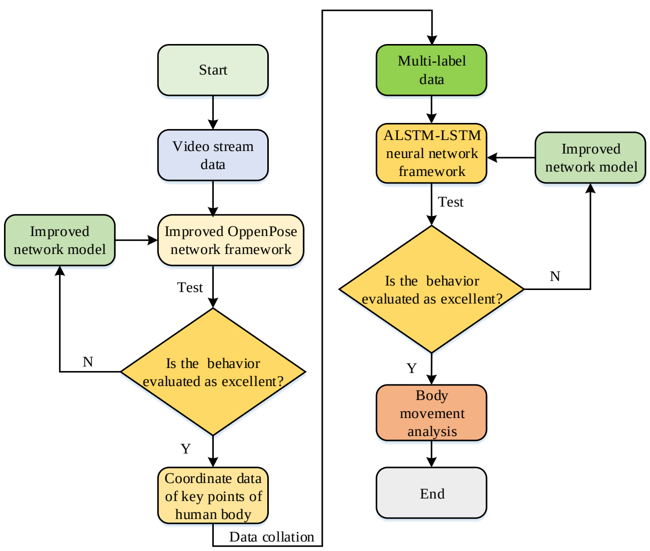


Fig. 4. Schematic diagram of analysis model flow of rope skipping.

The ALSTM-LSTM model can effectively transform the posture of the athlete during the jumping rope movement into a classification problem, and carry out a before-and-after correlation analysis. It makes a comprehensive judgment on the key points of the limbs in the posture analysis to achieve an effective analysis of the jumping rope movement.

B. Analysis of Physical Education Campaigns to Improve the CDA Module

Human motion detection is highly difficult in the computer recognition process due to the complexity of the movement of the human target and the interference of the external environment. Enhancing the relevance and accuracy of motion target detection and human motion recognition is the focus of current research. Most current human motion detection algorithms include both centroid-based and high-resolution feature-based examinations. Among them, anchor frame definition network features are more prone to target detection bias as well as sample imbalance problems, and they require higher accuracy in target detection for the interaction ratio between the labeled and real frames [31-32]. There are differences in limb node movements driven by jumping rope behaviour, and the task of detecting targets at different locations increases the difficulty of information processing and hyperparameter overload. Therefore, the study uses multi-level features for fusion to improve the target detection performance and give full play to the complementary feature of different dimensional levels of information detection. Content Descriptive Attention (CDA) module is introduced to achieve multi-scale feature extraction and adaptivity of fused information. Fig. 5 shows a schematic diagram of adaptive feature fusion.

Consistency in image size maintenance as well as non-linear characteristics is important to ensure that features are extracted by the CDA module. This means that the input image is sampled for matching, the convolution of the sampled image, the acquisition of features that feel different scales and the selection of features. It fuses several aspects to achieve the output of the processed image [33]. The global average pooling of the feature data gives the channel information, as equation (7).

$$Z_c = \frac{\sum_{i=1}^{H}\sum_{j=1}^{W} u_c(i,j)}{H*W} \tag{7}$$

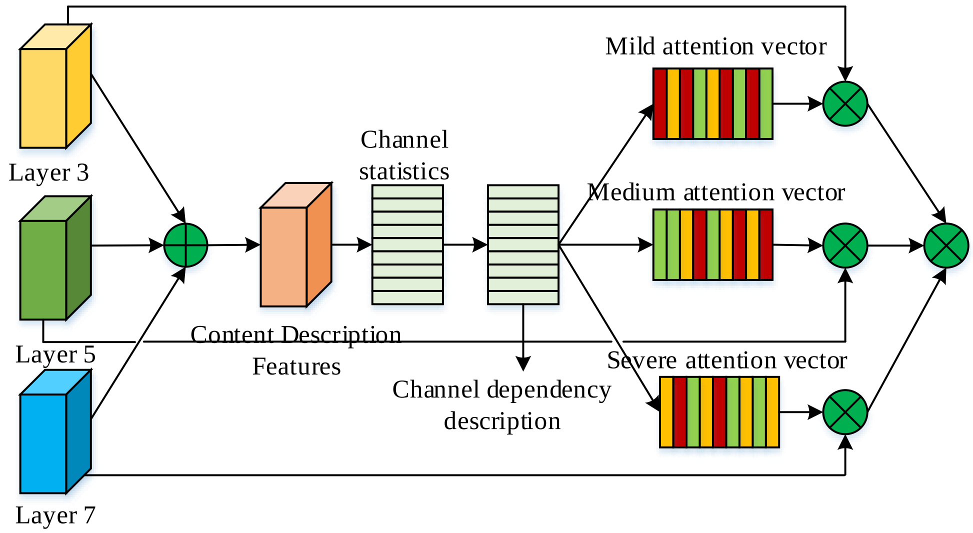


Fig. 5. Schematic diagram of adaptive feature fusion process.

