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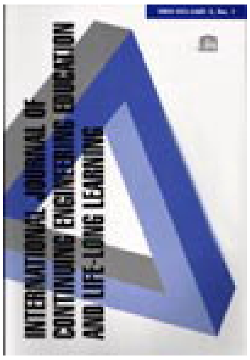

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Application of intelligent sensing and digital teaching mode in physical education teaching in colleges and universities

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Abstract: To address the limitations of traditional university physical education in time and space and its inability to meet individual student needs, this study proposes an intelligent sensing + digital teaching model. Centred on a smart sensor network, it collects real-time motion data via wearable devices, uses Kalman filtering for noise reduction, and applies CNNs for accurate movement recognition. K-means clustering analyses student profiles to generate personalised training programs. An interactive digital environment built on Moodle enables data visualisation, real-time feedback, and online guidance, forming a 'perception-analysis-feedback' closed-loop system. Experiments show improved data quality and recognition accuracy, with a 28.6% fitness improvement among low-level students, demonstrating the model's effectiveness in promoting scientific, precise physical education teachings.

Keywords: digital teaching; college physical education; personalised training; Kalman filter algorithm; convolutional neural networks.

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1 Introduction

With the rapid development of artificial intelligence technology, the field of education is undergoing a profound digital transformation. Especially in university physical education teaching, the traditional 'unified' teaching methods have been difficult to meet the increasingly significant learning needs of individual students. Limited by the length of teaching, site conditions, and the subjectivity of evaluation methods, traditional teaching has obvious shortcomings in real-time feedback and personalised guidance. Therefore, there is an urgent need to introduce information technology methods with high real-time and strong adaptability to improve the science and accuracy of the teaching process.

As the key carrier for realising intelligent perception and edge processing, intelligent sensing has increasingly prominent application potential in physical education teaching. Compared with general-purpose information technology platforms, it has the advantages of low-power operation, localised data processing and fast response, and can effectively deal with problems such as high data acquisition delay and poor recognition accuracy in traditional physical education teaching. Through the integration of sensor networks and lightweight AI algorithms, intelligent sensing can complete tasks such as motion capture and state discrimination in a resource-constrained environment. This technical feature provides solid support for the construction of a sustainable and scalable digital physical education teaching model.

Focusing on the real pain points of physical education teaching in colleges and universities, this paper proposes a new teaching model that integrates intelligent sensor networks and digital learning environments. This model uses intelligent sensing equipment as the front-end perception node, combines Kalman filtering to realise data preprocessing, and performs motion recognition based on CNN; the back-end relies on the Moodle platform to build an interactive learning space, supporting personalised training program generation, data visualisation, remote guidance and other functions. Through the closed-loop mechanism of 'perception-analysis-feedback', a complete chain from data-driven to behavioural intervention has been realised, and physical education teaching has been promoted to evolve in the direction of refinement and personalisation.

This article focuses on how intelligent sensing can form a synergistic effect with the digital teaching environment at the structural level, emphasising its unique value in terms of real-time, deployment flexibility, and energy consumption control. For the exploration of different single technologies, this article pays more attention to the overall design of the system architecture and its integration path in teaching practice. The influence of this model on students' physical fitness improvement and learning participation is verified through empirical methods, and the applicable boundaries and development potential of intelligent sensing technology in physical education scenarios are further revealed.

2 Related work

With the rapid development of artificial intelligence technology, the field of education is undergoing a profound digital transformation. By providing a practical and interactive learning platform, helping students deeply understand the combination of hardware and software, and cultivating innovation and problem-solving skills has become the key to teaching. Chen and Li (2024) constructed a sports teaching effect evaluation model based on embedded neural networks. Through the flexible processing capabilities of the efficient learning ability logic system embedded in the neural network, the sports teaching evaluation was realised intelligently and automatically. Pietersen and Smit (2024) explored how educators can adjust their practices to adapt to the potential advantages of artificial intelligence tools and proposed a new embedded system education method, in which students and large language models work together to create and solve problems. Pellicano et al. (2023) developed a series of new modular embedded tools aimed at improving students' abilities, learning motivation, and learning interest, and enhancing students' ability to complete project assignments independently. Oliveira et al. (2024) reviewed the evolution of embedded devices and wireless communication technologies in the past few decades, applied embedded machine learning in the context of the smart Internet of Things, and explored the trends in embedded system research. Wintle (2022) viewed current physical education as a tool to promote physical activity and suggested changing the physical education method that only focused on sports technology. A culturally relevant curriculum that included lifestyle sports and focused on mastering and enjoying through meaningful experiential methods was proposed as a feasible update to current practices. The shortcomings in physical education teaching are mainly reflected in the limited accuracy of complex movement recognition and the adaptability of personalised training strategies needs to be improved.

To solve the limitations of recognition effects, Hu (2022) used the classic factor analysis multivariate statistical technique and an iterative random forest algorithm. To evaluate the characteristics of machine learning in physical education courses, a comprehensive evaluation was conducted, and an optimised development strategy was proposed to promote physical education courses based on machine learning. Liu et al. (2022) designed and proposed an augmented reality solution for school sports training based on augmented reality technology: cloud network, Internet of Things, and remote users. The results of augmented reality simulation showed that the positive influence of the augmented reality environment, combined with the performance data of athletes and the input of sports coaches, was proven to improve the training and learning capabilities of school sports systems. Zong et al. (2022) based on the Internet of Things and deep learning algorithms, combined with psychological education, comprehensively evaluated the teaching effect and the impact on learning concepts by constructing a teaching evaluation index system for college sports majors. Jun believed that by using machine learning algorithms, physical education teachers could collect and analyse data on student performance and behaviour, and machine learning provided a more objective and accurate method for evaluating and grading students (Wang et al., 2024a). Wang (2024) proposed a Gaussian Hidden Chain Probabilistic Machine Learning, which used the Gaussian hidden chain model to estimate the characteristics of teaching quality evaluation and evaluate the factors related to physical education. The proposed model could improve students' physical education performance. However, these studies mostly focus on theoretical discussion or the application of a single technology, and lack systematic integration and practical verification of data-driven teaching models. In view of this shortcoming, this paper proposes a method of physical education teaching based on intelligent sensing and digitisation, which provides a new solution for scientific and precise physical education in colleges and universities.

