AEM JOURNAL.ORG

Artificial Intelligence-Enabled Physical Education: Design of a Personalized Teaching System for Track and Field Projects Based on Motion Recognition Technology

Lining Chen
Center for Public Physical Education Instruction, Zhongyuan Institute of Science and Technology, Xuchang 461000, Henan, China
Corresponding author: Lining Chen (e-mail: chenlining8@163.com)

ABSTRACT Personalized track-and-field teaching requires accurate recognition of human motion patterns, rapid feedback, and quantitative diagnosis of technical deviations. To address the limitations of conventional instruction in handling individual differences and delayed motion correction, this study designs an artificial-intelligence-enabled teaching system based on motion recognition technology. A high-definition camera is used to collect movement videos, and human skeletal key points are extracted and normalized to reduce the influence of body shape and shooting distance. A temporal graph convolutional network is constructed to model spatial skeleton topology and temporal movement evolution, enabling recognition and stage division of running, jumping, and throwing sub-actions. On this basis, a personalized evaluation model integrates biomechanical indicators and expert rules to identify technical deviations and generate targeted correction suggestions. Experimental results show that the recognition model achieves an average accuracy of 94.2%, recall of 93.8%, and F1 score of 93.9%. In classroom application, the system improves motor-skill scores, increases effective practice frequency, and raises overall learning satisfaction to 4.5/5. The study provides a practical framework for vision-based sensing, spatiotemporal motion analysis, and intelligent physical-education systems.

INDEX TERMS motion recognition, temporal graph convolution, vision-based sensing, spatiotemporal signal processing, personalized teaching

I. INTRODUCTION

THE current research in the field of physical education is developing in various aspects and researchers are indulging in a regular debate on issues like maximization of teaching models, amalgamation of values, invention of assessment approaches and professional growth of teachers. Physical education is a vital part of school education system as it fulfills an irreplaceable role in ensuring physical and mental well-being of the students, teamwork, and resilience. As the basic part of physical education, track and field includes some of the most basic motor skills, i.e. running, jumping, and throwing; the pedagogical approach directly influences the cultivation of students' fundamental athletic competencies and development of their interest in sports directly.

This paper concentrates on the teaching experience in a track and field, the design and construction of a customized teaching system using the motion recognition technology. The objective of the system is to solve real life issues in teaching of track and field e.g. the complications in the consideration of individual differences in movement, timeliness of response, insufficient availability of the teaching tool, where lightweight implementation, instant feedback and personal advisory are the primary goals. This research will evaluate the effective ways in which artificial intelligence can support physical education by building an entire chain of technology, which involves the data collection phase, motion recognition phase, evaluation models, and generation of the teaching strategy, which could serve as a guideline in the reform and use of technology in the area in future studies. According to the empirical requirements of AI-enabled physical education, this paper will design a customized instructional system based on the adaptation and use of motion recognition technology in track and field to offer realistic technical solutions and practical directions to the exact and intelligent transformation of physical education.

II. RELATED WORK

Baena-Morales et al. [1] pointed out that physical education can effectively cultivate students' critical and systematic thinking through experiential learning, interdisciplinary integration and reflective practice. Salahudin et al. [2] analyzed the feasible paths for integrating values education into physical education courses and proposed corresponding implementation strategies. Fernandez-Rio and Iglesias [3] found that different teaching models have positive effects on improving students' motor skills, learning motivation and socialemotional abilities, but the advantages of each model are different. Aliriad et al. [4] measured students' motor skill levels and learning motivation before and after the intervention and compared the differences between the two groups through statistical analysis. Kadhim et al. [5] explored the application mechanism of artificial intelligence technology in the benchmark test of physical education curriculum infrastructure.