In equation (7), Z, u_c represents the channel information and descriptive features, H, W are the two aspects of the spatial dimension and i, j are the number of elements in the channel information. The channel dependencies are described with the help of the fully connected layer (FC), for which the extracted mathematical expressions are given in equation (8).

$$s = \delta(W_0 z) \tag{8}$$

In equation (8), δ, W_0 denote the activation function and the weight of the first connected layer, respectively. The output value of the features under feature fusion is the product of the feature representation of each component and its corresponding attention vector. The output value of the CAD module can be a representation of the semantic features extracted from the network, and the mathematical expression is shown in equation (9).

$$U_{in} = U_{out} \odot U_{att} + U_{out} \tag{9}$$

In equation (9), U_{in}, U_{out} represent the inputs and outputs of the network, U_{att} is the attention map in the module and $\odot$ is the Hadamard product. Fig. 6 shows a schematic diagram of the application of the CAD module in target detection.

The High Resolution Network (HRNet), which is often applied to feature fusion, only adjusts and directly fuses features of different resolutions, without taking into account the differences in the representation of different resolution feature images and feature information data [34]. To reduce the distortion of image accuracy with direct fusion manipulation, a WFHRNet network that adds learning weights to the input features is proposed for feature extraction to distinguish the importance of different features in the overall network. The mathematical expression is shown in equation (10).

$$O_k = \sum_{i=1}^{x} \sigma(w_i) \cdot f(I_i, k) \tag{10}$$

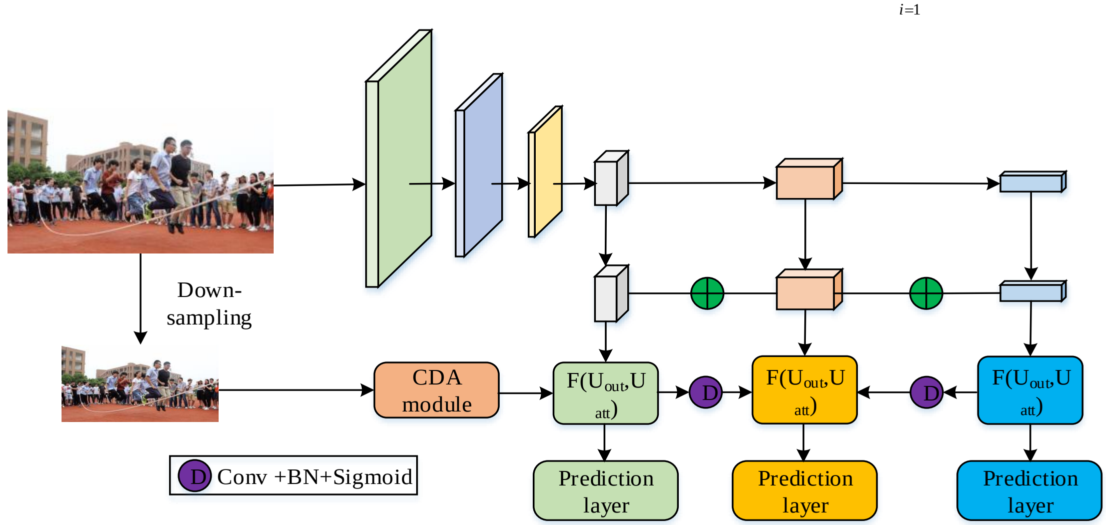


Fig. 6. Application diagram of CAD module in target detection.

