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# Research on intelligent evaluation system of postpartum rehabilitation training based on action recognition

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**SUMMARY:** *Action recognition and quality assessment of postpartum rehabilitation training are of great significance to improve the efficiency of rehabilitation guidance and reduce the risk of wrong training. The traditional postpartum rehabilitation evaluation mainly relies on the observation of therapists and the subjective feedback of puerpera, which is susceptible to differences in experience, training environment and feedback delay. To solve this problem, this paper proposes an intelligent evaluation system for postpartum rehabilitation training based on action recognition. Based on posture estimation, the system extracts key points such as shoulder, hip, knee, ankle and other bones, constructs joint Angle, pelvic stability, action amplitude and left-right symmetry features, and completes the recognition and quality score of bridge training, pelvic forward and backward tilt, lateral lying opening and closing, kneeling leg raising and supine leg raising through the time sequence action recognition model. At the same time, a lightweight action recognition network is constructed to support real-time feedback from the end side. Experimental results show that the average action recognition accuracy of the system is 93.3%, the quality assessment accuracy is 91.0%, and the real-time frame rate of the INT8 quantization model reaches 30.7 frame·s$^{-1}$, which verifies the effectiveness and application feasibility of the system in the intelligent evaluation of postpartum rehabilitation training.*

***KEYWORDS:*** *action recognition; Postpartum rehabilitation training; Pose estimation; Intelligent evaluation system*

# 1 Introduction

Postpartum rehabilitation training is an important part of maternal physical function recovery, which is related to pelvic floor muscle strength, core stability ability, pelvic control level and the quality of daily activities. With the development of mobile terminals, computer vision and intelligent health management technology, rehabilitation training evaluation based on action recognition has gradually become an important direction in the cross research of sports medicine and intelligent nursing. This kind of method can collect human posture data in the training process through cameras or mobile devices, and use posture estimation, skeleton key point analysis and timing action modeling technology to automatically judge the completion, stability and standardization of postpartum rehabilitation actions, thus providing data support for home rehabilitation and remote guidance.

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Traditional postpartum rehabilitation training evaluation mainly relies on on-site observation, manual records and maternal self-feedback. Although such methods have a certain clinical experience basis, it is difficult to ensure continuous supervision in home training scenarios, and they are also susceptible to differences in observation Angle, assessment experience and individual expression. Postpartum women have great differences in rectus abdominis separation, pelvic floor muscle relaxation, low back pain and lack of body control. Training movements often have the characteristics of small amplitude, slow rhythm and high stability requirements. Without fine-grained action recognition and quality assessment, the compensatory action, support instability and force deviation in the training process are not easy to be found in time, and the rehabilitation effect is difficult to form a quantifiable basis.

Action recognition technology provides a new realization path for postpartum rehabilitation training evaluation. The coordinates of key points such as shoulder, hip, knee and ankle are extracted by the video pose estimation model, and the features such as joint Angle, torso tilt, motion amplitude, motion rhythm and left-right symmetry can be further constructed. Combined with sequential neural network or lightweight graph structure model, the system can recognize typical rehabilitation actions such as bridge training, pelvic forward and backward tilt, lateral lying opening and closing, kneeling leg raising and supine leg raising, and output the training quality level. Compared with general motion recognition, postpartum rehabilitation scenarios put forward higher requirements for action safety, real-time feedback and device deployability. The algorithm not only needs to maintain recognition accuracy, but also should take into account low delay, low computational complexity and mobile terminal operation stability.

Based on this, this paper focuses on the intelligent evaluation needs of postpartum rehabilitation training, and constructs an intelligent evaluation system for postpartum rehabilitation training based on action recognition. Based on pose estimation, a rehabilitation motion feature extraction model was established. The skeleton key points were used to construct the action recognition and training quality evaluation module. Furthermore, a lightweight action recognition network for real-time evaluation is designed, and the effectiveness of the system in action classification, quality scoring and real-time output is verified by experiments. The research content of this paper is composed of six parts: the introduction explains the research background and significance; The related research part reviews the research progress of action recognition, rehabilitation evaluation and postpartum training digital. The system construction part introduces the action feature extraction, quality evaluation and lightweight network design. The experimental part tests the model recognition effect and real-time performance. The application value and improvement direction of the system are discussed. The conclusion section summarizes the research results.

# 2 Related Research

Intelligent evaluation of postpartum rehabilitation training involves multiple research directions such as human action recognition, rehabilitation action quality scoring, pose estimation, lightweight model deployment and digital health intervention. With the development of computer vision and mobile perception devices, motion assessment methods based on video, depth sensors and wearable devices are gradually applied to rehabilitation training scenarios. Sideridou et al. used mobile terminals to collect exercise process data and constructed a personal exercise assessment and guidance method, indicating that low-cost devices can support daily training feedback [1]. Esmaeeli et al. extracted skeleton nodes by Kinect sensor, and used timing and relative relationship analysis to complete motion recognition and scoring, proving that skeleton key points can not only describe action categories, but also reflect the quality of action completion [2]. Maskeliūnas et al. designed a human posture analysis system based on virtual reality and depth sensors, which enables rehabilitation training to obtain posture correction information in an immersive environment [3]. Aguilar-Ortega et al. constructed a physical rehabilitation training dataset and compared the performance of human pose estimation methods in rehabilitation actions, which provided a data basis for action recognition in rehabilitation scenarios [4].

In the evaluation of rehabilitation training, visual feedback and machine learning models are widely used to judge movement norms. Barzegar Khanghah et al. designed a motion biofeedback system based on vision, which enabled remote rehabilitation training to obtain more intuitive action prompts [5]. Khanghah et al. further applied machine learning algorithm to remote rehabilitation feedback to improve the system's ability to identify training action deviation [6]. Mottaghi et al. proposed an automatic evaluation method for exercise rehabilitation based on deep hybrid density neural network, which can deal with continuous changes in action execution [7]. Sardari et al. conducted a systematic review on skeletal data-driven rehabilitation motion evaluation, and pointed out that skeletal sequence, joint Angle and spatio-temporal graph structure are important feature sources for quality analysis of current rehabilitation motion [8]. Mourchid and Slama constructed a rehabilitation evaluation network combining spatio-temporal graph convolution, GRU and Transformer, which showed strong feature expression ability in patient action sequence modeling [9].

The performance improvement of action recognition model also provides technical support for the intelligent evaluation of postpartum rehabilitation training. Kanade et al. used an attention-guided deep learning framework for motion quality assessment, emphasizing that the model needs to extract local information related to action quality from key body parts [10]. Abedi et al. conducted a study on the segmentation and counting of repetition times of rehabilitation training, indicating that skeletal joint sequences can be used to identify training cycles and action completion times [11]. Hussain et al., Mekruksavanich et al., and Nouriani et al., respectively verified the feasibility of human activity recognition in motion monitoring from the perspectives of sensor collection, RNN deep learning and wearable device activity recognition [12-15]. Tharatipyakul et al. summarized the application of human pose estimation in motion feedback and believed that a complete chain should be formed between keypoint detection, action segmentation and feedback generation [16]. Cormier et al. proposed a skeletal action recognition enhancement method for real scenes, and showed that occlusion, viewpoint change and individual differences would significantly affect the generalization ability of the model [17]. Kaseris et al. and Shaikh et al. reviewed the research on deep learning and multimodal action recognition, and pointed out that CNN, RNN, graph convolution and Transformer have become important directions of action recognition models [18, 19].

Postpartum rehabilitation research emphasizes more on movement safety, differences in recovery stages, and individual training needs. Elliott-Sale et al. designed an intervention research program for postpartum physical function recovery, focusing on postpartum musculoskeletal health and occupational physical performance [20]. Selman et al. proposed a rehabilitation timeline from pregnancy to postpartum exercise recovery, emphasizing that postpartum training should be arranged gradually in combination with recovery stages [21]. Evenson et al. reviewed public health guidelines on postpartum physical activity and sedentary behavior in different countries, indicating that postpartum exercise needs to balance physical recovery, activity intensity and safety boundaries [22]. Deering et al. formed a consensus on training programs for postpartum return to running through an international

Delphi study, indicating that postpartum training evaluation should not only judge whether the movement is completed, but also pay attention to core control, pelvic stability and exercise load adaptability [23]. Hanach et al., starting from the demand of digital resources for postpartum women, pointed out that digital rehabilitation tools need to have the characteristics of understandability, accessibility and feedback [24]. ROSHkO et al. studied the influence of physical activity on postural stability of pregnant women, which provided a reference for balance control and stability indicators in postpartum movement evaluation [25]. In order to further sort out the supporting effect of existing research on the system design of this paper, this paper summarizes the related research directions, representative results and their enlightenment to the system construction, as shown in Table 1.