3 Methods

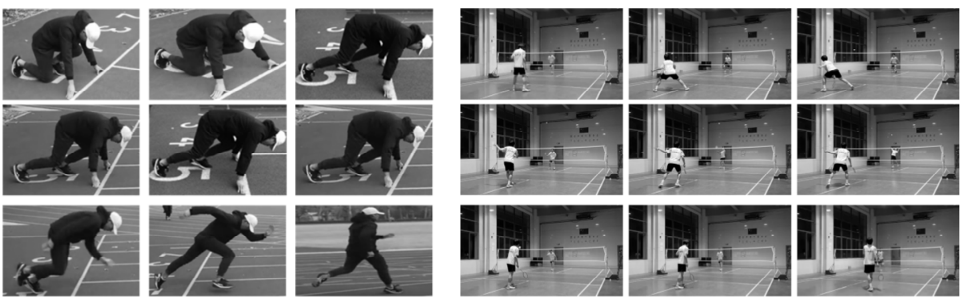
3.1 Smart sensor network and real-time data acquisition

In digital physical education teaching, real-time data collection is the core foundation. Through sensors and wearable devices, students' exercise status information can be captured, including key indicators such as heart rate, acceleration, steps, and trajectory.

These devices are usually based on micro-electro-mechanical systems (MEMS) technology, which can accurately perceive changes in human body movement and transmit data to the processing unit. The experimental subjects of this paper are 120 freshmen from a certain university, including 70 boys and 50 girls, aged between 18 and 20 years old. These students come from different professional backgrounds, are in good health, and have participated in the physical education courses prescribed by the school. To ensure the diversity and representativeness of the experimental data, the study divides the students into three sports level groups: high, medium, and low according to their physical fitness test scores and exercise habits. During the experiment, the LSM6DSL sensor is worn to collect motion data in real-time. The sensor has the advantages of small size, low power consumption, and fast response. Through a one-semester teaching experiment, the researchers track and record the students' performance in different training modes and their adaptation to the digital learning environment.

Some students' motion images are shown in Figure 1.

Figure 1 Some students' training images



In the digital sports teaching experiment, the reasonable division of the dataset is the basis for model training and evaluation. To ensure the generalisation ability and reliability of the action recognition model, this paper uses stratified random sampling to divide the data into a training set and a validation set. The training set is used for model parameter learning and feature extraction, accounting for 60% of the total data volume. By randomly selecting samples from each sports level group (high, medium, and low) in proportion, it is ensured that the training set contains the data distribution of all motion states. The validation set is used for hyperparameter tuning and model selection, accounting for 40% of the total data volume. The validation set is also generated by stratified random sampling to ensure that it has similar distribution characteristics to the training set.

After collecting the data, it is transmitted to the embedded main control unit (Raspberry Pi), and a simplified Kalman filter algorithm module is deployed on the terminal. The Kalman filter algorithm uses fixed-point operations instead of floating-point operations, reduces the complexity of matrix operations, and optimises the prediction and update steps. The Kalman filter algorithm is used to denoise the original signal (Wang et al., 2024b; Zhang et al., 2024). Its basic principle is as follows:

$$x_k = F_k x_{k-1} + B_k u_k + w_k \tag{1}$$

Among them, x_k represents the current state estimate; F_k is the state transfer matrix; B_k is the control input matrix; u_k is the control vector; and w_k is the process noise. Through continuous iterative updates, Kalman filtering can effectively reduce environmental interference and device errors, thereby improving data quality.

Kalman filtering uses the minimum mean square error criterion to suppress noise by combining the predicted and observed values of the system, thereby improving the accuracy of the data without losing key information (Bai et al., 2023). In addition, the algorithm has recursive characteristics and can update state estimates in real time. This efficient denoising method provides a more reliable data basis for subsequent action recognition and personalised training recommendations (Feng et al., 2023; Zhong et al., 2024).

In terms of data transmission, Bluetooth is used to upload the collected information to the cloud server. This process needs to consider data encryption and privacy protection, so the Advanced Encryption Standard (AES) algorithm is used to encrypt the data. The formula is as follows:

$$C = E(K, P) \tag{2}$$

Among them, C is the ciphertext; E is the encryption function; K is the key; P is the plaintext. In this way, the security of students' sports data is guaranteed.

Compared with the data processing architecture that the traditional cloud relies on, this article pays more attention to real-time and low-power characteristics. By completing data acquisition, filtering and preliminary identification on the terminal side, the dependence on external networks is reduced, and the response delay and energy consumption of the overall system are reduced.

3.2 Action recognition and analysis

Action recognition is a key link for the system to achieve precise feedback. By analysing the collected acceleration data and posture information, the student's movement type and execution quality can be judged (Bi and Liu, 2023). Common methods include threshold-based classification algorithms and deep learning models. For simple action recognition tasks, different motion modes can be distinguished by setting acceleration thresholds. For example, a threshold T_a is defined. When acceleration $a > T_a$, it is judged as 'running', otherwise it is 'walking'. The formula is as follows:

$$Action = \begin{cases} Running, & \text{if } a > T_a \\ Walking, & \text{if } a \le T_a \end{cases} \tag{3}$$

Although this rule-based method is simple, it is prone to misjudgement in complex scenarios.