Herrero-González et al. [6] retrieved and analyzed relevant research on formative and shared assessment in physical education and physical education teacher education. Wallace et al. [7] explored the interaction between teachers' digital competence, technology application strategies and students' learning experience. Fenandez-Rio et al. [8] revealed the key factors affecting students' course selection decisions through integrated analysis of quantitative and qualitative data. González-Calvo et al. [9] explored teachers' experiences and dilemmas in technology adaptation, teaching content reconstruction and teacher-student interaction maintenance. Baena-Morales et al. [10] found that physical education teachers generally agree on the importance of sustainable development goals. This paper is based on the practical needs of empowering physical education teaching with artificial intelligence. It designs a personalized teaching system around the adaptation and application of motion recognition technology in track and field projects, aiming to provide a feasible technical path and practical solution for the precise and intelligent transformation of physical education teaching.

III. METHODS

A. CONSTRUCTION OF TRACK AND FIELD EVENT MOTION DATA ACQUISITION AND PREPROCESSING MODULE

In an effort to ensure that the movements of the students in the track and field are properly recognized, this research initially developed a special motion data acquisition and preprocessing module. This module will employ a conventional high definition video camera as a video capture apparatus, positioned within the periphery of the teaching track and field to provide universal coverage of the most important areas of movement in respect to running, jumping, and throwing activities. The camera was placed at a height of 2.5 meters with a downward angle of 30 degrees of the ground to allow the camera to capture the important points of the human bodies in the frame despite the movement. The resolution was adjusted to 1920x1080, and the frame rate to 30 frames per second to trade off the image detail and the data processing burden. The system captures the identity of the student, the practice item, and the practice round and the time of the practice round in synchrony during the data collection process. Once all students, who are involved in the teaching experiment get into the specific collection facility, the system automatically begins to record videos until the conclusion of the practice round. To address the differences between the speed of various motions in track and field competitions, the system implements an adaptive frame sampling approach during the preprocessing phase. ITo ensure the capture of critical technical phases without missing force exertion details, the system adopts a stratified sampling strategy based on the minimum duration of submovements. For high-speed actions like sprinting and jumping, where technical transitions occur within milliseconds, all 30 frames of the video are stored. For relatively slower movements, data redundancy is lowered by recording one frame per three frames (10 fps). This reduced rate still provides sufficient temporal resolution (100ms per frame) to satisfy the Nyquist sampling requirements for these specific motion frequencies, ensuring the integrity of the force exertion and buffering phases while optimizing processing speed [11-12].

The main idea behind the preprocessing module is the recognition and coordinate recovery of landmarks in the human skeleton. The present study uses an enhanced high-resolution network as the important model of point detection. The network enhances the accuracy with which distal joints of the limbs are localized by aggregating multi-scale features, and retains high-resolution feature maps. The model reflects 17 prominent points in the skeleton of a human being such as head, shoulders, elbows, wrists, hips, knees, ankles and the central point of the torso. The model provides the two-dimensional pixel locations and the confidence value of the key point of a given frame. A confidence score below 0.7 indicates that the keypoint detection is unreliable. To mitigate this, the system evaluates the motion type: for low-velocity movements, linear interpolation is employed, whereas for high-speed dynamic segments such as sprinting or jumping, a cubic spline interpolation is utilized. This high-order approach better captures the non-linear trajectories of joint movements and minimizes motion artifacts that could otherwise mislead the spatiotemporal graph convolutional modules. In order to enhance the quality of the key point data to capture the movements in a track and field, the preprocessing module further makes the original coordinates normal. All key point coordinates are transformed to relative coordinates using the center of the left and right shoulders as the origin, the scale as the length of the torso and the scale as the length of the scale. This step removes the effect that differences between students in height and body shape, and shooting distance have on the features of movement, leaving the following model of movement recognition to concentrate on the geometrical properties of the movement posture itself. The processed data are stored sequentially where each sample has a continuous sequence of T frames of key points coordinates. T is varied dynamically depending on the event: two seconds to 60 frames of sprint movements, one and a half to 45 frames of throwing movements so that the full initiation of the entire technical movement, force exertion, release, and buffering phases are all involved.