*Table 1: Implications of related studies for the construction of the proposed system*

| Research Direction | Representative Studies | Main Content | Implications for This Study |
|---|---|---|---|
| Mobile motion assessment | Sideridou et al. [1] | Used low-cost mobile technologies for personal motion assessment and guidance | The system should support home-based training and mobile feedback |
| Skeleton-joint action scoring | Esmaeeli et al. [2]; Sardari et al. [8] | Analyzed action categories and movement quality through skeleton-joint relationships | Keypoints, joint angles, and temporal changes can serve as core features |
| Visual rehabilitation feedback | Khanghah et al. [5–6] | Realized remote rehabilitation action feedback based on vision and machine learning | Postpartum training requires real-time correction and movement deviation prompts |
| Spatiotemporal sequence modeling | Mourchid et al. [9]; Kanade et al. [10] | Used graph convolution, GRU, Transformer, or attention mechanisms to analyze movement quality | The model should represent both spatial posture and temporal continuity |
| Postpartum exercise rehabilitation | Selman et al. [21]; Deering et al. [23] | Focused on postpartum recovery stages, core stability, and safe return to exercise | Evaluation indicators should emphasize pelvic control, core stability, and movement safety |

In summary, the existing research has formed a good technical foundation in rehabilitation action recognition, movement quality scoring and postpartum exercise guidance, but there are still three deficiencies. First, most action recognition models are oriented to general fitness or general rehabilitation actions, and are not suitable for low-amplitude, slow-paced and core control actions in postpartum rehabilitation. Second, the existing rehabilitation evaluation methods pay more attention to the recognition of action categories, and the joint evaluation of pelvic stability, trunk compensation, left-right symmetry and training completion quality is still insufficient. Third, although complex deep networks have strong recognition ability, they are easily limited by device computing power, real-time feedback and privacy protection requirements in home postpartum rehabilitation scenarios. Therefore, aiming at the characteristics of postpartum rehabilitation training, this paper constructs an action feature extraction model based on pose estimation, a training quality evaluation module driven by skeletal key points, and a lightweight action recognition network to improve the recognition accuracy, evaluation interpretability, and real-time deployment ability of the system in the home rehabilitation environment.

# 3 Construction of postpartum rehabilitation training intelligent evaluation system based on action recognition

The existing evaluation of postpartum rehabilitation training mostly regards the training results as the problem of whether the action is completed, but the core of postpartum rehabilitation action is not to simply identify the action category, but to judge whether the action process is safe, stable and in line with the requirements of the rehabilitation stage. The range of movements such as bridge training, pelvic forward and backward leaning, lateral lying opening and closing, kneeling leg raising and supine leg raising are relatively limited, and some key changes focus on hip, waist and abdomen and lower limb support relationships. If only image classification methods are used to discriminate single frame posture, it is easy to ignore the action start and end interval, pelvic control, trunk compensation, and left-right symmetry changes. To solve this problem, this paper constructs an intelligent evaluation system for postpartum rehabilitation training based on action recognition, which combines video pose estimation, skeletal key point modeling, sequential action recognition and training quality scoring to realize the automatic recognition and quality evaluation of postpartum rehabilitation training actions.

In this paper, the system takes the postpartum rehabilitation training video as the input object, and forms a complete intelligent evaluation process through video preprocessing, human body region positioning, skeleton key point extraction, action feature calculation, training action recognition and quality score output. The system does not directly use the original image as the evaluation basis, but converts the human pose into computable bone structure parameters. This processing method can reduce the influence of background environment, clothing color and shooting equipment differences on recognition results, and enhance the adaptability of the model to home rehabilitation scenes. The overall system structure is shown in Figure 1.

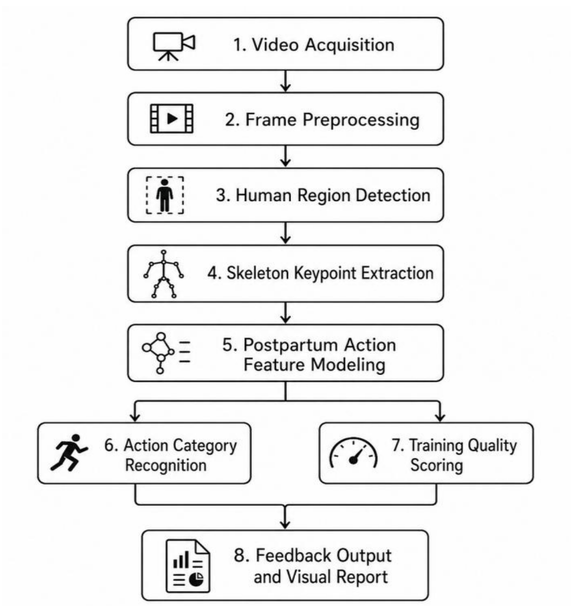


*Figure 1: Overall process of intelligent evaluation system for postpartum rehabilitation training based on action recognition*

Figure 1 shows that the core task of the system consists of two aspects: one is to identify the types of postnatal rehabilitation training actions from continuous video frames, and the other is to give training quality evaluation according to the execution process of actions. Compared with common fitness exercises, postpartum rehabilitation exercises emphasize more on control and safety. The system needs to pay attention to waist and abdomen stability, hip and knee coordination, pelvic offset and movement rhythm when recognizing movements such as bridge training, pelvic forward and backward leaning, lateral lying opening and closing, and leg raising in kneeling posture. Therefore, in this paper, the action recognition results and the quality score results are jointly used as the system output, so that the evaluation results can serve for subsequent rehabilitation guidance.

## 3.1 Construction of motion feature extraction model for postpartum rehabilitation training based on pose estimation

Motion feature extraction of postpartum rehabilitation training is the basic link of system construction. Postpartum rehabilitation actions usually have the characteristics of slow movement speed, small body displacement, and concentrated changes in key parts. If only the human body frame or the overall image texture is extracted, it is difficult to accurately express the subtle differences in the action process. Pose estimation technology can extract key points of human bones from video frames and transform the spatial positions of shoulder, hip, knee, ankle and other parts into structured data, which is suitable for action analysis of postpartum rehabilitation training [1-4]. Based on the pose estimation model, this paper constructs the action feature extraction process of postpartum rehabilitation training, focusing on extracting the features of joint Angle, body axis, motion amplitude, action stability and timing change. The postpartum rehabilitation training video is set as follows.

$$V=\{I_1,I_2,\cdots,I_T\} \tag{1}$$

where, V represents the input training video, $I_t$ represents the t-th frame image, and t represents the total number of video frames. After human pose estimation for each frame image, a set of key points of human skeleton can be obtained as follows.

$$P_t=\{p_t^1,p_t^2,\cdots,p_t^K\},\quad p_t^k=(x_t^k,y_t^k,c_t^k) \tag{2}$$

where, $P_t$ represents the set of keypoints in frame t, K represents the number of keypoints, $x_t^k$ and $y_t^k$ represent the horizontal and vertical coordinates of the KTH keypoint, respectively, and $c_t^k$ represents the keypoint confidence. Since postpartum rehabilitation training mostly takes place in the home environment, shooting distance, lighting conditions and body occlusion will affect the stability of key point detection. In order to reduce the interference of key points with low confidence on subsequent evaluation, this paper sets up key point filtering rules:

$$\hat{p}_t^k=\begin{cases} p_t^k, c_t^k\geq\tau \\ \dfrac{p_{t-1}^k+p_{t+1}^k}{2}, c_t^k<\tau \end{cases} \tag{3}$$

where, $\hat{p}_t^k$ represents the corrected keypoint and τ represents the confidence threshold. When the confidence of a keypoint is lower than the threshold, the system uses the adjacent frame position to smooth compensation to ensure the continuity of the action sequence. This processing is suitable for short-term occlusion or unstable local recognition in post-partum rehabilitation actions.