To improve recognition accuracy, a convolutional neural networks (CNNs) model is applied. The model learns the spatiotemporal characteristics of actions by extracting feature maps (Yang et al., 2023; Perez and Toler-Franklin, 2023).

First, the collected data is normalised, and the range of the input data is scaled to a fixed interval to ensure that all features have the same scale. The formula is as follows:

$$x' - = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

Among them, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the data, respectively. The time series data is divided into segments of fixed length (one set of data every 2 seconds) for subsequent input into the CNN.

The input layer is the basis of the CNN model and is responsible for receiving raw data and converting it into a format suitable for subsequent processing (Guan et al., 2022). In action recognition, the input layer usually receives time series data (such as acceleration, angular velocity, etc.) or multi-dimensional image data from sensors. Its importance lies in providing high-quality initial data for the entire network to ensure the accuracy of subsequent feature extraction and classification tasks. In the model, the input layer data is a three-dimensional tensor represented as $N \times T \times C$. Among them, N is the number of samples; T is the time step (that is, the number of time points for each sample); C is the number of channels.

The convolutional layer is the core of CNN and is responsible for extracting local features from the input data (Javed et al., 2022; Sun et al., 2022). In CNN, MobileNetV3 is used to lighten the CNN architecture. MobileNetV3 applies 5 × 5 depth convolutions to replace some 3 × 3 depth convolutions. The squeeze-and-excitation (SE) module and h-swish (HS) activation function are applied to improve the model accuracy. The 3x3Dconv, 1x1Conv, and other convolutional layers are removed from the network structure, which reduces the amount of calculation and parameters.

The core convolution operation mainly relies on the linear bottleneck layer and the depth-separable convolution combined with the SE attention mechanism to enhance the model's expressiveness on key feature channels. The calculation formula is as follows:

$$X_{out} = HS(BN(DWConv\left(SE\left(Bottleneck\left(X_{in}\right)\right)\right) \tag{5}$$

Among them, Bottleneck reduces the number of input channels through low-dimensional compression; the SE module globally pools the features of each channel and generates weights to achieve channel attention adjustment; DWConv uses deep separable convolution to extract local features; BN is the batch normalisation to improve training stability.

The main function of the pooling layer is to reduce the dimension of the features extracted by the convolution layer while retaining the most important information. Through maximum pooling or average pooling operations, the pooling layer can reduce the size of the feature map, reduce computational complexity, and improve the model's generalisation ability. In action recognition, the pooling layer helps to remove noise and redundant information, so that the model pays more attention to the significant features in the data. The maximum pooling formula is:

$$P(i, j) = \max\left(X(i : i + k, j : j + k)\right) \tag{6}$$

Among them, k is the pooling window size.

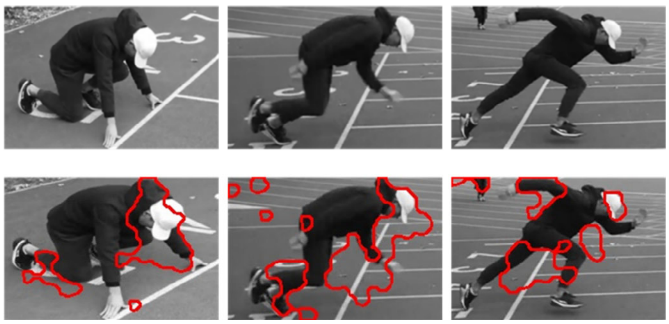
The fully connected layer is located at the end of the CNN and is responsible for integrating the previously extracted features and outputting the final result (Ren and Sun, 2024). In action recognition, the fully connected layer learns the relationship between different features by weighted summation of feature vectors, thereby judging the current action type. After multiple layers of convolution and pooling, the feature map is flattened into a one-dimensional vector and input to the fully connected layer for classification. Assuming that the flattened feature vector is F, and the output of the fully connected layer is O, the calculation formula is:

$$O = f\left(W_f * F + b_f\right) \tag{7}$$

Among them, W_f is the weight matrix of the fully connected layer; b_f is the bias term; f is the activation function.

Through multi-layer convolution and pooling operations, CNN can automatically capture high-dimensional features, thereby achieving more precise action classification. Some action recognition images are shown in Figure 2.

Figure 2 Action features (see online version for colours)



This structure not only retains the efficient characteristics of MobileNetV3, but also enhances the discrimination ability through SE and HS improving the nonlinear expression, so that the high motion recognition accuracy can still be maintained when running on the embedded terminal. Use CMSIS-NN to deploy the optimised model. The student movement data collected by the sensor will be preprocessed and input into the locally deployed CNN model, and the terminal will complete the feature extraction and motion recognition tasks.

3.3 Dynamic generation of personalised training plans

Based on the previous data analysis results, it is possible to formulate a personalised training plan for each student. First, the student groups are grouped by a clustering algorithm to better match the training needs. The grouping clustering method used in this paper is the K-means algorithm, whose goal is to minimise the sum of squared distances within the group:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \left\| x - u_i \right\| \tag{8}$$

Among them, C_i represents the i^{th} cluster, and u_i is the centre point of the cluster. Through iterative optimisation, K-means can divide students into several categories, each with similar sports characteristics (Sekhon and Singh, 2022; Gowda et al., 2022).