B. CONSTRUCTION OF TRACK AND FIELD ACTION RECOGNITION MODEL BASED ON TEMPORAL GRAPH CONVOLUTION

This paper builds a motion recognition model on the basis of temporal graph convolutional networks to classify and identify main steps of track and field dynamics with the help of motion data, which are performed by students automatically, on the basis of the preprocessing of the motion data. The model represents the chain of the important points in the skeleton of the human being as a spatiotemporal graph structure, where the important point in the spatial dimension is a topological graph and the important point is a continuity between the various frames of the temporal dimension. By using the operations of graph convolution, the model is able to concurrently discover the spatial structural attributes of the human skeleton and the temporal evolution attributes of the movement. It has an advantage compared to the traditional techniques that used RGB images in that it does not depend on the background interference, is computationally efficient, and it is highly capable of generalization [13-14].

The input of the model is a preprocessed sequence of keypoints whose size is Tx JxC, T the number of frames in a sequence, J the number of key points (17) and C the coordinate dimension (2). An initial spatial graph convolutional layer is then applied to obtain skeleton topological feature of a frame. The spatial graph convolution adjacency matrix is defined according to the natural connectivity of the human skeleton, i.e. adjacent joints are joined together by an edge. In order to add more movement parts into the model, this paper is splitting the adjacency matrix into three parts, namely, the root node itself, centripetal nodes, and centrifugal nodes, as parts of the stable ones, parts close to the torso, and far parts to the torso respectively. The model uses the multi-channel graph convolution to give inputs as coordinates of key points into high-dimensional vectors of features.

The model then adds several spatiotemporal graph convolutional modules, consisting of a spatial graph convolutional layer and a time convolutional layer. The temporal convolutional layer adopts the one dimensional convolutional kernel, it operates over a sequence of features of every key point along the temporal axis with a sliding window. The kernel size will be 9, the stride will be 1 and the padding method will make sure that the length of the output sequence matches with the input. The model can learn dynamic information, including motion velocity, acceleration and the rate of change of joint angle, by learning motion changes among successive frames in the time dimension. A batch normalization layer and a ReLU activation function come after every spatiotemporal graph convolutional module to expedite the model convergence and improve nonlinear expressive power.

The model is sequentially linked to a global average pooling layer and a fully connected classification layer. The global average pooling layer downsizes the multiple channel feature map output at the spatiotemporal graph convolution into a single dimensional feature vector, and the fully connected layer projects the feature vector into the probability distribution of each action category. Since the various actions in a track and field event differ greatly in length of time, critical postures, and distribution of force, another branch of action phase classification is added prior to the classification layer. It is a branch that sub-breaks the frame sequence of every sample into three which include preparation phase, main force exertion phase and buffer recovery phase and offers temporal synchronization to later personalized evaluation.

In this study, data gathered under actual teaching settings in tracks and fields was used as a training set during the model training phase. The training set was composed of 12 sub-movements in track and field including sprint start, mid-race run, sprint, long jump approach run, take-off, standing posture in air, landing, shot put glide, end exertion and release. There were 40 students playing each movement and 6 repetitions per student, which made a total of 2880 valid samples. The classification loss was the cross-entropy loss, and an auxiliary loss function was also presented the movement stage segmentation. The weighted sum of the two functions gave the total loss, in which the weight coefficients were set at 0.8 and 0.2 respectively. The Adam optimizer was adopted, with the initial learning rate of 0.001, that decreased to 0.1 of the original learning rate at the end of every 20 training epochs, making a total of 100 training epochs.

C. GENERATION OF PERSONALIZED EVALUATION MODEL AND TEACHING STRATEGIES FOR TRACK AND FIELD MOVEMENTS

This paper developed an individual evaluation model to track and field movements and teaching strategy generation module. The main concept of this module is to translate the masterful knowledge into quantifiable movement evaluation indicators, and when these are compared to the standard movement templates, the distinct deviation of students becomes detectable, thus creating the personalized content of the teaching instructions.