After the keypoint extraction is completed, the system further constructs the action structure features. For bridge training, the range of hip lift, the Angle of the line between shoulder, hip and knee and the horizontal displacement of pelvis are important criteria for evaluating the quality of movement. For the pelvis forward and backward, the change of the axis between the hip and the trunk can reflect the motion control ability. For kneeling leg lifts, hip-knee-ankle relative position and trunk stability can reflect the existence of compensation. In this paper, three-point joint angles are used to describe local body structural changes. Let the joint center point be b and the adjacent two points be a and c, then the joint Angle is calculated as follows.

$$\theta_t(a,b,c)=\arccos\frac{(p_t^a-p_t^b)\cdot(p_t^c-p_t^b)}{\|p_t^a-p_t^b\|\|p_t^c-p_t^b\|} \tag{4}$$

where, $\theta_t(a,b,c)$ represents the joint Angle formed by three key points in frame t. Parameters such as hip Angle, knee Angle, torso tilt Angle and shoulder-hip connection Angle can be calculated through Equation (4). The quality of postpartum rehabilitation training does not only depend on whether a certain frame Angle meets the standard, but also needs to observe the change trend in the whole movement cycle. Therefore, in this paper, the single frame attitude parameters are extended to a temporal feature sequence:

$$F_t=[A_t,D_t,S_t,R_t] \tag{5}$$

where $F_t$ represents the action feature vector of frame t, $A_t$ represents the joint Angle feature, $D_t$ represents the keypoint distance feature,$S_t$ represents the body stability feature, and $R_t$ represents the left-right symmetry feature. The key point distance features are mainly used to describe the hip lift height, knee distance, ankle distance and shoulder-hip distance. Body stability features are used to describe the amplitude of trunk axis swing. The left-right symmetry feature is used to judge whether the support on both sides of the body is balanced.

Figure 2 shows the structure of the action feature extraction model for postpartum rehabilitation training. The model converts the human pose in the video frame into a sequence of skeletal key points, and then generates multi-dimensional action features from the key points to provide input for subsequent action recognition and training quality scoring.

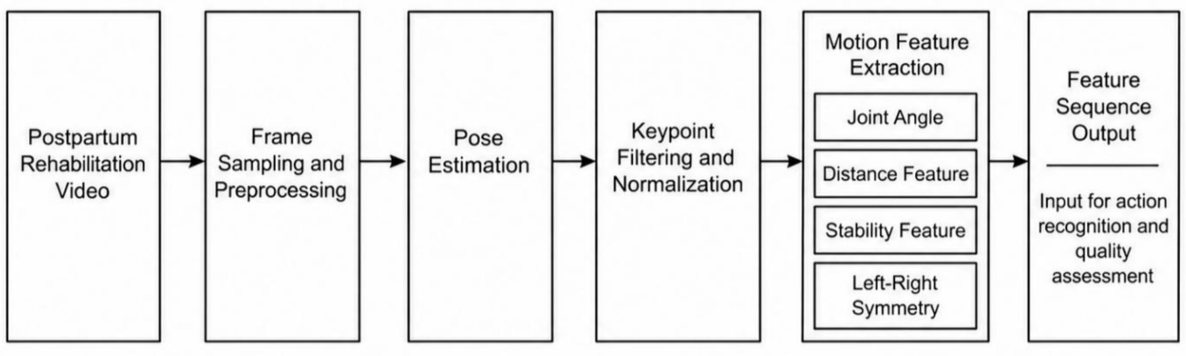


*Figure 2: Motion feature extraction model for postpartum rehabilitation training based on pose estimation*

To further improve the comparability of features, this paper performs scale normalization on the coordinates of key points. Due to different maternal heights, body shapes and shooting distances, the original coordinates cannot be directly used for model training. In this paper, the distance between the center of shoulder and hip is used as the reference of human scale, and the coordinates of key points are converted into relative coordinates:

$$\tilde{p}_t^k = \frac{p_t^k - o_t}{d_t + \varepsilon} \tag{6}$$

where, $\tilde{p}_t^k$ represents the coordinates of the keypoints after normalization, $o_t$ represents the center point of the human body, $d_t$ represents the distance between the shoulder and hip centers, and $\varepsilon$ is the minimum value to prevent the denominator from being zero. After normalization, the action differences between different individuals can be compressed into the same scale space, and it is easier for the model to learn common features of action execution quality.

Postpartum rehabilitation training emphasizes the movement stability and control process, so this paper introduces the movement stability index to measure the jitter of key parts in the training process:

$$S = \frac{1}{T-1} \sum_{t=2}^{T} \| \tilde{p}_t^{hip} - \tilde{p}_{t-1}^{hip} \| \tag{7}$$

where, S represents the hip stability index and $\tilde{p}_t^{hip}$ represents the normalized hip center point. When S is too large, it indicates that the pelvic control is unstable during the action, and there may be insufficient lumbar compensation or support. This index can be used to evaluate the quality of bridge training, pelvic control training, and kneeling support movements. Through the above processing, this paper establishes an action feature extraction model for postpartum rehabilitation training scenarios. Instead of simply extracting human body contours, the proposed model structured modeling around key body control relationships in postpartum rehabilitation. Compared with the general action recognition features, the proposed model pays more attention to hip control, core stability, lower limb support and action continuity, which can provide more targeted input for the subsequent action recognition module and training quality evaluation module.

## 3.2 Construction of postpartum rehabilitation action recognition and training quality evaluation module based on skeletal key points

After obtaining the coordinates of skeletal key points in the postpartum rehabilitation training video, the system needs to further complete the action category recognition, action interval division and training quality evaluation. Postpartum rehabilitation movements are different from general sports training movements, and the evaluation focus is not on the number of movements, but on whether the pelvis is stable, whether the core is effectively involved, whether the lower limb support is symmetrical, and whether the movement rhythm meets the rehabilitation requirements. Therefore, this paper constructs an action recognition and training quality evaluation module based on the skeleton key point features, so that the system can recognize the actions such as bridge training, pelvic forward and backward leaning, lateral lying opening and closing, and kneeling leg raising from continuous training videos, and give a normative score for each action cycle. The overall flow of this module is shown in Figure 3.