In equation (10), σ denotes the Sigmoid function, w_i is the learning scalar, and $f(I_i,k)$ denotes the input resolution I_i adjusted to the k resolution via the sampling step. The size of the distance between prediction frames in different images can have an impact on information recognition. Non Maximum Suppression (NMS) processing is mostly used to remove redundant frames, but this method uses the intersection ratio metric to assess the difference of the assessed frame and the real frame. When the intersection ratio of the two targets is high, the correctly predicted prediction frames will be removed due to non-maximum suppression, resulting in the algorithm missing detection,. The overlap of the redundant prediction frames and the equiposition relationship between different prediction frames will make the algorithm accuracy impaired. Therefore, the research proposes to improve the NMS with Manhattan Distance based Non Maxi-mum Suppression (MD-NMS), which can represent the sum of the distances of the prediction frames in the vertical and horizontal directions. Its mathematical expression is given in Equation (11).

$$MD(B_1,B_2)=MD(m,n)+MD(n,v)+MD(c_{B1},c_{B2}) \tag{11}$$

In equation (11), $(m,n),(n,v)$ denote the point in the vertical direction of the upper left and lower right corners of the two prediction frames B_1,B_2, and c_{B1},c_{B2} is the centroid of B_1,B_2. There is an inverse relationship between the value of Manhattan distance and image similarity. The mathematical expression of MD-NMS is shown in equation (12).

$$S_i=\begin{cases} S_i, & loU(M,b_i)-nom(MD(M,b_i))<N_i \\ 0\ , & loU(M,b_i)-nom(MD(M,b_i))\geq N_i \end{cases} \tag{12}$$

In equation (12), loU denotes the intersection ratio, S_i, is the threshold, b_i is the confidence score of the prediction frame, and M denotes the prediction frame at the highest confidence level.

IV. Analysis of Experimental Results for the Analysis of Physical Education and Sports Teaching

The participants' body movements during jumping rope were analyzed and identified, and the network was constructed after identifying the key points through the human body. The MPII motion data set and the jumping rope data set were used for this experimental dataset. The jumping rope data set was obtained from an experimental secondary school. In the process of data acquisition, the height and width of the video frames of different sizes were set uniformly in order to detect the node position of the research subject in the jumping rope movement. During the analysis of the posture estimation jumping rope movements, the data analysis and visualization effects were displayed with the help of the JupyterNotebook interactive application. The hardware environment was set as: CPU: Intel Core i7-8700K, 3.70GHz; memory: 32G; GPU: GTX 1080Ti. Performance evaluation of the ALSTM-LSTM model proposed in the study was carried out, and the results are shown in Fig. 7.

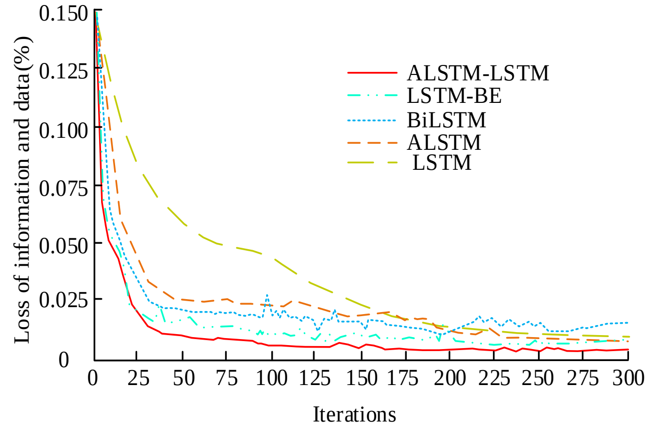


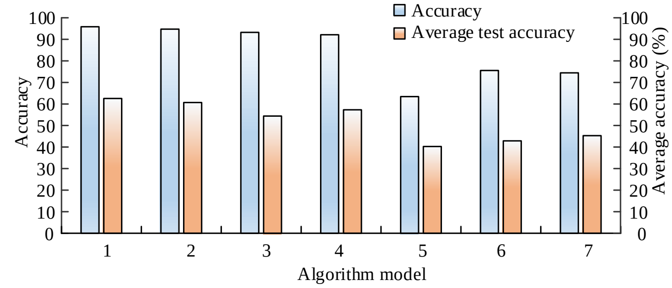
Fig. 7. Error comparison results of different algorithm functions for moving image analysis.