Through this clustering method, it is possible to identify groups of students with similar exercise patterns or needs, and lay the foundation for the subsequent formulation of targeted training plans. The advantage of K-means is that it is simple and efficient, can quickly process large-scale data, and adapt to the needs of dynamic adjustment (Kusy and Piotr, 2022). In digital sports teaching, this method not only improves the scientificity and rationality of grouping, but also ensures the precision of personalised training plans.

Next, based on the grouping results, combined with the students' goals and physical conditions, a personalised training plan is generated. For example, for strength training, the recommended load intensity L can be calculated by the following formula:

$$L = W * (1 + r / 100) \tag{9}$$

Among them, W is the base weight, and r is the adjustment coefficient, which is used to adapt to students of different levels.

In addition, the training plan will be dynamically adjusted to adapt to the progress of students. By regularly re-evaluating students' exercise data, the training content can be updated in a timely manner to ensure that it always meets the students' current abilities.

In the process of dynamic generation of personalised training programs, a stable two-way interaction mechanism has been established with the cloud platform, and closed-loop feedback from data collection to teaching intervention has been realised. The terminal collects students' motion data in real time through wearable devices, combines Kalman filtering for local denoising processing, and then uses a lightweight CNN model deployed on the edge to complete the motion recognition task. After the recognition results are encapsulated, they are uploaded to the teaching management platform built on Moodle via Bluetooth. After receiving the data, the platform combines the students' historical performance and current physical fitness status, uses the K-means clustering algorithm to classify them into corresponding group categories, and automatically generates personalised training instructions.

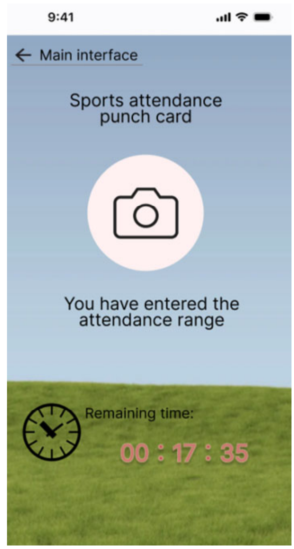
These training instructions will be further sent to the terminal through the cloud to achieve real-time feedback and dynamic adjustment. For example, when it detects that a student's centre rate continues to be low during running, the Moodle platform will analyse his training effect and issue a suggestion to 'increase the cadence' or 'increase the slope' to the smart bracelet to remind him to increase the training intensity; on the contrary, if a fatigue signal is detected, it may trigger 'reduce the load' or 'pause training' instructions to ensure the safety and science of training.

3.4 Interactive learning platform

An interactive learning platform is an important interface for interacting with users. The platform supports a variety of functional modules, including data visualisation, real-time feedback, and online guidance. This article applies Moodle as a learning platform to digital physical education teaching (Gamage et al., 2022; Mustafa and Ali, 2023).

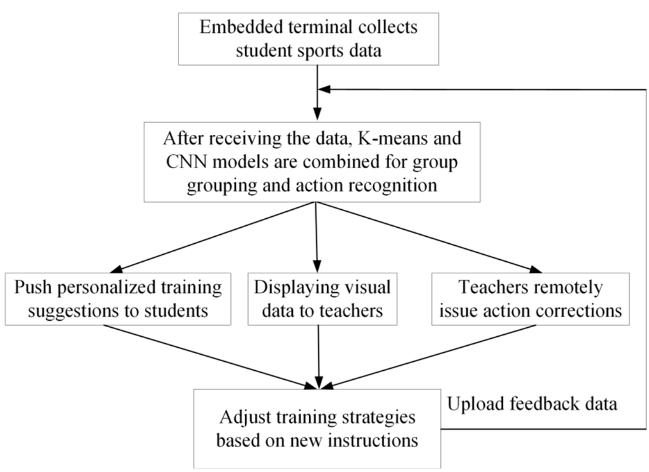
Moodle is an open-source learning management system that supports a variety of operating systems and server environments (Arifin et al., 2023). By deploying Moodle on the local server of the school, a stable learning platform can be quickly built. After installation, personalised configuration can be performed according to actual needs, such as creating course categories (such as running training, strength training, etc.), setting user roles (students, teachers, administrators), and enabling multi-language support (Makruf et al., 2022). To ensure cross-device access, Moodle's mobile support function is enabled, allowing students to log in to the platform anytime and anywhere through mobile phone apps or computer browsers. The system punch-in interface is shown in Figure 3.

Figure 3 System punch-in interface (see online version for colours)



As the core interactive learning platform, the Moodle platform undertakes key functions such as data aggregation, personalised training program display, teaching feedback, and teacher-student interaction. The platform receives student sports data uploaded from embedded terminals, including heart rate, acceleration, cadence, and other indicators, and presents them visually through the interface, so that teachers can intuitively grasp the training status and physical fitness change trend of each student. In addition, Moodle also supports historical data queries and multi-dimensional analysis to help teachers evaluate teaching effects and optimise subsequent training content.

Figure 4 Closed-loop process



To achieve a closed-loop teaching, the Moodle platform not only passively receives data, but also sends control instructions to embedded terminals based on data analysis results.

Teachers can use the platform to formulate personalised training tasks for students of different ability levels, and push information such as target intensity and movement specifications to student-end devices to achieve real-time intervention. At the same time, the system supports the automatic training suggestion generation function, combines the K-means clustering algorithm to classify students' sports performance, and dynamically adjusts the training plan based on the classification results. This two-way interactive mechanism effectively improves the pertinence and flexibility of teaching. The process of the closed-loop mode is shown in Figure 4.