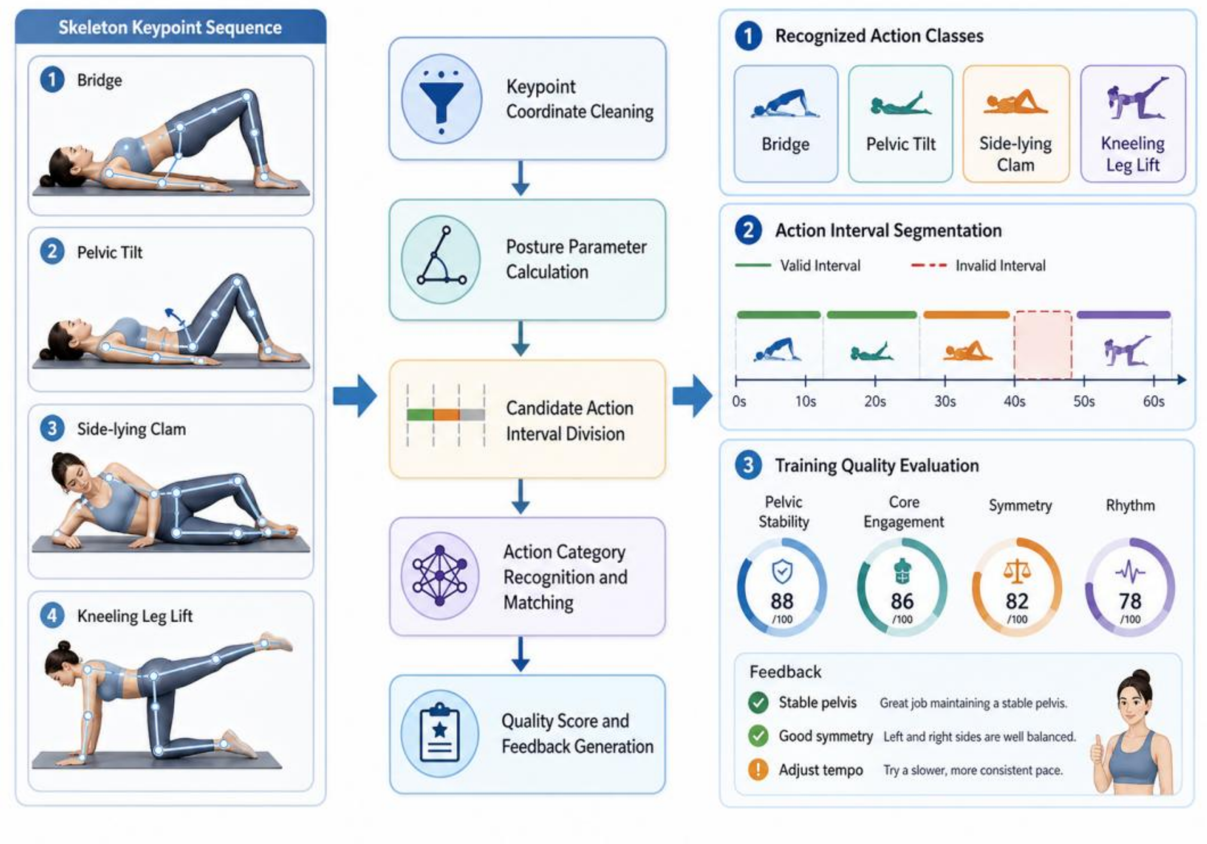


*Figure 3: Postpartum rehabilitation action recognition and training quality evaluation process based on skeletal key points*

Figure 3 shows that the module takes the skeleton keypoint sequence as input, calculates action-related posture parameters after the elimination of outliers and coordinate standardization, and divides the candidate action interval according to time continuity. The system matches the action category of each candidate interval, and combines the quality scoring function to determine whether the action meets the requirements of rehabilitation training. Since postpartum rehabilitation training is often completed in a home environment, there may be uneven illumination, partial body occlusion, and shooting Angle deviation in the video. In order to reduce the influence of abnormal frames on the recognition results, this paper marks the frames whose key point confidence is lower than the set threshold as frames to be corrected, and maintains the integrity of the action sequence by smoothing compensation of adjacent frames. If the continuous abnormal frame exceeds the set length, the action interval is judged as an invalid interval and does not participate in the quality score. Let the normalized skeleton keypoint matrix in frame t be as follows.

$$M_t=\begin{bmatrix} x_t^1 & y_t^1 \\ x_t^2 & y_t^2 \\ \cdots & \cdots \\ x_t^K & y_t^K \end{bmatrix} \tag{8}$$

where, $M_t$ represents the keypoint coordinate matrix in frame t, K represents the number of human keypoints, and $x_t^K$ and $y_t^K$ represent the normalized horizontal and vertical coordinates of the KTH keypoint, respectively. The recognition of postpartum rehabilitation action needs to pay attention to the relative changes between key parts. In this paper, the shoulder, hip, knee and ankle are selected as the core analysis nodes, and the posture parameter vector is constructed:

$$Q_t=[\theta_t^{trunk},\theta_t^{hip},\theta_t^{knee},d_t^{hip},d_t^{knee},s_t^{pelvis}] \quad (9)$$

where, $Q_t$ represents the posture parameter vector of frame t, $\theta_t^{trunk}$ represents the torso tilt Angle, $\theta_t^{hip}$ represents the hip Angle, $\theta_t^{knee}$ represents the knee Angle, $d_t^{hip}$ represents the hip lift or movement amplitude, $d_t^{knee}$ represents the distance change between both knees, and $s_t^{pelvis}$ represents the pelvic stability parameter. Bridge training is mainly based on the hip lift range, the relationship between the shoulder, the hip and the knee, and the pelvic left and right deviation to judge the movement quality. Pelvic anteversion was identified mainly according to changes in hip Angle and trunk axis. For lateral decubitus opening and closing, the distance between the knees and the rotation amplitude of the hips were calculated. In the action interval division, this paper takes the time change of posture parameters as the basis. Let a sequence of key parameters be $q=\{q_1,q_2,\cdots,q_T\}$, and the inter-frame rate of change is calculated as follows.

$$\Delta q_t=|q_t-q_{t-1}| \quad (10)$$

when $\Delta q_t$ continuously exceeds the action initiation threshold, the system marks the position as a candidate action starting point. When the key parameter falls back to the stable range and lasts for several frames, the system marks the position as the candidate action end point. In order to prevent small jitter from being misclassified as the start of an action, this paper introduces a minimum number of continuous frames constraint:

$$C_i=\{I_{t_s},I_{t_s+1},\cdots,I_{t_e}\}, \quad t_e-t_s+1\geq L_{min} \quad (11)$$

where, $C_i$ represents the ith candidate action interval, $t_s$ and $t_e$ represent the action start and end frames, respectively, and $L_{min}$ represents the minimum number of frames in a valid action interval. This constraint can filter shooting jitter, short pauses and non-training pose transitions, and improve the stability of action recognition.

In the action category recognition stage, the system feeds the sequence of pose parameters in the candidate interval into the action classifier. Considering that the number of postpartum rehabilitation action categories is relatively limited, but the difference in action quality is subtle, this paper adopts the combination method of "action template matching + lightweight classification network". The action template is used to ensure the interpretability of action recognition, and the lightweight classification network is used to improve the recognition accuracy under complex posture changes. The similarity between the candidate action interval and the standard action template is calculated as follows.

$$Sim(C_i,T_j)=\frac{\sum_{t=1}^{n} F_{i,t}\cdot F_{j,t}}{\sqrt{\sum_{t=1}^{n}\|F_{i,t}\|^2}\sqrt{\sum_{t=1}^{n}\|F_{j,t}\|^2}} \quad (12)$$

where, $Sim(C_i,T_j)$ represents the similarity between the candidate action interval $C_i$ and the standard action template $T_j$ of the JTH class, $F_{i,t}$ represents the feature vector of the candidate action at the TTH time point, and $F_{j,t}$ represents the feature vector of the standard template at the corresponding time point. The higher the similarity, the closer the candidate action is to the corresponding postpartum rehabilitation action type. The training quality evaluation module runs on the basis of the action recognition results. The quality evaluation of postpartum rehabilitation movement needs to simultaneously consider movement amplitude, rhythm stability, left-right symmetry and compensatory risk. The comprehensive quality scoring function is constructed as follows.

$$Score_i=100-\sum_{r=1}^{m}\lambda_r P_{i,r} \tag{13}$$

where, $Score_i$ represents the training quality score of the ith action interval, $P_{i,r}$ represents the action deviation penalty value of the RTH class, $\lambda_r$ represents the corresponding penalty weight, and m represents the number of deviation types. Motion deviations mainly included insufficient hip lift, left and right pelvic deviation, excessive trunk swing, abnormal knee distance and uneven movement rhythm. If the score is below the eligibility threshold, the system will output corresponding feedback, such as "maintain pelvic level", "reduce waist compensation", "control leg lift speed", etc. The core parameter thresholds and penalty weights for different actions are shown in Table 2.

*Table 2: Thresholds and penalty weights for quality assessment parameters of postpartum rehabilitation actions*

| Action Type | Core Evaluation Parameter | Quality Judgment Threshold | Penalty Weight |
|---|---|---|---|
| Bridge exercise | Hip elevation amplitude | ≥ 0.18 | 0.30 |
| Bridge exercise | Left–right pelvic displacement | ≤ 0.08 | 0.25 |
| Pelvic anterior–posterior tilt | Hip angle variation | ≥ 12° | 0.20 |
| Side-lying clamshell | Change in distance between knees | ≥ 0.15 | 0.20 |
| Quadruped leg raise | Trunk sway amplitude | ≤ 0.10 | 0.25 |
| Supine leg raise | Left–right movement difference | ≤ 0.12 | 0.20 |

The thresholds in Table 2 are derived from the structural characteristics of post-natal rehabilitation movements and the pre-experimental sample statistical results. Bridge training requires the hip to be raised to a certain extent, while avoiding the pelvic tilt to one side; Pelvic anteroposterior tilt requires a discernible change in hip Angle, but should not be accompanied by significant trunk sway; Lateral decubution opening and closing mainly reflected the ability of hip abduction control. Kneeling leg lift and supine leg lift need to focus on the identification of waist and abdomen compensation and the difference between left and right movements. By combining the threshold judgment with the penalty weight, the system can avoid the single classification result covering up the action quality problem, and make the evaluation results more in line with the actual needs of postpartum rehabilitation training.