What can be seen from Fig. 7 is that there are large differences in the error results of different algorithmic models under different numbers of iterations. Specifically, when it is less than 25, the data loss curves of the five algorithm models are slanted larger, and the error values between different models do not exceed 0.2%. When the number of iterations increases, the increase of data information will cause different degrees of redundancy to the algorithm performance. The average error in information for the LSTM model is 4.23% between 25 and 200 iterations, and only gradually plateaus when the number of iterations exceeds 200, with the value remaining at 1.37%. Meanwhile, the maximum error in information extraction between the LSTM model and the proposed ALSTM-LSTM model reached 26.35% at more than 25 iterations. The LSTM model with the addition of a residual network (ResNet), the LSTM model with a bi-directional mechanism (Bi-directional) and the LSTM model with a unidirectional attention mechanism all showed varying degrees of improvement in algorithmic loss compared to the single LSTM model. The loss curves also leveled off in the later stages of the algorithm, with the average errors of 15.24%, 10.28% and 9.36%, respectively, but the fluctuations of the nodes were more obvious. The above results indicate that the proposed model can enhance the information extraction accuracy capability. Subsequently, the model performance was further explored, and for the convenience of data statistics, the study referred to the five algorithmic models as Models 1-5, where the model proposed in the study was Model 1. Two other models are added, namely the Multi-label k-Nearest Neighbor algorithm (Model 6) and the Channel-Split Human Pose Estimation algorithm (Channel-SplitResidual StepsNetwork (Channel-SplitRSN) (Model 7). The result is Fig. 8.

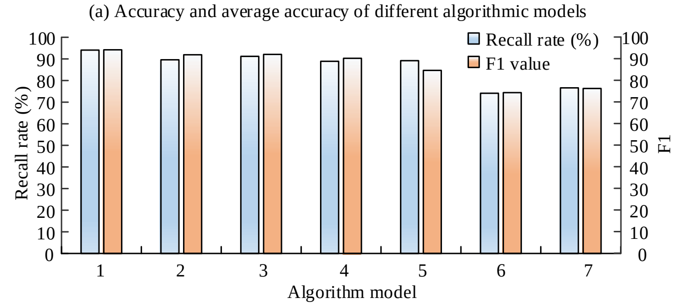
What can be seen in Fig. 8 is that the performance expressed by the different algorithmic models varies considerably. In terms of accuracy values, the models with values above 90 are models 1-4, while models 5-7 have accuracy values in the range 60-75. The average accuracy of models 1-7 is 95.83, 94.73, 93.23, 92.13, 63.43, 75.53 and 74.43 respectively, which reflects the stable performance of the algorithm in information extraction. The average accuracy of several models improved compared with LSTM in the figure is basically above 40%, among which the average accuracy of the model proposed in the study reaches 62.57%, and its accuracy error is 22.3% higher than the traditional LSTM model, and 19.32% and 17.31% higher than the ML-KNN model and RSN model. The results in Fig. 8(b) show that the models performing in order from best to worst in terms of recall metrics are ALSTM-LSTM model > LSTM-BN model > ALSTM-BN model > LSTM model > BiLSTM model > RSN model > ML-KNN model. The recall rate of the proposed model was 94.21%, corresponding to an F1 value of 94.1, and the maximum difference between this model and the other models in terms of recall index was 17.9. The above results show that the ALSTM-LSTM model can better take into account the correlation between sequence information, achieve the extraction of feature information data, and effectively avoid the problem of missing and omitted data. To further evaluate the performance of the ALSTM-LSTM model, the study was designed to compare it with the LSTM model at different values, the results of which are shown in Fig. 9.

In Fig. 9, the two models exhibit different ROC curve characteristics under different target fetch values. In Fig. 9(a), the single LSTM model is more influenced by the fetching values and the AUC areas under each label are 0.781, 0.829, 0.891, 0.765, 0.831 and 0.944 respectively. In Fig. 9(b), the improved LSTM model has a higher accuracy rate in image information prediction selection and is less disturbed by the fetching values, and its average accuracy reached 86.37%. The above data tells that the model created in the study has good application performance. The results of limb movement localization in jumping rope movements were then analyzed and the results are shown in Table I.

The results in Table I show that the ALSTM-LSTM model has a high localization accuracy for feature extraction of different limb parts with a maximum value of 95.2 and it performs best in the comparison results with other models with a high improvement in the loss of data. The maximum localization accuracy values of the other six models were 90.4, 78.3, 78.9, 81.8, 76.1 and 71.7 respectively, all of which were smaller than the proposed mode in the study. It was then analyzed and the results are shown in Fig. 10.