To begin with, based on the principles of sports biomechanics and teaching experience in physical education, a set of quantitative evaluation indicators was extracted in this research regarding every track and field submovement. Using the mid-running movement in sprinting as an example, indicators used in the evaluation would be the lowest knee angle during support movement, the angle of the trunk and thigh during the swing movement, the front bending angle of the trunk, the amplitude of the hip extension at the time the supporting leg is off-ground, the equality of both the left and right steps and the proportion of contact time on the ground to time in the air. In the case of the long jump take-off movement, the emphasis is placed on the angles of the hip, knee and ankle joint at the time the take-off leg lands, the maximum angle of knee flexion during the cushioning step of the take-off leg and also the forward swing angular velocity of the swing leg and also the extent of trunk backward lean. Every evaluation indicator has the ideal range and acceptable range. The recommended range is the excellent technical standard and the satisfactory range is the basic technical standard.

The personalized model of evaluation applies to compute the individual value of the above mentioned evaluation indicators on the basis of the key points sequence output of the middle layer of the motion recognition model. In the case of joint angle indicators, the angle value can be computed based on the spatial coordinates of three neighbouring key points using the law of cosine. The duration and the proportion of each stage are mined using time related indicators by analyzing the rate of change of the key point coordinates between time intervals and combination of the results of the motion stage segmentation. In the case of indicators of symmetry, the difference coefficient of related joint angles or motion amplitudes on the left and right sides is then obtained. The calculation of all indicators is done in a real-time stream of data with a delay of at most one image processing frame.

Having calculated the indicators, the system compares the evaluation indicator of movement of the student with the standard template one item at a time. This general template is set by statistical evaluation of high level student mobility by skilled instructors and quantitative accounts of track and field technical criterion. The system generates a weighted scoring model of each sub-movement in order to fully assess the quality of the movement. The weight of each evaluation indicator is calculated based on the effect on movement and the risk of injury, and all have a weight of 100. The scoring model will give out a percentage value which is the intuitive representation of the degree of technical completion of this movement by the student. According to the results of the deviation analysis, the teaching strategy generation module consults an existing error correction knowledge base that reacts to generate appropriate instructions in teaching and visual prompts. This base of error-correcting knowledge, which experts in physical education, through several years experience, accumulated, relates typical deviations in movement to typical causes, the common correction techniques, and suggested practice aids. To illustrate, in an instance where the system finds the "minimum knee angle during the support phase" of a student too large during a sprint it decides that this is a failure of the cushioning by the supporting leg, that the support time has been made too long, and the student experiences the biomechanical sensation of explosive knee extension and therefore the knowledge base suggests the correction to bolster ankle rigidity, shorten the support phase, and experience the sense of In the event of multiple deviations, the system identifies the overriding correction direction depending on the relevance of the seriousness of the deviation, and the level of priority in influencing the chain of movement, without overloading the information.

IV. RESULTS AND DISCUSSION

A. PERFORMANCE EVALUATION AND EXPERIMENTAL ANALYSIS OF ACTION RECOGNITION MODEL

To verify the practical effectiveness of the constructed temporal graph convolutional action recognition model in track and field teaching scenarios, this study conducted a systematic performance evaluation in a real teaching environment. The evaluation dataset was independent of the model training data, consisting of 1080 test samples from 30 students who did not participate in training, each performing each sub-action three times. Evaluation metrics included classification accuracy, recall, F1 score, and average processing time, while also recording the model's performance differences across different action categories.

Table 1 summarizes the recognition accuracy and recall data for each major track and field sub-movement.

TABLE 1. Performance Statistics of Track and Field Sub-Motion Recognition Model

Action categories	Accuracy (%)	Recall rate (%)	F1 score (%)
sprint start	89.6	88.9	89.2
Sprinting during the middle of the race	96.3	96.1	96.2
sprint	94.2	93.8	94.0
Long jump approach run	90.3	89.7	90.0
Long jump take-off	96.8	96.5	96.6
Straight-up aerial posture	94.5	94.0	94.2
Long jump landing	92.7	92.2	92.4
Shot put glide	95.1	94.8	94.9
Final push in the shot put	96.0	95.6	95.8
Shot put release	93.4	93.1	93.2
average	94.2	93.8	93.9