### 3.3 Construction of lightweight action recognition Network for real-time evaluation

The intelligent evaluation system for postpartum rehabilitation training needs to run for application scenarios such as home training, mobile terminals and remote rehabilitation guidance. If all the complete training videos are uploaded to the cloud for pose estimation and action recognition, it will not only increase the consumption of network bandwidth, but also bring pressure on video privacy protection and high concurrent service. Postpartum rehabilitation training actions usually have a short duration, and the system needs to give timely prompts during the execution of actions. If the inference speed of the model is slow, the feedback information will lag behind the training process, and it is difficult to play an immediate correction role. Therefore, this paper constructs a lightweight action recognition network for real-time evaluation, which combines lightweight pose estimation, skeleton sequence compression, temporal feature modeling and end-to-side quantization deployment to meet the requirements of low latency, low computing power and stable output.

In this paper, the lightweight network takes video frames as input. Firstly, the body key point heat map and limb connection are extracted through the lightweight pose estimation backbone network, and then the key point coordinates are converted into a normalized skeleton sequence. Then, the system uses depthwise separable temporal convolution to extract action change features, and uses a lightweight classification layer to output the postpartum rehabilitation action categories and training quality levels. The overall structure is shown in Figure 4.

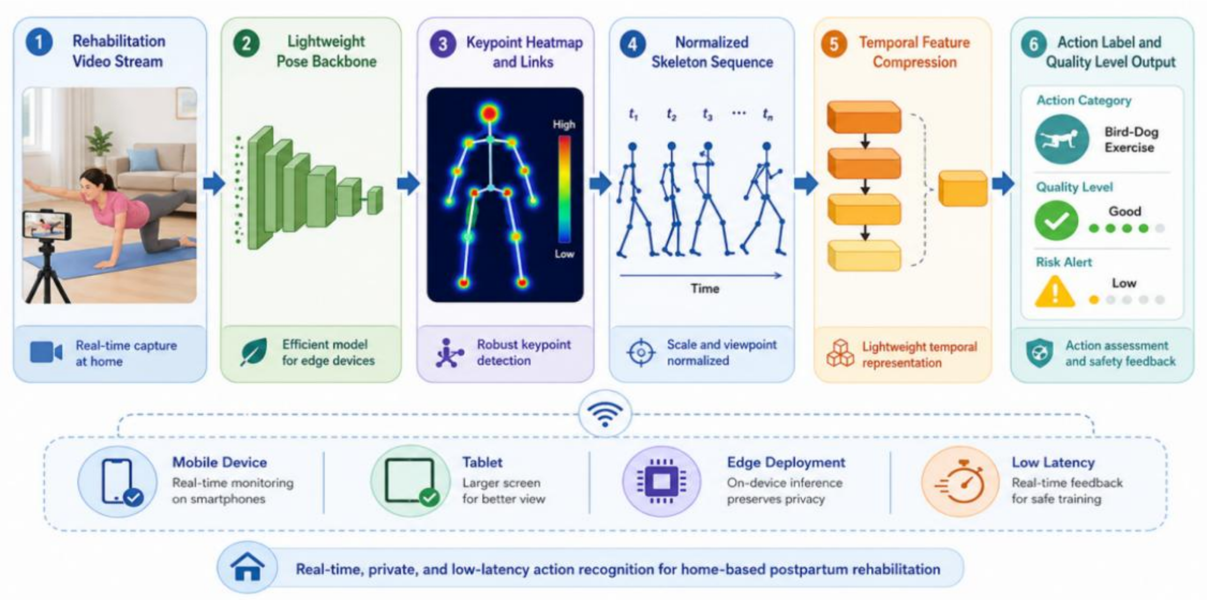


*Figure 4: Structure of lightweight action recognition network for real-time evaluation*

In Figure 4, the lightweight pose estimation backbone network is used to complete the keypoint localization and output the coordinates of shoulder, hip, knee, ankle and other parts. In order to reduce the number of model parameters, this paper replaces the regular convolution with the depthwise separable convolution. Let the size of the convolution kernel be k, the number of input channels be $C_{in}$, the number of output channels be $C_{out}$, and the number of conventional convolution parameters be:

$$P_{std}=k^2C_{in}C_{out} \tag{14}$$

Depthwise separable convolution is composed of channel-wise convolution and pointwise convolution, and the number of parameters is expressed as follows.

$$P_{ds}=k^2C_{in}+C_{in}C_{out} \tag{15}$$

According to Equations (14) and (15), the depthwise separable convolution is able to significantly reduce the parameter scale when $C_{out}$ is large. The proposed architecture is suitable for deployment on tablets, mobile phones and edge computing devices, and enables the system to improve the inference speed without significantly reducing the accuracy of key point positioning.

In the action recognition stage, this paper does not directly classify the original image, but uses the skeleton keypoint sequence to construct a lightweight temporal input. Let the skeleton features of consecutive L frames be as follows.

$$X=[F_{t-L+1},F_{t-L+2},\cdots,F_t] \quad (16)$$

where, X represents the skeleton sequence in the current time window and $F_t$ represents the feature vector of frame t consisting of joint angles, keypoint distances, pelvic stability, and left-right symmetry. This window slides dynamically with the video stream, enabling the system to capture the trend of pose change when the training action is not yet completely finished. For bridge training, the network focused on identifying the hip lift and the connection between shoulder, hip and knee. For pelvic forward and backward tilt, the network mainly focused on hip Angle changes and trunk axis changes. For side-lying opening and closing and kneeling leg lifts, the network focused on lower limb opening and closing amplitude, pelvic offset, and trunk swing.

To further reduce the end-to-end reasoning burden, this paper introduces the INT8 quantization method in the model deployment phase, which maps floating-point parameters to 8-bit integer parameters. The quantization process is expressed as follows.

$$q=\mathrm{round}\left(\frac{x}{s}+z\right) \quad (17)$$

where x represents the original floating-point parameter, q represents the quantized integer parameter, s represents the scaling factor, and z represents the zero offset. After quantization, the storage space and computational overhead of the model are compressed, and the end-side device can complete the pose estimation and action recognition with lower power consumption. In order to avoid the fluctuation of quality score caused by quantization, this paper retains the key threshold calculation in the training quality evaluation layer, and performs a second smooth judgment on the action clips whose classification confidence is lower than the set range.

Through lightweight pose estimation, skeletal sequence input, depthwise separable temporal convolution and INT8 quantization, the action recognition network constructed in this paper can adapt to the real-time evaluation needs of postpartum rehabilitation training. The proposed network reduces the original video upload frequency and cloud computing dependency, while retaining the ability to recognize pelvic control, core stabilization, and movement rhythm. The system output includes action categories, real-time quality levels and risk tips, which can provide continuous, timely and interpretable intelligent feedback for postpartum women's home training.

# 4 Experiment and result analysis of postpartum rehabilitation training intelligent evaluation system

In order to verify the effectiveness of the intelligent evaluation system for postpartum rehabilitation training based on action recognition, this paper carried out experiments around the accuracy of action recognition, the consistency of training quality score, the ability of abnormal action recognition and the stability in different training environments. The experimental data includes two parts: on-site video collection and home simulation training video. The data collected in the field are from the training guidance scene in the rehabilitation room, and the home simulation data are from the living room, bedroom and low light home environment. The dataset included 5 common postpartum rehabilitation actions, including bridge training, pelvic forward and backward leaning, lateral lying opening and closing, kneeling leg raising and supine leg raising. A total of 180 videos were collected, and 3240 effective action clips were extracted. Each video was labeled by the rehabilitator with the action category, the start and end frames of the action, and the training quality level, and the quality level was divided into standard, mild deviation, and obvious deviation. In order to improve the adaptability of the model to different shooting conditions, the training samples are enhanced by brightness disturbance, slight rotation of view Angle, time cropping and random occlusion of key points.

## 4.1 Accuracy test of action recognition and training quality assessment for postpartum rehabilitation training

In order to test the output effect of the system in action recognition and training quality evaluation of postpartum rehabilitation training, the experiment was divided into training set, validation set and test set according to the ratio of 7:2:1. The test set contains 18 complete training videos and 326 valid action clips, covering different postpartum recovery stages, different body types, and different training environments. The experimental metrics include action recognition accuracy, quality assessment accuracy, Macro-F1, average scoring error, and single video processing time. The action recognition accuracy was used to measure the system's ability to judge the rehabilitation action category, the quality assessment accuracy was used to measure the system's ability to evaluate the normalization of the action, and the average scoring error was used to compare the deviation between the system score and the score of the rehabilitator.