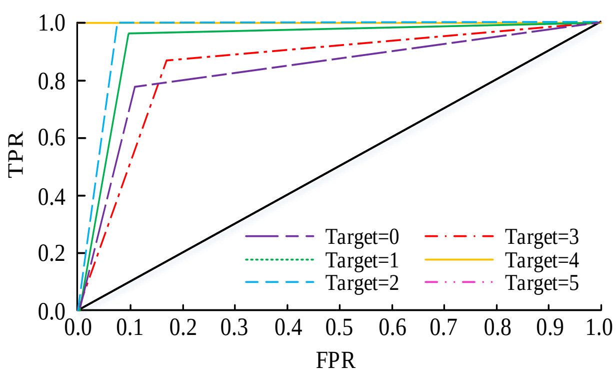


(a) Accuracy and average accuracy of different algorithmic models

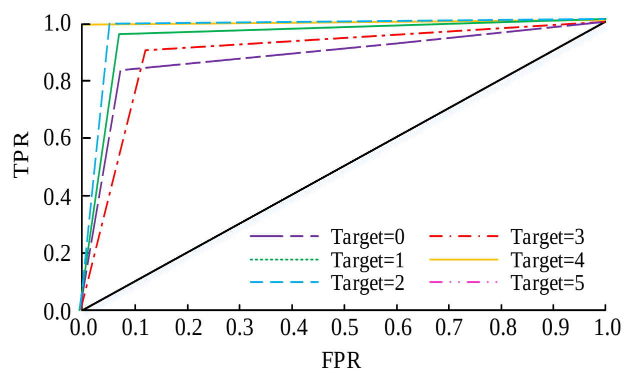


(b) Recall and F1 values for different algorithmic models

Fig. 8. Performance comparison of different algorithm models.



(a) Curves for single-layer LSTM models



(b) Curves of the ALSTM-LSTM model

Fig. 9. ROC and AUC curves of LSTM model and ALSTM-LSTM model.

TABLE I. LIMB POSITIONING RESULTS OF ROPE SKIPPING UNDER DIFFERENT ALGORITHM MODELS

Model	Head	Shoulder	Elbow	Wrist	Hip	Knee	Ankle
ALSTM-LSTM	95.2	87.3	75.8	72.5	78.6	70.1	64.8
ALSTM-BE	90.4	82.5	71	67.7	73.8	65.3	60.4
LSTM-BE	78.3	70.4	58.9	55.6	61.7	53.2	47.9
BiLSTM	78.9	71.0	59.5	56.2	62.3	53.8	48.5
LSTM	81.8	73.9	62.4	59.1	65.2	56.7	51.4
ML-KNN	76.1	68.2	56.7	53.4	59.5	51.2	45.7
RSN	71.7	63.8	52.3	49	55.1	46.6	41.3

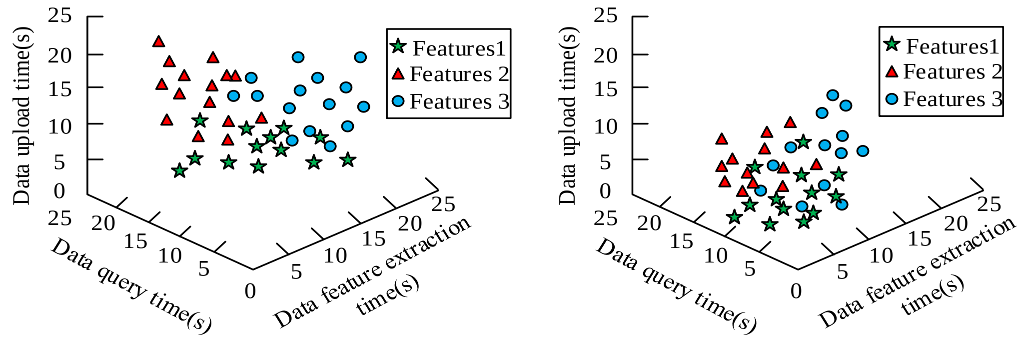


Fig. 10. System test results of two models.

In Fig. 10, the system processing performance of the LSTM model for all three pose features is poor, with the average time consumed for data upload, data query and feature extraction all greater than 15s. The system processing performance of the ALSTM-LSTM model proposed in the study is better and more balanced, with an average time consumption of 11.23s. The human posture recognition algorithm is applied to the classroom evaluation of a certain jumping rope teaching, and it evaluates students' physical performance in the final stage. Firstly, perform a result analysis on its matching accuracy, as shown in Fig. 11.