The platform also has a complete remote guidance function. Teachers can publish course resources, assign training tasks, and comment on and give feedback on the training records submitted by students through modules such as announcements, quizzes, and forums. Students can check their training progress, watch standard action video tutorials, and participate in online discussions at any time to enhance the autonomy and interactivity of learning. The mobile support of the Moodle platform also ensures that learning and teaching activities are not restricted by time and space, and improves the ease of use and coverage of the system (Manurung and Syafrayani, 2024; Chang et al., 2022). This data-driven approach provides a scientific basis for subsequent teaching decisions. The student punch-in interface is shown in Figure 5.

Figure 5 Student punch-in interface (see online version for colours)

Using Moodle's multimedia resource function, video tutorials or decomposition diagrams of standard actions can be embedded to help students understand the correct exercise posture. At the same time, teachers can publish personalised feedback information on the platform. This method of combining data analysis and visual teaching can improve the precision and efficiency of action guidance.

After grouping students using the K-means clustering algorithm, teachers can design exclusive training tasks for different groups and publish these tasks to the Moodle course module. After students log in to the platform, they can view their training goals, progress, and completion status. In addition, Moodle's test and questionnaire functions can help teachers regularly evaluate students' athletic ability and training effects, and dynamically adjust training plans based on the evaluation results.

Moodle's interactive function is one of its core advantages. Through forums, chat rooms, and announcement modules, teachers and students can communicate and cooperate efficiently. Students can share their training experiences or ask questions in the forum, and teachers can publish motivational information or important notices through announcements.

4 Experiments

4.1 Performance evaluation of data acquisition system

4.1.1 Sensor node performance

In order to verify the applicability and stability of the sensor node in the physical education teaching scenario, its core performance indicators need to be systematically evaluated. This study selects the current mainstream low-power inertial measurement unit (IMU) – LSM6DSL as the sensor of the experimental group, and carries out a multi-dimensional comparison with the traditional solutions MPU6050 and ADXL345. The results are shown in Table 1.

Table 1 Sensor performance comparison

Index	*LSM6DSL*	*MPU6050*	*ADXL345*
Type	IMU (accelerometer + gyroscope)	IMU (accelerometer + gyroscope)	Accelerometer
Maximum sampling rate (Hz)	1.6k	1k	3.2k
Power consumption (mA)	0.5 (low power mode)	3.8	0.13
Communication protocol	I^2C/SPI	I^2C	I^2C/SPI
Integration level	High (built-in filtering algorithm)	Medium	Low
Applicable scenarios	Complex action recognition	Basic motion monitoring	Simple step counting

From the core parameters, the maximum sampling rate of LSM6DSL is significantly higher than that of MPU6050, indicating that it can capture fast dynamic motion while avoiding redundant energy consumption caused by simply pursuing high sampling rate; its power consumption of only 0.5 mA in low power mode is much lower than that of MPU6050 and close to that of ADXL345, taking into account both real-time monitoring needs and device endurance. In terms of functional integration, LSM6DSL has a built-in filtering algorithm that can directly output pre-processed signals and reduce the computing load of the main control chip, which is especially suitable for resource-constrained embedded terminals; MPU6050 needs to rely on an external processor to achieve similar functions, and ADXL345 only provides raw acceleration data, which is difficult to meet the needs of complex action recognition. From the perspective of applicable scenarios, the 'accelerometer + gyroscope' combination of LSM6DSL enables it to fully perceive three-dimensional motion postures and match the needs of multi-dimensional motion analysis in physical education.

4.1.2 Data processing effect

To evaluate the performance of the system in data acquisition and processing, including the accuracy of sensor data, the denoising effect of the Kalman filter algorithm, and the security of data transmission, the experiment selects the sports data of 120 students for a semester, focusing on analysing key indicators such as heart rate, acceleration, and number of steps. The original data of walking, running, and jumping are compared with those after Kalman filtering. The results are shown in Figure 6.

Figure 6 Comparison of data before and after Kalman filtering (see online version for colours)

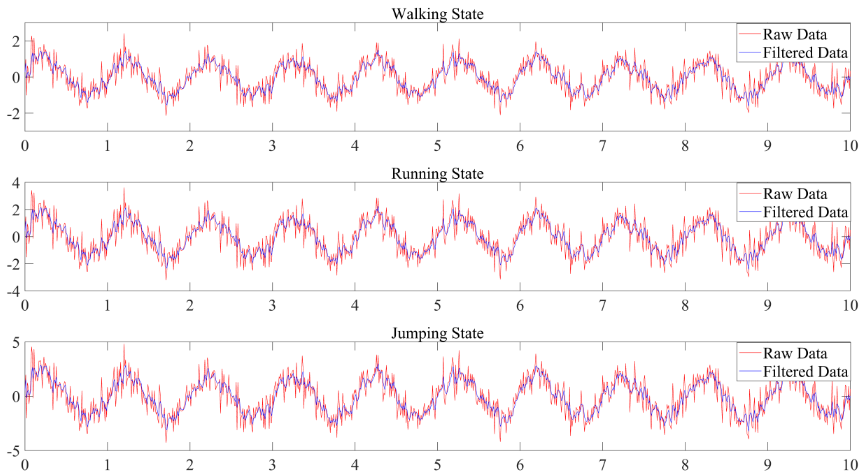


Figure 6 shows the comparison of original data and Kalman filtered data in three different motion states: walking state, running state, and jumping state. In each sub-graph, the red curve represents the original data (sinusoidal signal with noise), while the blue curve is the smoothed data after Kalman filter processing. It can be seen that the Kalman filter effectively reduces the noise in the original data. Especially in the walking state, the filtered data shows a more stable trend, and in the running and jumping states, the filter also smoothes the fluctuation of the data, making the overall signal more stable. This shows that the Kalman filter can effectively extract more accurate motion trends when processing noisy motion data.