Figure 5 shows the recognition accuracy and quality assessment accuracy of five categories of postpartum rehabilitation actions. On the whole, the recognition effect of bridge training and pelvic tilt forward and backward is better, and the accuracy of action recognition reaches 96.4% and 94.8%, respectively. The recognition accuracy of side-lying opening and closing and kneel leg raising is slightly lower because some key points are easy to be occluded by the body, but it still remains above 90%. The quality assessment accuracy of supine leg lift is 89.7%, which is lower than the accuracy of action recognition. The main reason is that the quality judgment of this action depends not only on the amplitude of leg lift, but also is affected by pelvic fixation, lumbar compensation and the difference between left and right side control.

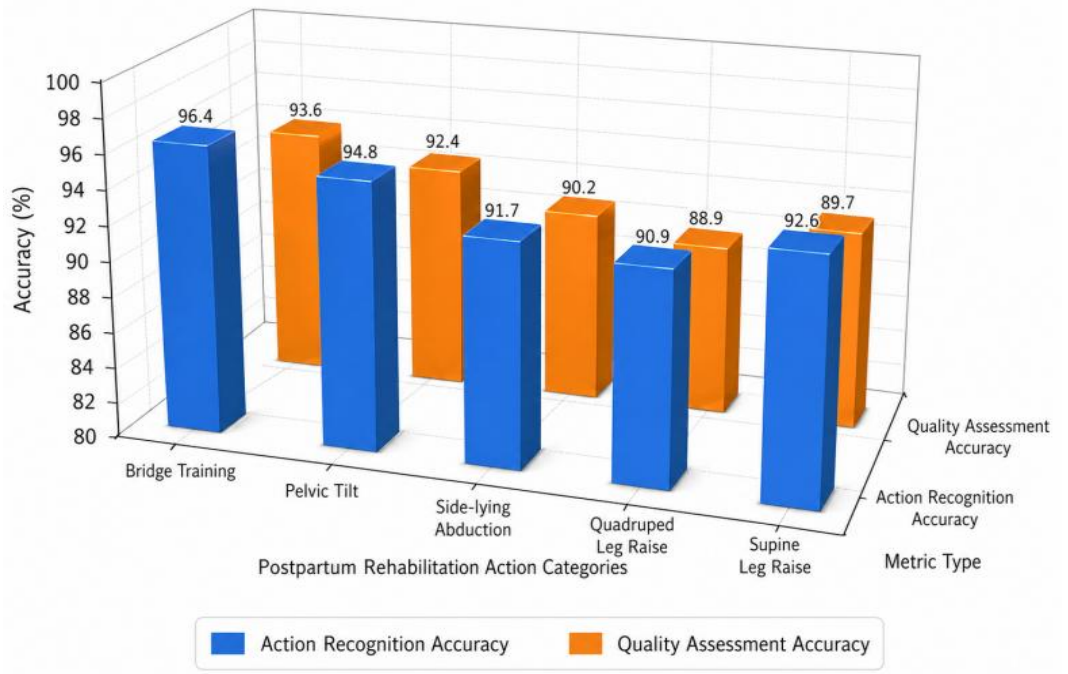


*Figure 5: Recognition and quality assessment accuracy of different postpartum rehabilitation actions*

Figure 5 shows that the proposed system has good recognition ability for different action categories. The recognition result of bridge training is the highest, because the hip lifting trajectory, the change of the line of shoulder, hip and knee and the position of pelvis in this action are relatively obvious, and the sequence of skeletal key points can form a stable timing pattern. The quality assessment accuracy of kneel leg lift is relatively low, because the knee support point is occluded in some test videos, and the system's capture of subtle torso swing is affected. Nevertheless, the accuracy of each action quality assessment was higher than 88%, indicating that skeletal key points, joint angles and stability parameters can better reflect the quality of postpartum rehabilitation training.

In order to further test the stability of the system in different training environments, the test videos were divided into four categories: rehabilitation room, living room, bedroom and low-light home environment. Figure 6 shows the comprehensive recognition accuracy and the average processing time in different environments. In the rehabilitation room environment, the background is simple and the light is stable. The comprehensive recognition accuracy of the system reaches 95.8%, and the average processing time is 0.42s. In low-light home environment, the confidence of some key points decreases, the comprehensive recognition accuracy decreases to 89.6%, and the average processing time increases to 0.61s.

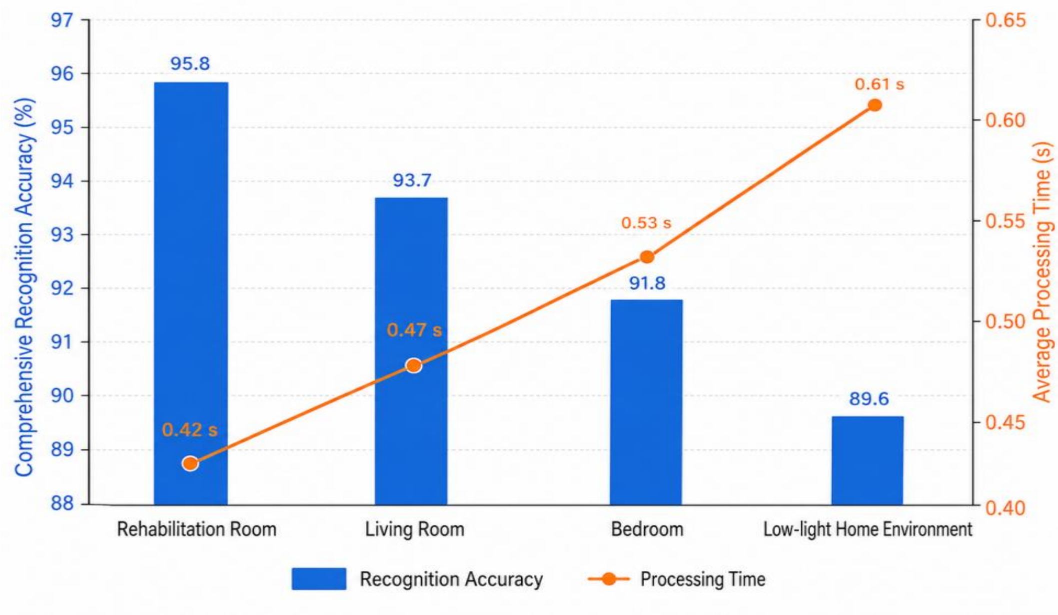


*Figure 6: System accuracy and processing time under different training environments*

Figure 6 shows that the environment changes have some impact on the pose estimation and action quality score, but the system maintains usable recognition performance in the home scene. In the living room environment, the training space is relatively sufficient, and the action recognition accuracy is close to the results of the rehabilitation room. In the bedroom environment, the bed body, wardrobe and sundry objects are easy to form background interference, and the system processing time is slightly increased. In the low light environment, the confidence of the key points of the shoulder and hip decreased more obviously, resulting in increased fluctuations of the pelvic stability parameters. In this paper, after adding adjacent frame smoothing compensation in the key point correction step, the misjudgment rate of low-light scenes is controlled to a certain extent, which indicates that this processing method is necessary for home training scenes.

Table 3 presents the detailed test results for different action types, including action recognition accuracy, quality assessment accuracy, Macro-F1, average scoring error, and average processing time. The mean rating error in Table 3 represents the absolute difference between the system rating and the rehabilitator rating, with smaller values indicating better rating agreement.

