Personalized Intervention Research on University Table Tennis Training Based on Artificial Intelligence and Learning Analytics Technology

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Abstract. To address the problems of lack of personalized guidance, subjective action evaluation, and delayed feedback in traditional table tennis teaching in universities, this paper proposes and implements a personalized training intervention system integrating computer vision, deep learning, and learning analytics technology. The system employs the OpenPose pose estimation algorithm to extract coordinates of 14 upper limb keypoints from students in real time. Targeting the characteristics of fast table tennis movements and frequent occlusions, multi-scale feature fusion and temporal consistency constraints are introduced for optimization, improving keypoint detection accuracy from 86.3% to 91.7% while maintaining a detection frame rate above 25fps. On this basis, an action recognition model based on Spatial Temporal Graph Convolutional Networks (ST-GCN) is constructed. Through three optimizations—introduction of attention mechanisms, multi-scale temporal convolution kernels, and label smoothing regularization—the model achieves automatic classification of four fundamental movements (forehand drive, backhand push, forehand chop, and backhand chop) with a recognition accuracy of 92.7%, representing an 8.4 percentage point improvement over 3D-CNN. Furthermore, a continuous scoring model integrating three dimensions—keypoint position accuracy, joint angle matching degree, and motion trajectory smoothness—is designed, achieving a correlation coefficient of 0.81 between model scores and expert ratings with a root mean square error of 4.18. Finally, a learning analytics module based on bidirectional Long Short-Term Memory (Bi-LSTM) networks is introduced, combined with attention mechanisms to dynamically track student training trajectories, categorizing students into four learning stages and matching personalized intervention strategies. A quasi-experimental study was conducted in a university table tennis course, with 86 students randomly divided into experimental and control groups. After an 8-week teaching experiment, results show that students in the experimental group improved their forehand drive scores by 16.3 points and backhand push scores by 15.2 points, significantly higher than the 7.8-point and 7.3-point improvements in the control group ($p<0.001$), while their skill acquisition cycle was shortened by 23.4%. The proposed method effectively realizes intelligent and personalized table tennis training, providing a reference technical pathway for the reform of university physical education.

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1 Introduction

University physical education is undergoing a critical transition from experience-based to data-driven approaches. As an important component of university physical education curriculum, table tennis demands fine motor skills and high coordination. The traditional teaching model of "unified explanation—group practice—teacher correction" has obvious limitations: teachers cannot simultaneously attend to the detailed movements of multiple students; evaluation criteria are subjective and lack quantitative basis; feedback is delayed, preventing timely correction and potentially leading to the reinforcement of incorrect movement patterns.

In recent years, artificial intelligence and learning analytics technologies have shown great potential in physical education. However, a systematic review of the existing literature reveals that current research in this domain suffers from several notable limitations. First, existing studies predominantly focus on competitive sports scenarios, with systems designed for elite athletes using high-precision but costly equipment such as multi-camera motion capture systems, making them unsuitable for general university classroom settings. Second, most research addresses isolated technical problems—such as action recognition or performance prediction—rather than constructing complete pedagogical systems that integrate multiple AI technologies into a coherent teaching workflow. Third, the majority of existing systems lack personalized learning analytics capabilities; they treat all students uniformly, failing to account for individual differences in learning pace, error patterns, and skill development trajectories. Fourth, few studies have conducted rigorous pedagogical experiments to validate the educational effectiveness of their technical approaches, leaving the practical impact on teaching outcomes largely unexamined.

Tang et al. [1] achieved table tennis action recognition with 98.88% accuracy using deep learning combined with intelligent cameras, demonstrating the feasibility of automated movement analysis. However, their work focused exclusively on action classification without providing corrective feedback or pedagogical integration. Ma et al. [2] developed a table tennis coaching system based on multimodal large language models, achieving over 73% recognition accuracy for beginners' erroneous movements, yet their system primarily targets individual practice rather than classroom teaching contexts. Na et al. [3] proposed a tactical recommendation system based on deep reinforcement learning, achieving up to 59% improvement in winning rate, but this research is oriented toward competitive match analysis rather than fundamental skill instruction for beginners. Xie et al. [4] conducted a quasi-experimental study based on the TPACK framework, demonstrating that digital technology-enhanced teaching significantly improves students' table tennis performance, yet their work employed general digital tools rather than AI-driven personalized systems.[5]