The error analysis results of data collection for five common sports types (walking, running, jumping, push-ups, and badminton) include root mean square error (RMSE), signal-to-noise ratio (SNR) and data loss rate. The results are shown in Table 2.

Table 2 Error results of data collection under different sports states

Sports type	*RMSE (original)*	*RMSE (after filtering)*	*SNR (original)*	*SNR (after filtering)*	*Data loss rate (%)*
Walking	0.35	0.1	22.5	36.8	1
Running	0.7	0.2	18	33.5	1.5
Jumping	0.85	0.25	16.5	31	1.8
Push-ups	1	0.3	14	29	2
Badminton	1.2	0.35	12	27.5	2.2

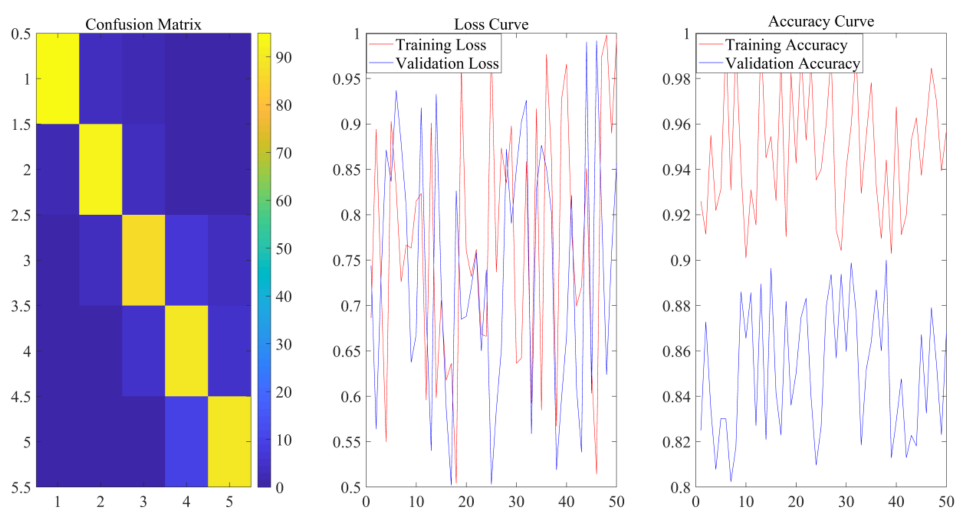
In Table 2, through the error analysis of walking, running, jumping, push-ups, and badminton, it can be seen that the Kalman filter algorithm shows a good denoising effect in different types of sports, significantly improving data quality and signal-to-noise ratio. Among them, walking and running are simple actions, and the filtering effect is the most significant; badminton is a complex action. Although the initial error is large, the quality of the filtered data can still meet the needs of subsequent analysis. In addition, the overall data loss rate remains at a low level, indicating that the stability and reliability of the system are effectively guaranteed. These results provide a high-quality data foundation for subsequent action recognition and personalised training.

4.2 Action recognition accuracy evaluation

To evaluate the performance of CNN in the action recognition task, its classification accuracy for different types of sports is analysed. The effect of the model optimisation strategy is explored, and the classification accuracy is tested. Five common types of sports (walking, running, jumping, push-ups, and badminton) are represented by 1–5 respectively.

Figure 7 shows the classification accuracy of the CNN model on the dataset, which contains three sub-graphs: confusion matrix, loss function curve, and accuracy curve. The confusion matrix shows the classification results of the model for five common types of sports (1–5: walking, running, jumping, push-ups, badminton). It can be seen from the matrix that the model has a high classification accuracy for running and jumping, 95% and 93%, respectively, while the classification accuracy for push-ups is slightly lower, only 87%. This may be due to the high complexity of push-ups, which makes it difficult for the model to fully capture their spatiotemporal characteristics. The loss function curve and the accuracy curve reflect the convergence of the model during training. With the increase in the number of training rounds, the loss function gradually decreases; the accuracy rate steadily increases and finally reaches a stable state in the 50th round, with the training set accuracy rate reaching 92.5%.

Figure 7 CNN classification effect detection (see online version for colours)



To comprehensively evaluate the classification performance of the CNN model on five common types of sports and deeply analyse its performance in different dimensions, the traditional core indicators such as classification accuracy, recall rate, precision, and F1 score are tested, and multi-dimensional data such as statistical significance (P value), inter-group difference (t value), and area under the ROC curve (AUC) are also applied. The results are shown in Table 3.

Table 3 CNN model performance results

Action type	*Accuracy (%)*	*Recall rate (%)*	*Precision (%)*	*F1 score (%)*	*P*	*t*	*AUC*
Walking	95	96	94	95	< 0.001	8.76	0.97
Running	93	94	92	93	< 0.001	7.12	0.95
Jumping	92	91	93	92	< 0.01	6.45	0.94
Push-ups	87	85	88	86	< 0.05	5.23	0.88
Badminton	88	86	89	87	< 0.05	4.89	0.89
Average	91	90.4	91.2	90.6	-	-	0.93

From the data in Table 3, it can be seen that the model's recognition effect on simple actions (such as walking and running) is significantly better than that on complex actions (such as push-ups and badminton). The classification accuracy of walking is as high as 95%, and its P value <0.001 and t value of 8.76 indicate that the model has extremely high statistical significance and inter-group distinction ability in this category; the classification accuracy of badminton is 88%, and the P value <0.05 and t value of 4.89 show that although its classification results are significant, the difference between them and other categories is small and easy to be confused. In addition, the AUC indicator further verifies the overall performance of the model. The AUCs of walking and running are both over 0.95, while the AUCs of push-ups and badminton are 0.88 and 0.89, respectively, indicating that the classification boundaries of complex actions are relatively fuzzy. The data in Table 3 not only reflects the classification ability of the model, but also provides a clear direction for optimising feature extraction and reducing misclassification.