*Table 3: Action recognition and quality assessment test results of postpartum rehabilitation training*

| Action Type | Number of Test Segments | Action Recognition Accuracy / % | Quality Assessment Accuracy / % | Macro-F1 / % | Mean Scoring Error | Mean Processing Time / s |
|---|---|---|---|---|---|---|
| Bridge exercise | 68 | 96.4 | 93.6 | 94.2 | 3.8 | 0.43 |
| Pelvic anterior–posterior tilt | 64 | 94.8 | 92.4 | 93.1 | 4.1 | 0.45 |
| Side-lying clamshell | 62 | 91.7 | 90.2 | 90.8 | 4.9 | 0.49 |
| Quadruped leg raise | 66 | 90.9 | 88.9 | 89.5 | 5.3 | 0.52 |
| Supine leg raise | 66 | 92.6 | 89.7 | 90.6 | 5.1 | 0.50 |
| Average | 326 | 93.3 | 91.0 | 91.6 | 4.6 | 0.48 |

Table 3 shows that the average action recognition accuracy of the system is 93.3%, the average quality assessment accuracy is 91.0%, Macro-F1 is 91.6%, and the average scoring error is 4.6 points. The results show that the system can not only identify the types of postpartum rehabilitation actions, but also make a more stable quantitative judgment on the quality of training. The bridge training had the smallest scoring error of 3.8 points, indicating that the system's judgment of the relationship between hip lift, pelvic offset, and body support was relatively close to the therapist's annotation. Knee leg lifts had the largest scoring error of 5.3 points, mainly related to the occlusion of the knee on the support side and slight rotation of the torso. Further analysis of misjudgment samples shows that the recognition difficulty of obvious deviation actions is lower than that of mild deviation actions. The reason is that the obvious deviation is usually accompanied by a large pelvic deviation or trunk sway, while the mild deviation is more manifested by insufficient movement amplitude, uneven rhythm or short-term support instability, and weak characteristic changes.

The experiment also tested the ability of abnormal action recognition. The system set five kinds of common deviations: lateral deviation of pelvis, lumbar compensation, too fast lifting leg, unstable support and insufficient movement range. The test results show that the recognition accuracy of lateral pelvic deviation is 93.5%, the recognition accuracy of waist compensation is 90.8%, the recognition accuracy of excessive leg raising is 92.1%, the recognition accuracy of unstable support is 89.4%, and the recognition accuracy of insufficient movement amplitude is 91.7%. Among them, the recognition accuracy of support instability is relatively low, mainly due to the close boundary between some short-term swaying and normal motion adjustment. The system reduces the single frame false alarm through the continuous frame stability judgment, which makes the abnormal action detection result more stable.

## 4.2 Output accuracy test of lightweight postpartum rehabilitation action recognition model

In order to verify the output effect of the lightweight postpartum rehabilitation action recognition model on the end-side device, the lightweight network constructed in Section 3.3 is deployed to the edge reasoning device for testing. The experiment uses 326 valid action clips from the same test set, the input resolution is set to 256×256, and the time window length is set to 32 frames. Model training was performed on Ubuntu 22.04 with Python 3.11 and PyTorch 2.2 as development environments. The end-side inference test was done on a low-power embedded device configured with a quad-core ARM processor, 4GB memory, and an integrated GPU to simulate real-time assessment conditions in a home rehabilitation scenario. The comparison models include the full pose estimation model, the uncompressed skeleton timing network, the lightweight network, and the lightweight quantization network. The evaluation metrics include action recognition accuracy, quality assessment accuracy, model file size, average inference time, and real-time frame rate.

Figure 7 shows the comparison results of different models in terms of accuracy and computational complexity. The complete pose estimation model has the highest action recognition accuracy of 94.1%, but its calculation amount reaches 31.8 GFLOPs, which is difficult to adapt to end-to-side continuous reasoning. The accuracy of the uncompressed skeletal temporal network is 93.6%, and the computational complexity is 18.4 GFLOPs. The lightweight network reduces the amount of computation to 6.7 GFLOPs and maintains the action recognition accuracy at 92.8%. After INT8 quantization, the calculation amount is further reduced to 4.2GFLOPs, and the accuracy of action recognition is 92.1%, which is 0.7 percentage points lower than that before lightweight, and it still maintains good usability.

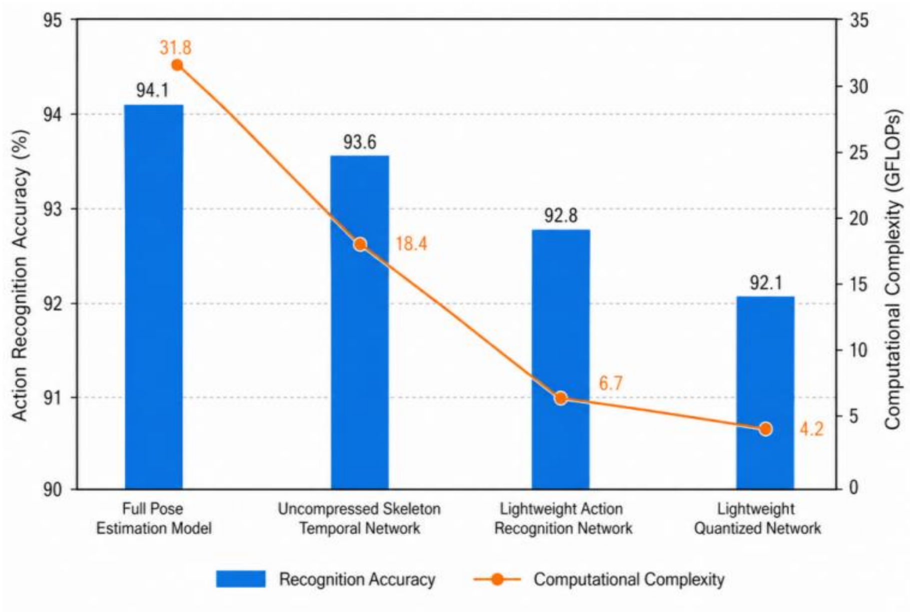


*Figure 7: Comparison of accuracy and computational complexity of different models*

It can be seen from Figure 7 that the lightweight processing significantly reduces the amount of model calculation, while the recognition accuracy does not suffer a large loss. The results show that postpartum rehabilitation action recognition does not need to completely rely on high-dimensional image features, and the skeletal key point sequence has been able to express the main structural changes of bridge training, pelvic forward and forward tilt, lateral lying opening and closing, and kneeling leg raising. The lightweight network compressed the spatial features by depthwise separable convolution, and then extracted the action change trend by using a short time series window, which could reduce the end-side computational pressure while maintaining the recognition accuracy.

Table 4 further shows the file size, average inference time, real-time frame rate, and quality assessment accuracy of different models. Table 4 shows that the file size of the full pose estimation model is 184.6MB, the average inference time is 186.4ms, and the real-time frame rate is only 5.4 frame·s$^{-1}$. The file size of the lightweight action recognition network was reduced to 18.7MB, the average inference time was shortened to 47.8ms, and the real-time frame rate was increased to 20.9 frame·s$^{-1}$. After INT8 quantization, the model file size was further compressed to 7.9MB, the average inference time was shortened to 32.6ms, and the real-time frame rate reached 30.7 frame·s$^{-1}$, which could meet the real-time feedback requirements of postpartum rehabilitation training.

*Table 4: Output performance test results of lightweight postpartum rehabilitation action recognition model*

| Model Type | File Size / MB | Action Recognition Accuracy / % | Quality Assessment Accuracy / % | Mean Inference Time / ms | Real-Time Frame Rate / frame·s$^{-1}$ |
|---|---|---|---|---|---|
| Full pose estimation model | 184.6 | 94.1 | 91.8 | 186.4 | 5.4 |
| Uncompressed skeleton temporal network | 76.3 | 93.6 | 91.5 | 102.7 | 9.7 |
| Lightweight action recognition network | 18.7 | 92.8 | 90.9 | 47.8 | 20.9 |
| Lightweight quantized network | 7.9 | 92.1 | 90.2 | 32.6 | 30.7 |

The results in Table 4 show that the lightweight quantization network has a clear advantage in terms of model volume, inference speed, and real-time frame rate. Although the accuracy of action recognition is reduced by 2.0 percentage points and the accuracy of quality assessment is reduced by 1.6 percentage points compared with the full model, the inference time is reduced by 153.8ms and the model file size is reduced by 176.7MB. In the scenario of postpartum rehabilitation training, the system needs to give stable feedback during action execution rather than offline analysis after training. Therefore, the lightweight quantization network forms a good balance between accuracy and efficiency.