Experimental results show that the action recognition model achieved an overall classification accuracy of 94.2% across 12 track and field sub-actions, with a weighted average recall of 93.8% and a weighted average F1 score of 93.9%. Looking at individual class performance, the recognition accuracy for typical actions such as the mid-race running phase of sprints, the take-off in the long jump, and the final push in the shot put all exceeded 96%, indicating that the model is highly sensitive to actions with distinct posture features and force exertion rhythms. In contrast, the recognition accuracy for the sprint start and the long jump approach run were 89.6% and 90.3%, respectively, slightly lower than the overall average. Analysis revealed that the posture changes in these two types of actions are relatively continuous over time, with a short transition interval between the preparatory posture and the instant of launch during the start phase, and high similarity in the amplitude and period of different phases during the approach run, leading to slight confusion at phase boundaries.

To verify the superiority of the temporal graph convolutional network (ST-GCN) used in this study, comparative experiments were conducted against traditional baselines, including Support Vector Machine (SVM) and a standard Convolutional Neural Network (CNN). The results showed that while SVM and CNN achieved overall accuracies of 78.4% and 86.2% respectively, the ST-GCN reached 94.2%. The performance gap was most pronounced in complex multi-phase actions like the shot put release, where the ST-GCN's ability to model spatial skeletal connectivity and temporal dependencies simultaneously provided a significant advantage over models that ignore the topological structure of the human body.

B. VERIFICATION OF THE ACCURACY OF THE PERSONALIZED EVALUATION MODEL IN DIAGNOSING STUDENT BEHAVIORAL DEVIATIONS

The most important feature of the personalized evaluation model is that it is able to detect the technical deviations of the movements of students and can deliver the diagnostic results with pedagogical guidance value. In order to check on the validity of this model, this study developed a comparative validation experiment, which was in the choice of 30 normal students as a test subject. Every student performed 5 repetitions of three common track and field movements, as sprint during the race, long jump take-off, and shot put final push, consisting of 450 movement samples. The system automatically estimated different evaluation indicators in each sample and produced a deviation diagnostic report. At the same time, three professional teachers who have more than ten years of training experience in track and field were proposed to independently view the movement videos of the students and manually detect the same group of samples, indicating the key features of deviations in each movement.

The consistency of diagnostic results of the system and the expert diagnostic results was compared, and the Kappa coefficient was used as the index of consistency. At the same time, the precision of the system diagnosis was estimated (most experts opinion was the gold standard). The findings indicated that in the case of the mid-running motion in sprinting, the mean Kappa coefficient between the system and the expert diagnostic outcome was 0.82, where the rate of accuracy stood at 89.3; in the case of the take-off motion in long jump, the mean Kappa coefficient was 0.79, the accuracy rate was 87.5; and in the case of the final force exertion The overall average Kappa coefficient of the three motions is equal to 0.82, which suggests that the level of consistency between the diagnosis of the system and the expert diagnosis is great, meaning that the system is capable of defining the key technical deviations of the movements in students.

Table 2 below will demonstrate the format of the output and diagnostic content of the personalized evaluation model, with a sample of a sprint running motion used to exemplify the evaluation indicators calculated by the system concerning a single motion of a student, the deviation analysis of the template, and the suggestions of corrections. The student had notable deviations in three indicators, minimum knee angle during the support phase, knee lift amplitude of swing leg, and hip extension amplitude at the point where the supporting leg has been off-loaded. The total of 74 points were obtained, and the system revealed two key issues, namely, a lack of cushioning and a lack of knee lift amplitude and offered specific training recommendations.

To further verify the effect of personalized evaluation models on students' technical progress, this study compared the improvement effects of two groups of students—one using systematic feedback and the other receiving only traditional teacher guidance—on their sprint running movements. Forty students with similar initial technical levels were randomly divided into an experimental group and a control group, with 20 students in each group. The experimental group received a personalized evaluation report and error correction suggestions generated by the system after each practice session, while the control group received equivalent individualized feedback provided manually by professional coaches. This setup ensures that the

experimental comparison isolates the efficacy of the AI-driven system itself, rather than simply demonstrating the advantage of personalized attention over group instruction. After four weeks of targeted practice twice a week, the running movements of both groups were re-evaluated. The results showed that the experimental group's average improvement in overall movement score was 12.4 points, while the control group's average improvement was 7.1 points, indicating that the experimental group's improvement was significantly higher than that of the control group.