4.3 Effectiveness evaluation of personalised training programs

4.3.1 Experimental design

In this study, a controlled experiment method was used to verify the effectiveness of the personalised training model based on intelligent sensing and digital teaching. A sample of 120 college students was classified into three physical fitness categories (high, middle, and low) and then randomly allocated to either a control group or an experimental group. The experimental period is 16 weeks, with 3 physical education classes per week (50 minutes each). Among them, the control group continues to use a unified intensity training plan, while the experimental group dynamically generates a training plan based on the embedded sensor network and the Moodle platform.

During the experiment, students in the experimental group wear LSM6DSL multimodal sensors to collect motion data in real-time. After optimising the signal quality through Kalman filtering, the lightweight CNN model recognises the action type and completion degree, and uses the K-means clustering algorithm to dynamically adjust the training intensity and goals in combination with historical performance.

The physical fitness test results use cardiopulmonary endurance (VO2max) and strength quality (maximum load weight) as the core evaluation indicators. The baseline value is obtained through laboratory standardised tests, and the increase in the data after the experiment is compared. In addition, record the frequency and response time of the adjustment of the personalised plan of the experimental group, and analyse the dynamic adaptability. Mixed variables such as initial physical fitness level and course duration were controlled throughout the experiment to ensure the validity of the comparison between the two groups.

4.3.2 Evaluation indicators

To evaluate the effect of personalised training programs on improving students' athletic ability, the physical fitness changes of different sports level groups before and after training are analysed. High, medium, and low are replaced by 1–3 in the figure. The results are shown in Figure 8.

Figure 8 Training effects on students at different levels (see online version for colours)

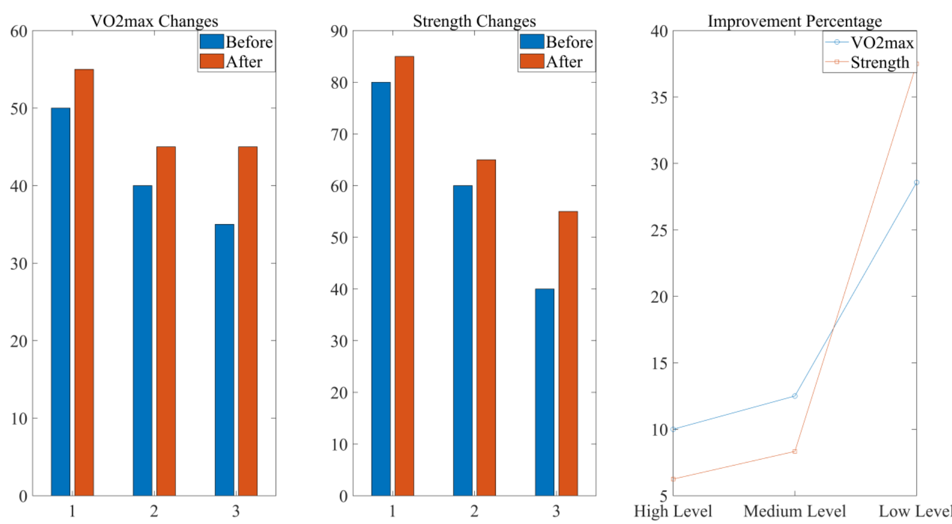


Figure 8 shows the change trends of cardiopulmonary endurance (VO2max) and strength quality (maximum load weight) before and after training in the three sports level groups of high, medium, and low. It can be seen from the figure that the physical fitness indicators of all groups have been significantly improved, but the degree of improvement varies from group to group. The VO2max of the low-level group increases from 35 mL/kg/min to 45 mL/kg/min, an increase of 28.6%, while that of the high-level group only increases from 50 mL/kg/min to 55 mL/kg/min, an increase of 10%. This shows that personalised training programs are more effective for students with weaker foundations. In addition, the change in strength quality also shows a similar trend. The maximum load weight of the low-level group increases by 37.5%, which is much higher than the 6.3% of the high-level group. Overall, the low-level group has the largest improvement, followed by the middle-level group, and the high-level group has the smallest improvement, which reflects the pertinence and effectiveness of the personalised training program, especially in improving the physical fitness of students with weak foundations.