While these studies provide valuable technical foundations, they collectively reveal a gap in the literature: there exists no comprehensive system that integrates pose estimation, action recognition, continuous scoring, and learning analytics into a unified personalized training intervention framework specifically designed for university table tennis instruction. Moreover, existing research has not adequately addressed the pedagogical challenges of providing real-time, individualized feedback in classroom settings with limited instructor resources.

This paper addresses this gap by constructing a personalized training intervention system that integrates computer vision, deep learning, and learning analytics technologies. The research focuses on three aspects: optimizing OpenPose for table tennis movement characteristics; constructing and optimizing ST-GCN for action recognition and scoring; and designing Bi-LSTM for learning state tracking and personalized intervention generation. This study distinguishes itself from prior work in three significant ways. First, it integrates multiple AI technologies into a coherent end-to-end system rather than addressing isolated technical problems. Second, it emphasizes personalization through dynamic learning stage classification and adaptive intervention strategies, moving beyond uniform treatment of all students. Third, it validates pedagogical effectiveness through a rigorous quasi-experimental design with pre-test and post-test comparisons, demonstrating measurable improvements in actual teaching outcomes.

2 System Architecture

The personalized table tennis training intervention system proposed in this paper consists of three layers: data acquisition layer, intelligent analysis layer, and intervention decision layer. This layered architecture ensures system modularity, scalability, and functional separation.

Data Acquisition Layer: A monocular camera is used to capture student training videos at 30fps with a resolution of 1280×720. The camera is fixed at the side of the training area, approximately 3 meters from the student and level with the table height, ensuring complete capture of the student's upper body movements. Video data undergoes preprocessing including format conversion, frame extraction, and noise reduction before being input to the pose estimation module.

Intelligent Analysis Layer: Contains three core modules working in sequence. The pose estimation module uses an optimized OpenPose algorithm to extract human keypoint coordinates from video frames. The action recognition module processes keypoint sequences through an ST-GCN model to output movement type classification results and quality scores. The learning analytics module uses a Bi-LSTM network combined with historical training data to construct dynamic student capability profiles and identify current learning stages.

Intervention Decision Layer: Based on the student status and stage information output by the learning analytics module, personalized intervention plans are matched from the strategy library. Feedback is delivered through two channels: voice prompts broadcast correction suggestions in real time during training, while visual reports display quantitative scores and movement comparison analyses after training sessions.

Table 1 presents the main functions and technical implementations of each layer's modules.

Table 1. Module Functions and Technical Implementations by System Layer

Layer	Module	Main Function	Core Technology
Intervention Decision	Personalized Plan Generation	Match intervention strategies based on learning status	Strategy Rule Base
Intervention Decision	Real-time Voice Feedback	Broadcast correction suggestions	Text-to-Speech
Intervention Decision	Visual Report	Display training data and progress curves	Data Visualization
Intelligent Analysis	Pose Estimation	Extract human keypoint coordinates	Optimized OpenPose
Intelligent Analysis	Action Recognition	Classify action types	ST-GCN with Attention
Intelligent Analysis	Action Scoring	Quantify movement quality	Multi-dimensional Scoring Model
Intelligent Analysis	Learning Analytics	Track training trajectories	Bidirectional LSTM with Attention
Data Acquisition	Video Capture	Acquire training video streams	Industrial Camera
Data Acquisition	Video Preprocessing	Format conversion and frame extraction	OpenCV

3 Key Technical Methods and Optimizations

3.1 OpenPose-Based Pose Estimation Optimization

Human pose estimation serves as the foundation for personalized training intervention. This study adopts the OpenPose algorithm to extract keypoint coordinates during students' movements. OpenPose employs a bottom-up detection strategy, achieving joint association matching through Part Affinity Fields (PAFs), enabling simultaneous detection of multiple individuals—suitable for classroom teaching scenarios.