C. ANALYSIS OF THE SYSTEM'S TEACHING APPLICATION EFFECTIVENESS AND STUDENT ACCEPTANCE

A systematic teaching experiment was used to fully assess the application impact of the personalised teaching system developed in this research in a real situation of teaching within an eight week teaching course on the topics of track and field. The experimental group was a group of 2 classes consisting of 76 students and the second year of junior high school and 38 students in the experimental group and 38 students in the control group. Informed consent was obtained from all participants. The basic track and field skills of the two classes had previously not been found to differ significantly before the experiment. Both classes were taught by the same instructor, the teaching material and the plan of the lesson was similar. The system was introduced in the experimental class along with regular teaching. Students were able to view their individual recognition of movement, evaluation, deviation analysis and personal practice suggestions after each session of track and field practice using a terminal device. The control group was taught using the

TABLE 2. Examples of Personalized Evaluation and Diagnostic Results for Mid-Running Movements in Sprints

Evaluation indicators	Student measured values	Standard template range	Deviation	Error correction suggestions
Minimum knee joint angle during the support phase (°)	148	140-145	+3.2	Strengthen foot and ankle rigidity and shorten support time
Range of motion of the swinging leg knee lift (°)	92	100-110	-8.0	Strengthen hip flexors and improve forward swing during folding.
Forward tilt angle of the torso (°)	12	10-15	normal	-
Hip extension (°) at the moment the supporting leg leaves the ground.	172	165-170	+2.5	Exercises to improve hip flexibility
Left and right step size symmetry (%)	93	95-105	Slightly lower	Strengthen the specific strength of the weak leg
Time to ground/time to air	1.21	1.0-1.2	+0.01	normal
Overall score	74	A score of 80 or above is considered excellent.	-	It is recommended to perform back kick running exercises and high knee folding running exercises.

conventional techniques of teaching, which utilized the on-site teacher instruction and group responses only.

Four dimensions, namely the level of mastering skills, the level of teaching efficiency, the level of student participation, and the level of learning satisfaction, were assessed as the application effect of the teaching experiment. The degree of mastering the skills was measured with a standardized track and field skills test that consisted of 50 meter sprint, standing long jump, and forward shot put. The tests were rated by three physical education teachers who were not part of the experiment on their own and the mean value was taken as the final result. Teaching efficiency was quantified by the number of ‘effective practice sessions,’ defined as complete motion cycles where the athlete’s technical execution reaches at least 70% of the standard template score without injury-risk deviations, alongside the frequency of corrective feedback provided per unit of time. To evaluate the student participation, a combination of classroom observation scale and exercise heart rate monitoring was used in which the time in which students were focused and the average heart rate of students was recorded. The satisfaction scale on learning was acquired by way of a questionnaire survey, employing a five-point Likert scale; 76 questionnaires were given out and 76 valid questionnaires were returned. In the skills tests, the results yielded an average of 84.6, 82.3 and 85.1 in the 50meter sprint event, the standing long jump and the medicine ball throw respectively with the experimental classroom scoring 76.2, 74.8 and 77.9 respectively. The scores of the experimental group of the 3 tests were significantly higher than that of the control group, and they were statistically significantly different. Further discussion showed that the experimental group was especially unmatched in standardization of movement techniques particularly in areas where specific control was essential as starting reaction, position during long jump, and the angle of the throw. This means that real-time movement feedback and personalized guidance given by the system positively impact on students who develop the right movement representations and lighten the burden on making the wrong movements entrenched.