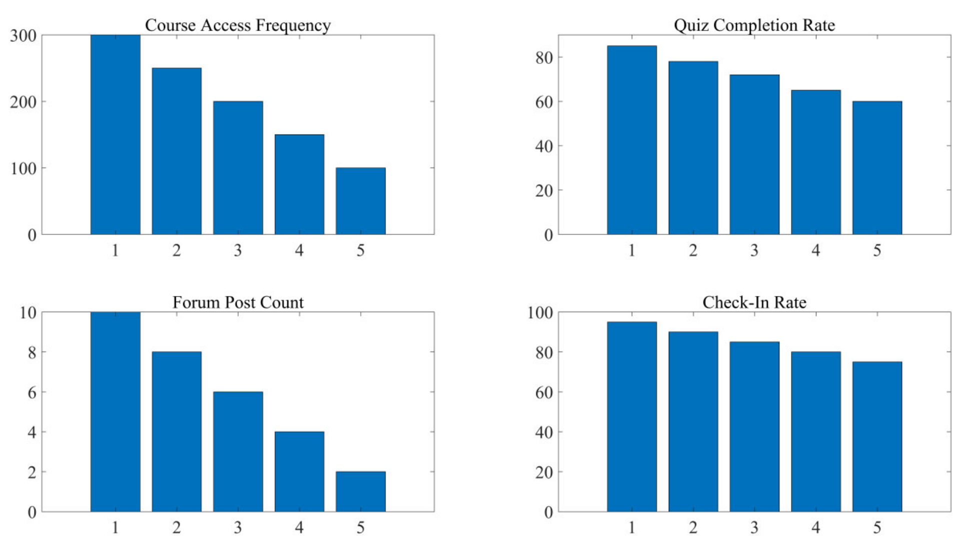
4.4 Overall performance evaluation

4.4.1 Technical indicators

To evaluate the application effect of Moodle platform in digital physical education teaching, the satisfaction and usage frequency of students and teachers on its functional modules are analysed, and the frequency distribution of students' and teachers' use of each functional module of Moodle platform is statistically analysed. The results are shown in Figure 9.

Figure 9 shows the frequency distribution of students and teachers using each functional module of the Moodle platform, including the number of course visits, test completion rate, forum posting volume, and punch-in rate. It can be seen that the number of course visits and punch-in rate are high, indicating that students have a strong dependence on the learning resources and daily record functions of the platform, reflecting the core role of these modules in digital physical education. However, the number of forum posts is relatively low, reflecting the weak willingness of teacher-student interaction and communication between students, which may be related to the students' participation enthusiasm or the design of the forum function. In addition, the test completion rate remains at a high level, indicating that students have a strong motivation to complete the evaluation tasks on the platform. Overall, the data in Figure 9 reveals the advantages of the Moodle platform in resource provision and learning tracking, but the frequency of use of the interactive function is low, suggesting that the interactive module needs to be further optimised in the future to improve user participation and the platform's overall effectiveness.

Figure 9 Frequency of use of each functional module of the platform (see online version for colours)



4.4.2 Teaching effect

To comprehensively evaluate the application effect of the Moodle platform in digital physical education, Table 4 conducts an in-depth analysis of the satisfaction of each functional module of the platform from multiple dimensions, including students' and teachers' scores on sub-dimensions such as functionality, ease of use, and interactivity. A weight calculation and comprehensive scoring mechanism are also applied to more scientifically reflect the overall user satisfaction with the platform. In addition, Table 4 also combines the correlation analysis (R value) of the satisfaction of the functional modules, aiming to reveal the relationship between user behaviour and evaluation, and provide data support for optimising platform functions.

Table 4 Multi-dimensional satisfaction scores of Moodle platform functional modules

Functional modules	*Sub-dimensions*	*Student rating*	*Teacher rating*	*Weight (%)*	*Overall rating*	*R-value*
Course management	Functionality	9.2	9.5	30	9.4	0.87
	Ease of use	8.8	9	25		
	Data accuracy	9	9.3	20		
	Response speed	8.5	8.7	25		
Data visualisation	Functionality	8.9	9.1	35	9	0.82
	Ease of use	8.6	8.8	30		
	Visualisation	8.7	8.9	25		
	Real-time update capability	8.4	8.6	10		
Tests and questionnaires	Functionality	8.5	8.7	40	8.6	0.75
	Question diversity	8.2	8.4	25		
	Automatic scoring accuracy	8.3	8.5	20		
	Feedback timeliness	8	8.2	15		
Forum interaction	Functionality	7.8	7.9	30	7.8	0.68
	Interactivity	7.5	7.6	25		
	Content organisation	7.6	7.7	20		
	User participation incentive mechanism	7.4	7.5	25		
Punch-in and record	Functionality	9	9.2	35	9.1	0.91
	Interface friendliness	8.8	9	30		
	Data integrity	8.9	9.1	25		
	Reminder function	8.7	8.9	10		

From the data in Table 4, it can be seen that there are significant differences in satisfaction with different functional modules. The 'course management' and 'punch-in and record' modules have the highest comprehensive scores, indicating that these functions are relatively complete in design and meet user needs. In contrast, the 'forum interaction' module has the lowest comprehensive score of 7.8, and the correlation coefficient value of 0.68 is also low, reflecting that this function is insufficient in attracting user participation. In addition, teachers' scores are generally slightly higher than students', such as in the 'data visualisation' and 'quiz and questionnaire' modules, which may be related to the fact that teachers pay more attention to the platform's functionality and data accuracy. Overall, the data in Table 4 reveals the real experience of users on each functional module and provides a clear direction for the subsequent optimisation of interactive functions and the improvement of user participation.

5 Conclusions

This study discusses the application of intelligent sensing and digital teaching in physical education. Through real-time collection and analysis of student exercise data, a personalised and accurate teaching model is proposed. The experiment uses the Kalman filter algorithm to effectively improve the data quality, and uses CNN to achieve high-precision action recognition, especially in simple actions. The personalised training program significantly improves the physical fitness of low-level students, reflecting its targetedness and scientificity. In addition, the interactive learning platform based on Moodle performs well in resource provision and learning tracking, but the interactive function is used less frequently and needs further optimisation. The study shows that this model not only breaks through the time and space limitations of traditional teaching, but also provides theoretical support and practical reference for the reform of physical education in colleges and universities, promoting the innovative application of digital learning environments in the field of sports.

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Declarations

All authors declare that they have no conflicts of interest.

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