Considering the characteristics of fast table tennis movements and frequent limb occlusions, two optimizations were implemented for OpenPose. First, a multi-scale feature fusion strategy was adopted, incorporating skip connections in the base network to combine shallow detail features with deep semantic features. Shallow features retain more spatial detail information and are more sensitive to small-amplitude rapid movements; deep features possess stronger semantic expression capabilities and better understand overall posture. Their fusion enhances detection capability for small-amplitude rapid movements such as subtle wrist adjustments at the moment of impact. Second, temporal consistency constraints were introduced, using keypoint positions from adjacent frames to correct detection results in the current frame. When detection results for a particular frame are abnormal due to rapid motion or limb occlusion, the system references detection results from preceding and following frames for interpolation and smoothing, reducing detection loss and jitter. This temporal smoothing mechanism is particularly effective for brief occlusions occurring during rapid arm swings in table tennis.

Following optimization, keypoint detection accuracy improved from 86.3% to 91.7%, while detection frame rate remained above 25fps, meeting real-time requirements. Extracted keypoints include 14 points: head, neck, shoulders, elbows, wrists, hips, knees, and ankles. Given the characteristics of table tennis movements, particular attention is paid to the motion trajectories and angular changes of upper limb keypoints, especially the coordinated movement relationships among wrists, elbows, and shoulders. To eliminate camera perspective differences, coordinates are normalized using the neck as the reference point to calculate relative coordinates.

3.2 ST-GCN-Based Action Recognition Model Optimization

Table tennis technical movements exhibit significant spatiotemporal characteristics: both spatial topological relationships among keypoints and dynamic trajectories over time. Traditional convolutional neural networks process spatial and temporal dimensions separately, making it difficult to effectively model this spatiotemporally coupled structure. This study employs Spatial Temporal Graph Convolutional Networks (ST-GCN) for action recognition, which constructs spatiotemporal graphs from sequences of human keypoints and simultaneously learns spatial structural features and temporal evolution features through spatiotemporal graph convolution operations.

The spatiotemporal graph is constructed as follows: the vertex set consists of all keypoints across all frames; the edge set includes two types—spatial edges and temporal edges. Spatial edges connect keypoints naturally linked by human skeletal structure within the same frame, such as connections between shoulder and elbow, and between elbow and wrist; temporal edges connect the same keypoint across adjacent frames, forming temporal trajectories. This graph structure preserves the topological relationships of the human skeleton while capturing the evolution of movements over time.

Three optimizations were implemented for the ST-GCN model to address table tennis movement characteristics. First, an attention mechanism was introduced in spatial graph convolution to assign different weights to different keypoints. In table tennis, wrist and elbow movements are most critical—they are key to distinguishing forehand drive from forehand chop and determining movement quality—while the torso and head are relatively static and contribute little to movement classification. The attention mechanism enables the model to automatically learn these importance differences, focusing computational resources on critical regions. Second, multi-scale convolutional kernels were applied in the temporal dimension to capture movement features at different temporal scales. The explosive force at the moment of impact is reflected in rapid changes within a few frames, requiring small-scale convolution kernels for capture; the backswing and recovery processes span dozens of frames, requiring large-scale kernels for modeling. This multi-scale design ensures the model can capture both types of temporal features simultaneously. Third, label smoothing regularization was added to the loss function to prevent overfitting. Novice students' movements often exhibit significant individual differences; standardized label smoothing prevents the model from relying too heavily on specific samples in the training set, improving generalization for recognizing non-standard movements.

After optimization, the ST-GCN model can recognize four fundamental movements: forehand drive, backhand push, forehand chop, and backhand chop. Each movement outputs corresponding confidence scores, with the highest score taken as the classification result. Table 2 presents the performance comparison between the ST-GCN model and baseline models.