Regarding teaching efficiency, the experimental group had an average of 18.4 effective practice sessions to each student in the lesson compared to 12.7 effective practice sessions to each student in the control group. The mean time that the teachers of the experimental class devoted to the work with the group of error correction and explanation was 6.3 minutes per lesson, on the contrary, in the control class, it was 14.2 minutes. Since much of the repetitive motion diagnosis and feedback are delegated to the system, teachers are able to devote more energy to individualized instruction and maximizing the teaching organization, which increases dramatically the levels of classroom practice. In terms of student engagement, the students of the experimental classes had a focused rate of attention of 86.3 in classroom practice compared to 74.5 in the control classes. The mean of the students in the experimental class was in a range of 68 percent to 82 percent of the maximum of the heart rate, which was in the effective exercise intensity range, and the average heart rate of the students in the control class was lower and was more variable, which was indicative of a range of students: some of the students were lazy or going through the motions in the traditional teaching. The results of the learning satisfaction survey are shown in Table 3. Students in the experimental class scored significantly higher than those in the control class on three indicators: “I can clearly understand my own movement problems,” “I know how to improve after class,” and “I am more interested in physical education class.” On the indicator “Physical education class brings me a sense of accomplishment,” the experimental class scored 4.4 points, while the control class scored 3.7 points, indicating that the personalized teaching system, through precise feedback and visualized progress, enhanced students’ sense of learning achievement and self-efficacy. It is worth noting that the control class scored slightly higher than the experimental class on the indicator “I like my physical education teacher,” but the difference was not statistically significant. This suggests that the introduction of the system did not weaken the teacher-student relationship; on the contrary, by freeing teachers from repetitive tasks, teacher-student interaction became more focused on indepth guidance and emotional exchange.

TABLE 3. Comparison of Student Teaching Satisfaction Survey Results

Survey Project	Average score of the experimental class (out of 5)	Average score of the control group (out of 5)
I am able to clearly understand the problems with my movements.	4.6	3.4
After class, I learned how to improve my movements.	4.5	3.2
Physical education class gives me a sense of accomplishment	4.4	3.7
I am more interested in physical education class	4.3	3.5
I like my PE teacher	4.7	4.6
Overall satisfaction	4.5	3.6

Based on the above experimental results, the personalized teaching system designed in this study, based on motion recognition technology, demonstrates significant advantages in improving students' motor skills, increasing teaching efficiency, and enhancing student participation and satisfaction. The system's value lies not only in its technical capabilities for motion recognition and evaluation, but also in its reshaping of feedback mechanisms and learning paths in physical education, making previously difficult-to-achieve personalized teaching truly possible.

V. CONCLUSION

This study addresses the challenges of accommodating individual differences, delayed motion feedback, and limited teaching resources in track and field instruction. It designs and implements a personalized teaching system based on motion recognition technology. The system constructs a track and field motion recognition model using high-precision human skeletal keypoint detection and a temporal graph convolutional network, achieving accurate classification and stage division of various track and field submovements such as running, jumping, and throwing. Building upon this, a personalized evaluation model integrating sports biomechanical indicators and expert knowledge is constructed. This model enables multi-dimensional quantitative assessment of student movements, identifies individual technical deviations, and automatically generates targeted error correction suggestions and teaching guidance.

This study provides a reproducible technical solution and practical basis for the deep application of artificial intelligence technology in physical education. Future research can be further advanced in the following directions: First, expand the types of track and field events covered by the motion recognition model to include more technical movements such as hurdles, middle- and long-distance running, and javelin, forming a more complete track and field teaching support system. Second, optimize the model's robustness to complex scenarios by improving recognition stability under conditions of changing lighting and occlusion through data augmentation and multimodal fusion. Third, explore combining wearable sensor data with inertial measurement units and visual information to improve the recognition ability of deep technical features such as force transmission and muscle activation timing. Finally, promote deep integration of the system with the school's existing teaching management platform to achieve long-term tracking and analysis of student technical growth data, providing data support for physical education research and reform.

AUTHOR CONTRIBUTIONS

Lining Chen designed, collected and analyzed the data, and drafted the manuscript. Lining Chen conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Lining Chen participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] S. Baena-Morales, G. Merma-Molina, and A. Ferriz-Valero, "Integrating education for sustainable development in physical education: fostering critical and systemic thinking," International Journal of Sustainability in Higher Education, vol. 24, no. 8, pp. 1915-1931, 2023, doi: 10.1108/IJSHE-10-2022-0343.