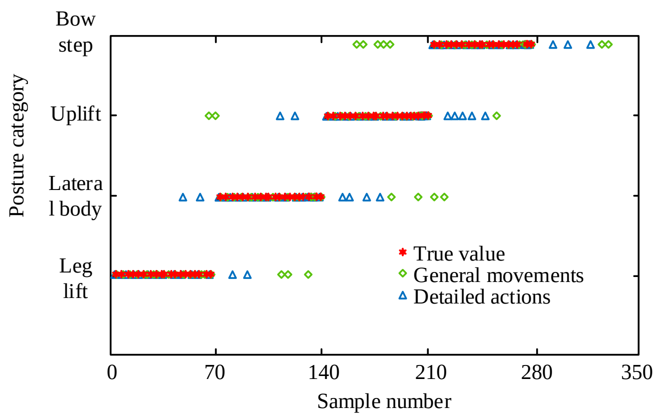


Fig. 11. Evaluation accuracy of human pose recognition algorithm.

The results in Fig. 11 indicate that the pose recognition model proposed in the study achieved motion recognition accuracy of 94.7% and 93.5% for the general and detailed movements of jumping rope on two types of data, respectively. Among them, the matching accuracy of the lunge movement was the highest (98.77%), and its posture matching error situation was effectively improved. The results indicate that the recognition algorithm has good application effect in physical education teaching evaluation. The satisfaction of students is collected during the evaluation process, and the results are shown in Fig. 12.

In Fig. 12, the satisfaction score obtained by the action recognition algorithm used in the study in student sports evaluation reached over 90 points. Compared to other algorithms, students are more satisfied with the proposed one. The results indicate that the recognition algorithm can effectively assist in the jumping rope sport teaching and help students improve their academic performance. In future sports teaching, teachers can use this motion analysis system to help students master the standard movements of jumping rope. Appropriate teaching strategy adjustments can be made based on the feedback from students, in order to continuously improve teaching effectiveness and quality.

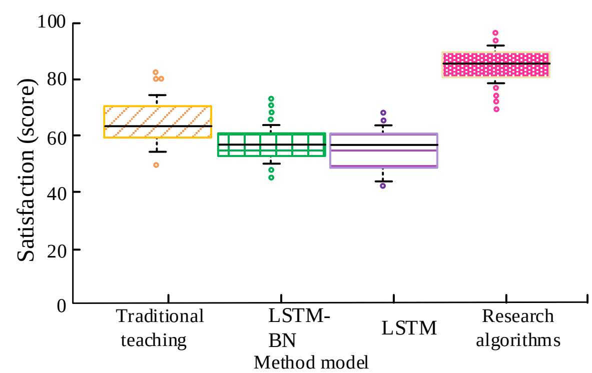


Fig. 12. Student satisfaction in the evaluation process of physical education teaching.

V. Conclusion

The study analyses the pose in jumping rope movement scenarios and introduces an attention mechanism to improve the neural network, converting the video analysis problem into a limb key point coordinate analysis problem. The results of the proposed model system were analyzed and it was found that the average error of the LSTM model information extraction between 25 and 200 iterations was 4.23%, which gradually leveled off at more than 200 iterations and remained at 1.37%. It was much larger than the maximum error of information extraction of the proposed ALSTM-LSTM model at more than 25 iterations, which was 26.35%. The maximum error in information extraction with the proposed ALSTM-LSTM model at more than 25 iterations was 26.35%, larger than that of the LSTM-RE, BiLSTM and ALSTM models at 15.24%, 10.28% and 9.36%. For information extraction accuracy, the accuracy value of the ALSTM-LSTM proposed in the study reached 95.83, and its average accuracy was 62.57%, which was 22.3%, 19.32% and 17.31% higher compared with the LSTM model, ML-KNN model and RSN model. The ALSTM-LSTM model also has a larger AUC area than the single LSTM model, with a maximum value of 95.2 for the localization of the subdivision of the jumping rope pose movements. The jumping rope motion system constructed with the ALSTM-LSTM model shows better performance. Further research is needed to enhance the motion scene analysis ability and to widen the dimension of pose estimation.

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