Table 2. Action Recognition Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
3D-CNN	84.3	83.7	84.1	83.9
LSTM	81.6	80.9	81.3	81.1
GCN	88.2	87.9	88.1	88.0
ST-GCN (Ours)	**92.7**	**92.4**	**92.6**	**92.5**

Confusion matrix analysis shows that the misclassification rate between forehand drive and backhand push is below 5%, as these two movements have distinct force application directions and arm trajectories. A misclassification rate of approximately 8% exists between forehand chop and backhand chop, primarily due to both being rubbing-type movements with similar arm trajectories, requiring more refined wrist movement features for differentiation.

3.3 Action Scoring Model Design

Building upon action classification, a continuous scoring model was constructed to enable quantitative evaluation of students' movement quality. The scoring model was trained using regression loss functions, with expert-annotated action quality scores serving as supervision signals, enabling the model to learn the mapping from keypoint sequences to quality scores.

The scoring model integrates three feature dimensions. First, keypoint position accuracy is measured by calculating the Euclidean distance between student keypoints and standard action templates. Smaller positional deviation indicates closer approximation to the standard posture. Second, joint angle matching degree is evaluated by calculating deviations in shoulder, elbow, and wrist joint angles from standard angles. These three joints form the kinetic chain for table tennis strokes; angle deviations directly affect stroke quality. Third, motion trajectory smoothness is assessed by computing the rate of change in keypoint acceleration to measure movement fluidity. Jerks and pauses indicate lack of proficiency, while smooth motion trajectories reflect good control capability.

Standard action templates were constructed using clustering methods. Keypoint sequences extracted from demonstration videos of multiple national second-level and above athletes were aligned using dynamic time warping, followed by calculation of mean sequences. Considering technical style differences, three representative templates are retained for each movement type, with the best matching result used for scoring. The weights of the three dimensions were determined through expert consultation, with joint angle matching receiving the highest weight due to its decisive role in technical quality.

Table 3 presents the performance of the action scoring model on the test set.

Table 3. Action Scoring Model Performance Evaluation

Action Type	RMSE	MAE	R^2
Forehand Drive	3.86	2.97	0.84
Backhand Push	4.12	3.24	0.81
Forehand Chop	4.35	3.48	0.78
Backhand Chop	4.58	3.62	0.76
Weighted Average	4.18	3.27	0.80

The Pearson correlation coefficient between model scores and expert ratings is 0.81, indicating that the model effectively fits expert scoring standards. From the perspective of movement types, forehand drive scoring accuracy is highest, while backhand chop accuracy is relatively lower. Analysis suggests that the forehand drive has a relatively fixed movement trajectory, making it easier to establish standard templates; the backhand chop involves more subtle wrist adjustments with greater movement variability, posing greater challenges to the scoring model. Scoring errors are primarily distributed within ±5 points. Scoring accuracy is higher for students with better technical foundations, while some deviation is observed for students with non-standard movements, which relates to the limited representativeness of standard templates.

3.4 Bi-LSTM-Based Learning Analytics Module Optimization

To track student capability changes over time and generate personalized intervention strategies, a bidirectional Long Short-Term Memory (Bi-LSTM) network was introduced to construct the learning analytics module. LSTM effectively processes time-series data and retains long-term dependencies through gating mechanisms, making it suitable for modeling the dynamic process of skill evolution—skill improvement is often non-linear, with plateau periods and breakthrough periods, and LSTM can capture these complex temporal patterns.

The student training state vector contains four dimensions. Action score reflects current movement quality and serves as the core indicator for evaluating student proficiency. Error type encoding captures specific technical deficiencies, including five categories: racket angle deviation, insufficient backswing amplitude, improper hitting point position, inappropriate center of gravity transfer, and slow recovery speed. Progress margin measures score change relative to the previous three training sessions, reflecting learning rate. Training engagement index is comprehensively calculated based on training duration and number of completed movements, reflecting student commitment.

The bidirectional LSTM structure is a key optimization in this study. Traditional LSTM can only utilize past information, whereas bidirectional LSTM includes both forward and backward processing directions, enabling more accurate evaluation of individual training session effectiveness by combining pre-training foundation levels with post-training improvement outcomes. For example, when a student's score improves in one session but subsequently declines, bidirectional LSTM can integrate information from both sides to determine whether this represents genuine progress or a temporary fluctuation.