[2] S. Salahudin, E. Irawan, and F. Furkan, "The Role of Physical Education and Sports in Shaping the Nation's Character," Champions: Education Journal of Sport, Health, and Recreation, vol. 2, no. 1, pp. 1-8, 2024, doi: 10.59923/champions.v2i1.91.

[3] J. Fernandez-Rio and D. Iglesias, "What do we know about pedagogical models in physical education so far? An umbrella review," Physical Education and Sport Pedagogy, vol. 29, no. 2, pp. 190-205, 2024, doi: 10.1080/17408989.2022.2039615.

[4] H. Aliriad, S. Adi, G. Manullang J, et al., "Improvement of motor skills and motivation to learn physical education through the use of traditional games," Physical Education Theory and Methodology, vol. 24, no. 1, pp. 32-40, 2024, doi: 10.17309/ tmfv.2024.1.04.

[5] A. Kadhim M A, A. Mashi A A, H. Al-Diwan L, et al., "Understanding the mechanism of conducting benchmark test for the infrastructure of physical education curricula in the age of artificial intelligence," International Journal of Elementary Education, vol. 13, no. 1, pp. 8-12, 2024, doi: 10.11648/j.ijeedu.20241301.12.

[6] D. Herrero-González, M. López-Pastor V, C. Manrique-Arribas J, et al., "Formative and shared assessment: Literature review on the main contributions in physical education and physical education teacher education," European Physical Education Review, vol. 30, no. 3, pp. 493-510, 2024, doi: 10.1177/1356336X231220995.

[7] J. Wallace, D. Scanlon, and A. Calderón, "Digital technology and teacher digital competency in physical education: a holistic view of teacher and student perspectives," Curriculum Studies in Health and Physical Education, vol. 14, no. 3, pp. 271-287, 2023, doi: 10.1080/25742981.2022.2106881.

[8] J. Fenandez-Rio, S. García, and A. Ferriz-Valero, "Selecting (or not) physical education as an elective subject: Spanish high school students' views," Physical Education and Sport Pedagogy, vol. 30, no. 5, pp. 563-575, 2025, doi: 10.1080/17408989.2023.2256762.

[9] G. González-Calvo, A. Barba-Martín R, D. Bores-García, et al., "The (virtual) teaching of physical education in times of pandemic," European Physical Education Review, vol. 28, no. 1, pp. 205-224, 2022, doi: 10.1177/1356336X211031533.

[10] S. Baena-Morales, A. Prieto-Ayuso, G. Merma-Molina, et al., "Exploring physical education teachers' perceptions of sustainable development goals and education for sustainable development," Sport, Education and Society, vol. 29, no. 2, pp. 162-179, 2024, doi: 10.1080/13573322.2022.2121275.

[11] F. Jastrow, S. Greve, M. Thumel, et al., "Digital technology in physical education: a systematic review of research from 2009 to 2020," German Journal of Exercise and Sport Research, vol. 52, no. 4, pp. 504-528, 2022, doi: 10.1007/ s12662-022-00848-5.

[12] O. Østerlie, J. Sargent, C. Killian, et al., "Flipped learning in physical education: A scoping review," European Physical Education Review, vol. 29, no. 1, pp. 125-144, 2023, doi: 10.1177/1356336X221120939.

[13] R. Burgueño, Á. Abós, J. Sevil-Serrano, et al., "A circumplex approach to (de) motivating styles in physical education: Sit uations-in-school-physical education questionnaire in Spanish students, pre-service, and in-service teachers," Mea surement in Physical Education and Exercise Science, vol. 28, no. 1, pp. 86-108, 2024, doi: 10.1080/1091367X.2023.2248098.

[14] D. Scanlon, M. Coulter, K. Baker, et al., "The enactment of the Socially-Just Teaching Personal and Social Responsibility (SJ-TPSR) approach in physical education teacher education: Teacher educators' and pre-service teachers' perspectives," Physical Education and Sport Pedagogy, vol. 31, no. 2, pp. 256-272, 2026, doi: 10.1080/17408989.2024.2319071.