Figure 8 shows the performance changes before and after model compression and inference acceleration. After pruning, the average inference time was reduced from 102.7ms to 63.5ms, and the real-time frame rate was increased from 9.7 frame·s$^{-1}$ to 15.8 frame·s$^{-1}$. After adding depthwise separable convolution, the inference time was reduced to 47.8ms, and the real-time frame rate was increased to 20.9 frame·s$^{-1}$. With INT8 quantization, the inference time is further reduced to 32.6ms, and the real-time frame rate is increased to 30.7 frame·s$^{-1}$. The decline of accuracy in each stage is controlled within an acceptable range.

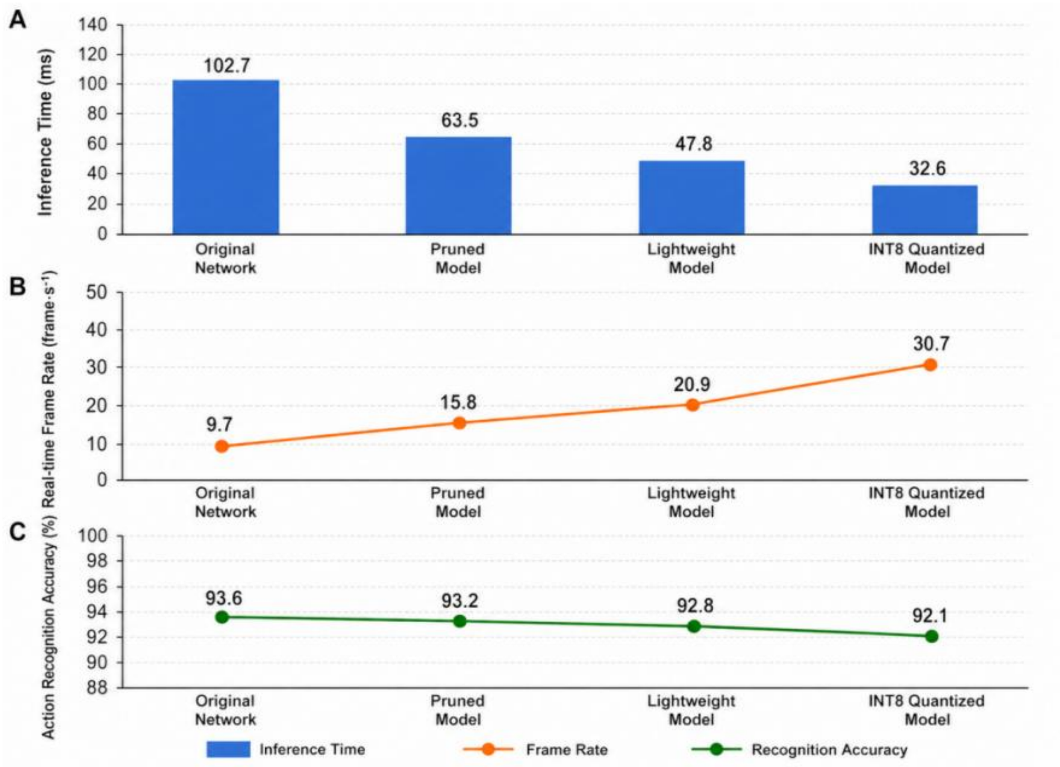


*Figure 8: Model inference performance changes before and after lightweight processing*

Figure 8 illustrates that inference speedup does not result in a significant decrease in model discrimination. Pruning mainly reduces redundant channels and has little impact on the key temporal expression of skeleton sequence. Lightweight convolution reduces the multiplication and addition computation in the feature extraction process. INT8 quantization further compresses parameter storage and computation overhead. The analysis of misjudgment samples shows that the quantized model is more likely to have mild deviation grade confusion in lateral lying opening and supine leg raising, because the quality judgment of these two types of movements depends on small hip changes and left and right side control differences. In order to reduce this kind of misjudgment, the system adds a continuous frame smoothing strategy before the end-side output. When the score fluctuation of adjacent

Windows exceeds the set range, the average result of the last three Windows is used as the final output.

# 5 Discussion

With the continuous expansion of computer vision, pose estimation and edge intelligence technology in the field of rehabilitation health, postpartum rehabilitation training evaluation based on action recognition provides a new technical path for home rehabilitation and remote guidance. The existing postpartum rehabilitation evaluation mostly relies on manual observation and periodic review, which is difficult to continuously capture the details of pelvic deviation, core instability and unequal support of lower limbs during training. The intelligent evaluation system constructed in this paper combines video pose estimation, skeletal key point modeling, action category recognition and training quality scoring, which turns postpartum rehabilitation training from empirical judgment to data analysis.

The experimental results show that the system has a clear performance difference between different action categories. Bridge training and pelvic forward and backward leaning depend on hip lifting, trunk axis and pelvic control changes, and the key point sequence is easy to form a stable discriminant pattern. Kneel leg lifts and supine leg lifts involve occlusion of the support side, mild compensation, and control differences between the left and right sides, and the quality assessment is relatively difficult. The recognition effect of bridge training and pelvic forward and backward tilt is higher, the main reason is that the hip lift, trunk axis and pelvic control change more obviously, and the model can form a stable time sequence discrimination basis. The quality assessment error of kneel leg lift and supine leg lift is relatively large, indicating that mild compensation, short-term shaking and left-right side difference are still difficulties in the system discrimination.

The lightweight model test further proves that the end-to-end deployment can improve the usability of intelligent assessment for postpartum rehabilitation training. The INT8 quantization model achieves an action recognition accuracy of 92.1%, an quality assessment accuracy of 90.2%, and a real-time frame rate of 30.7 frame$\cdot$s$^{-1}$, which significantly reduces the model size and inference time with a slight decrease in accuracy. The results show that the system can reduce the upload frequency of original training videos, reduce the dependence on cloud computing, and protect the privacy of postpartum women's home training data to a certain extent. For rehabilitation training scenarios that require immediate correction, real-time end-side feedback is more practical than off-line analysis.

However, there is still room for improvement of the proposed system. Low light, partial occlusion, and shooting Angle offset will affect the stability of key points such as shoulder, hip, and knee, and then affect the quality scoring results. The differences between correct and incorrect movements of some postpartum rehabilitation movements are subtle, and it may still be difficult to identify deep core force states by simply relying on visual skeletal sequences. Subsequent studies could incorporate wearable sensors, EMG signals, or pressure pad data to further enhance the system's ability to identify core activation, support stability, and exercise load, and expand sample sources to adapt the model to different postpartum stages, body size differences, and home environments.

# 6 Conclusions

The traditional evaluation of postpartum rehabilitation training mainly relies on the observation of therapists, periodic review and maternal self-feeling records, and the evaluation results are easily affected by observation experience, training environment and feedback delay. Aiming at the problems of small movement range, high control requirements and insufficient home training supervision in postpartum rehabilitation training, this paper constructs an intelligent evaluation system for postpartum rehabilitation training based on action recognition. Based on posture estimation, the system extracts key points such as shoulder, hip, knee and ankle, and combines joint Angle, pelvic stability, action amplitude and left-right symmetry parameters to realize postpartum rehabilitation action recognition, training quality scoring and abnormal action suggestion. The experimental results show that the average recognition accuracy of the system is 93.3%, the average quality evaluation accuracy is 91.0%, Macro-F1 is 91.6%, and the average scoring error is 4.6 points on five types of actions: bridge training, pelvic forward and backward tilt, lateral lying opening and closing, kneel leg raising and supine leg raising. In the test of different training environments, the comprehensive recognition accuracy of rehabilitation room, living room, bedroom and low-light home environment is 95.8%, 93.7%, 91.8% and 89.6%, respectively, indicating that the system still has good stability in complex home scenes. Test results of the lightweight model show that the model file size of the INT8 quantized network is reduced to 7.9MB, the average inference time is shortened to 32.6ms, and the real-time frame rate is 30.7 frame·$s^{-1}$, which can meet the real-time feedback requirements in the postpartum rehabilitation training process. This study proves that the skeletal keypoint-driven action recognition method can provide a more objective, continuous and interpretable evaluation basis for postpartum rehabilitation training. However, low illumination, partial occlusion, and mild compensatory movements still affect the model judgment. Follow-up studies can further integrate wearable sensors, EMG signals and pressure data, expand the sample size, and optimize the individual assessment rules under different postpartum recovery stages, so as to improve the generalization ability and clinical auxiliary value of the system.

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