The second optimization is the introduction of attention mechanisms to assign weights to learning states at different time steps. Throughout the 8-week training process, certain key nodes hold special significance: when a student first reaches a certain skill threshold, experiences consecutive days of significant improvement, or achieves a breakthrough after a plateau period. The attention mechanism enables the system to focus on these key nodes, assigning higher weights and thus more accurately identifying changes in learning stages.

Based on the hidden states output by the bidirectional LSTM, students are categorized into four learning stages. Novice stage: unfamiliar movements, high error rates, with students still learning basic movement patterns. Improvement stage: basically standardized movements, insufficient stability, with students able to perform movements correctly but susceptible to fatigue or interference. Consolidation stage: stable movements, details requiring refinement, with students having mastered basic techniques but needing to optimize finer aspects. Proficiency stage: standardized movements, capable of combined training, with students possessing the foundation for tactical training. Each stage is matched with corresponding intervention strategies, including demonstration guidance, decomposed practice, comparative feedback, and intensive training. The strategy library is constructed and expanded based on the "3+1" digital teaching model proposed by Xie et al. [4].

4 Experimental Design and Result Analysis

4.1 Dataset Construction

To train and evaluate the models, training video data was collected from a university table tennis course. A total of 86 students (48 male, 38 female) participated, all undergraduate students enrolled in table tennis elective courses with beginner-level or no prior table tennis experience. Each student completed 8 training sessions, one per week, with 10 valid action videos collected per session, resulting in 6,880 video samples.

Video data was annotated by three national second-level table tennis athletes. Annotation included action type (forehand drive, backhand push, forehand chop, backhand chop), action quality score (0-100), and error type (five categories). Each video was independently annotated by all three annotators, with the mean value taken as the final annotation. The inter-annotator consistency coefficient was 0.87, indicating high annotation reliability. The dataset was divided into training, validation, and test sets at a ratio of 7:1:2.

4.2 Experimental Setup

Experimental equipment included an Intel Core i7-12700 CPU, NVIDIA RTX 3080 GPU, and 16GB RAM. The camera was a Hikvision industrial camera with 1280×720 resolution and 30fps frame rate. Model training was conducted using the PyTorch framework with the Adam optimizer, initial learning rate of 0.001, batch size of 32, and 100 training epochs. The ST-GCN model comprised 9 layers of spatiotemporal graph convolution, each followed by a Dropout layer with dropout rate of 0.5. The Bi-LSTM model consisted of 2 layers of bidirectional structure with hidden layer dimension of 128.

4.3 Teaching Effectiveness Validation

To validate the system's effectiveness in improving teaching outcomes, a quasi-experimental study was conducted. The 86 students were randomly divided into an experimental group and a control group, with 43 students in each group, and an 8-week (16-session) teaching experiment was conducted. Both groups were taught by the same instructor with consistent teaching content, schedule, and training volume. The only difference was that the experimental group received real-time feedback from the proposed system, while the control group received only unified teacher instruction.

Students in the experimental group received system feedback during each training session, including action scores, error prompts, and correction suggestions. Feedback was delivered through two modalities: voice broadcast provided brief evaluations immediately after movement completion, while on-screen visualization displayed keypoint trajectories and comparisons with standard movements. Students in the control group received only verbal instruction from the teacher during training.

Pre-test (week 1) and post-test (week 8) assessments evaluated students' forehand drive and backhand push movements, scored independently by three professional teachers with the mean value taken. Table 4 presents the pre-test and post-test score comparisons between the experimental and control groups.

Table 4. Pre-test and Post-test Score Comparison Between Experimental and Control Groups

Group	Action Type	Pre-test Score	Post-test Score	Improvement	Improvement Rate
Experimental	Forehand Drive	72.4	88.7	16.3	22.5%
Control	Forehand Drive	71.8	79.6	7.8	10.9%
Experimental	Backhand Push	68.3	83.5	15.2	22.3%
Control	Backhand Push	67.9	75.2	7.3	10.7%

The experimental group's average forehand drive score increased from 72.4 to 88.7, an improvement of 16.3 points; the control group increased from 71.8 to 79.6, an improvement of 7.8 points. The experimental group's average backhand push score increased from 68.3 to 83.5, an improvement of 15.2 points; the control group increased from 67.9 to 75.2, an improvement of 7.3 points. Independent samples t-test showed that post-test scores of the experimental group were significantly higher than those of the control group (forehand drive: $t=4.32$, $p<0.001$; backhand push: $t=3.98$, $p<0.001$).

From the perspective of learning efficiency, the average number of training sessions required for experimental group students to reach a score of 80 or above was 5.2, compared to 6.8 for the control group, representing a 23.4% shortening of the skill acquisition cycle. Questionnaire survey results indicated that 89% of experimental group students found the system feedback "very helpful," and 84% expressed willingness to continue using the system for autonomous training.

4.4 System Operation Effect Analysis

Analysis of system operation data shows that during the 8-week training period, the experimental group triggered a total of 2,147 intervention strategies, averaging approximately 50 per student. Strategy distribution varied significantly across learning stages: in the novice stage, "decomposed practice" strategies dominated, accounting for 68%; in the improvement stage, "demonstration guidance" and "comparative feedback" strategies increased to 45%; in the consolidation stage, "intensive training" strategies had the highest proportion at 52%. The changes in strategy distribution align with students' progression through learning stages, indicating that the system can dynamically adjust intervention methods according to student status.

5 Discussion and Conclusion

5.1 Technical Advantages

The system demonstrates three technical advantages. First, an end-to-end action analysis pipeline avoids subjectivity in manual feature extraction. ST-GCN achieves 8.4 percentage point improvement over 3D-CNN. Second, learning analytics and intervention strategies are deeply integrated, with Bi-LSTM dynamically tracking trajectories and adaptively adjusting strategies. Third, quantitative evaluation combined with visual feedback supports both objective assessment and intuitive understanding.

Furthermore, compared to existing research, this study offers several distinct contributions. Unlike prior work that focuses on isolated technical problems, this system integrates pose estimation, action recognition, scoring, and learning analytics into a unified pedagogical framework. Unlike systems designed for competitive athletes, this work is specifically tailored for beginner-level university students, with lightweight deployment requirements suitable for classroom settings. Unlike approaches that treat all students uniformly, this system implements personalized intervention strategies based on dynamic learning stage classification, adapting to individual progress trajectories.

Third, quantitative evaluation is combined with visual feedback. Action scoring transforms originally subjective evaluations into objective numerical values, helping students establish clear awareness of movement quality. Combined with keypoint trajectory visualization, students can intuitively see differences between their own movements and standard movements, enhancing training focus and effectiveness.

5.2 Limitations and Future Directions

This study has certain limitations. First, the dataset scale is limited, containing training data from only 86 students from a single university. Model generalization capability requires validation with larger-scale, more diverse data. Second, action recognition covers only four fundamental movements, without including more technical types such as serving, footwork, and combination techniques, which also require personalized guidance. Third, intervention strategies are currently based on expert rule-base matching. Although capable of meeting basic teaching needs, rule coverage is limited. Future research could explore reinforcement learning methods to achieve more intelligent strategy generation.

Future research directions include: expanding dataset scale through multi-institution collaboration to collect more student samples; enriching action types to cover the complete table tennis technical system; exploring multimodal data fusion by incorporating wearable sensor data to improve motion capture accuracy; introducing generative adversarial networks for personalized action demonstration video generation; and developing mobile applications to reduce system deployment costs and promote technology accessibility.

6 Conclusion

This paper proposed a personalized training intervention system integrating computer vision, deep learning, and learning analytics for university table tennis instruction. The system employs OpenPose for pose estimation, ST-GCN for action recognition and scoring, and Bi-LSTM for learning state tracking. By systematically reviewing the limitations of existing research and addressing the identified gaps through an integrated, personalized, and pedagogically validated approach, this study provides a certain breakthrough over prior work. Experimental results demonstrate effective improvement in students' table tennis skill levels and shortened skill acquisition cycles. This study provides a feasible solution for applying artificial intelligence to university physical education.

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