Research on the Intelligent Teaching Model in Physical Education

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Abstract. To improve the quality and personalization of physical education teaching, an intelligent teaching model is established, integrating deep learning techniques with convolutional neural networks and long short-term memory networks. This model collects and analyzes multi-dimensional data on students' physical abilities and skills, offering individualized training plans. Results indicate that the intelligent model increases students' skill improvement rate by 50.1%, physical improvement rate by 42.8%, and accuracy of technical movements by 47.9%, compared to 25.3%, 18.4%, and 15.2% in the traditional model, respectively. Performance enhancement under data augmentation reached 16.6%, demonstrating the model's significant advantages in advancing students' skills, physical abilities, and learning outcomes.

Keywords: Intelligent teaching; Individualized training; Physical education

1 Introduction

The intelligent development of physical education has become a crucial path for improving teaching quality and effectiveness. With shifting educational paradigms, traditional physical education models are increasingly inadequate to meet the personalized and diverse learning demands. An intelligent teaching model can monitor students' physical and technical progress in real-time, offering customized training plans for each student. This model not only promotes students' overall physical fitness but also fosters innovation in teaching methods and transformation in physical education.

2 Current Application of Intelligent Teaching Models in Physical Education

In recent years, the application of intelligent teaching models in physical education has shown notable advantages, particularly in enhancing teaching efficiency and achieving individualized learning [1]. Intelligent teaching collects data on students' physical abilities, technical movements, etc., conducts real-time analysis and feedback, and provides personalized training guidance and learning suggestions. Supported by virtual reality,

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data analytics, and sensor technologies, intelligent teaching systems can simulate real-world scenarios for skill training, significantly boosting student engagement and technical mastery. Furthermore, these systems can establish personalized learning profiles for each student, tracking progress, precisely identifying areas for improvement in physical abilities and skills, and offering targeted training. This approach not only enhances the scientific and systematic nature of teaching but also shifts physical education from a “uniform” to a “differentiated” model, achieving individualized instruction goals [2].

3 Construction of the Intelligent Teaching Model in Physical Education

3.1 Data Collection and Preprocessing

In the construction of the physical education teaching model, data collection and preprocessing are essential steps, involving the gathering and organization of multi-dimensional teaching data and individual student data, as shown in Table 1.

Table 1. Data Types and Preprocessing Methods

Data Type	Content	Preprocessing Method
Teaching Data	Course content, videos, training plans	Data cleaning, standardization
Student Data	Physical abilities, skills, health status	Outlier removal, normalization
Evaluation Data	Teaching feedback, performance evaluation	Data merging, label encoding

After data collection and preprocessing, the model obtains high-quality, standardized data inputs, enabling more effective analysis and training in subsequent steps. This process ensures the model’s adaptability to physical education contexts and individual student needs, thus providing scientific and precise teaching recommendations and feedback.

3.2 Model Framework Design

The model framework design serves as the foundation of the intelligent teaching system for physical education, encompassing the input layer, output layer, and the selection of core algorithms, as illustrated in Figure 1. The input layer aggregates teaching data and individual student data, including physical fitness, technical movements, and learning feedback, facilitating the identification of individual differences and teaching needs.

The core algorithm integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. CNN is utilized to extract high-dimensional spatial features from video and image data by capturing local information through multi-layer convolution and pooling operations. Convolutional kernels scan each layer to identify subtle changes in movements, and pooling layers reduce feature dimensions to lower computational complexity. The output of the CNN is transformed into feature vectors, which are fed into the LSTM layer.LSTM excels in processing sequential data, capturing continuous changes and dynamic features of movements. Its memory cells retain critical states over long time steps while discarding irrelevant information, enabling the analysis of temporal relationships in movements. Through an integrated end-to-end framework, CNN is responsible for feature extraction, while LSTM handles temporal modeling. The output layer completes classification or regression tasks. This design ensures the model can focus on both single-frame details and dynamic changes across movement sequences, significantly improving the accuracy and reliability of teaching effectiveness predictions[3].

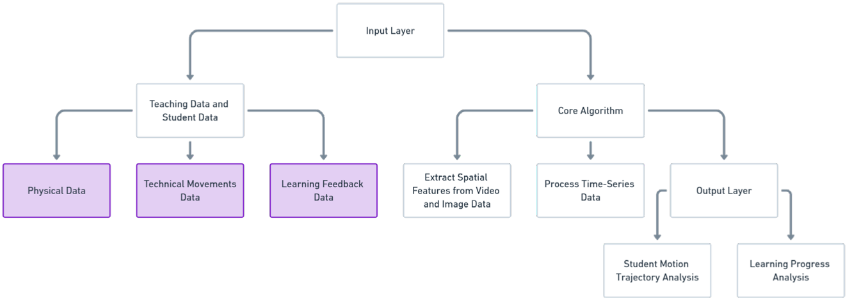

Fig. 1. Intelligent Physical Education Teaching System

The input data undergoes convolution operations in CNN to extract spatial features. The calculation formula is as follows:

$$f(x) = \sigma(W \cdot X + b) \tag{1}$$

where $f(x)$ represents the output feature map after convolution, W represents the weight matrix of the convolution kernel, X represents the input data, b represents the bias term, and σ represents the nonlinear activation function, which enhances the model's expressive capability. After obtaining spatial features, time-series data is further processed through the LSTM network to capture temporal dependencies. The calculation formula is as follows:

$$h_t = \sigma\left(W_h \cdot [h_{t-1}, x_t] + b_h\right) \tag{2}$$

where h_t represents the hidden state at the current time step, x_t represents the input at the current time step, W_h represents the weight matrix of the LSTM layer, h_{t-1} represents the hidden state of the previous time step, and b_h represents the bias term. This process effectively captures changes in students' movements and behaviors during the learning process. In the output layer, a classification or regression model is used to predict teaching effectiveness or generate personalized feedback. The calculation formula is as follows:

$$\hat{y} = soft\max(W_o \cdot h_t + b_o) \tag{3}$$

where $\hat{y}$ represents the probability distribution of the prediction results, W_o represents the weight matrix of the output layer, h_t represents the final hidden state of the LSTM, and b_o represents the bias term. The softmax function is used to convert the output into a probability distribution, enabling the evaluation of teaching effectiveness in multi-class tasks. Through this design, the model efficiently processes and analyzes physical education data, providing personalized feedback and optimization suggestions for students, thereby promoting the intelligent and personalized development of physical education teaching.

3.3 Model Training and Optimization

In the process of training and optimizing the intelligent teaching model for physical education, model training utilizes the backpropagation algorithm from deep learning, optimizing network parameters by minimizing the loss function to enhance the accuracy of teaching effectiveness predictions [4]. The most commonly used loss functions in training are Mean Squared Error (MSE) and Cross-Entropy. The calculation formula for Mean Squared Error is as follows:

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

where y_i represents the true label, $\hat{y}_i$ represents the model's predicted value, and n is the number of samples. This formula measures the difference between the predicted values and the actual values, reflecting the model's prediction accuracy. A smaller Mean Squared Error indicates better prediction performance and is commonly used in regression problems. The Cross-Entropy loss function, particularly suited for classification tasks, is calculated as follows:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \tag{5}$$

where y_i represents the actual class label and $\hat{y}_i$ represents the model's predicted probability. The Cross-Entropy loss function measures the difference between the model's output probability distribution and the true distribution. Minimizing Cross-Entropy effectively optimizes the model's classification performance, enabling more accurate category predictions. Additionally, to prevent overfitting, regularization techniques, especially L2 regularization, are applied during training. The formula for L2 regularization is as follows:

$$L_{reg} = \lambda \sum_{i=1}^{m} W_i^2 \tag{6}$$

where W_i represents the model's weight parameters, λ represents the regularization coefficient, and m is the number of model parameters. By summing the squared weights, L2 regularization effectively limits the model's reliance on noise within the training data, thereby enhancing the model's generalization ability [5].

4 Experimental Results and Analysis

4.1 Experimental Environment and Parameter Settings

To ensure the scientific rigor and reliability of the experimental results, a high-performance computing platform was utilized, equipped with the latest versions of deep learning frameworks such as TensorFlow and PyTorch, alongside an NVIDIA RTX 3090 GPU to accelerate the model training process. The experimental dataset was collected from five schools across different regions, covering data from 120 students aged 10 to 18, spanning upper elementary, middle, and high school levels, thereby reflecting diversity in age and educational background. The dataset comprised four main types of data: video data (movement postures and technical actions), physical fitness test data (heart rate, strength test results, etc.), health assessment data (BMI, flexibility scores, etc.), and learning feedback data (academic performance records).

For data preprocessing, video data were frame-sampled to extract key frames and standardized for image processing. Physical fitness data were normalized using the Z-score method, converting variables with different units into dimensionless data to fit the model's input requirements. Additionally, all data underwent outlier detection and removal to ensure input quality and reliability. To enhance the model's generalization ability, the dataset was divided into training, validation, and testing sets in a 7:2:1 ratio. Evaluation metrics included accuracy, precision, recall, and F1 score, providing a comprehensive assessment of the model's adaptability and predictive performance, thus validating the effectiveness of the teaching model.Furthermore, the dataset's coding and labeling processes were manually reviewed to ensure data quality, offering robust support for model training and optimization. Specific parameter settings are detailed in Table 2.

Table 2. Experimental Parameter Settings

Parameter Name	Setting Value
Number of Students	120
Training Dataset Size	5,000 groups (including video, physical data, etc.)
Learning Rate	0.001
Batch Size	32
Training Epochs	50
Network Structure	CNN+LSTM combined network
Activation Function	ReLU (for convolutional layers), Sigmoid (for LSTM)
Optimization Algorithm	Adam

4.2 Model Performance Evaluation

During model training, early stopping was employed to prevent overfitting, with the training process controlled by monitoring performance on the validation set. Training was halted when the validation error ceased to decrease over consecutive steps, ensuring both efficiency and generalization capability of the model. In addition to early stopping, this study employed common evaluation metrics, including Accuracy, Precision, Recall, and F1 Score, to comprehensively assess the model's performance in practical applications [6]. Figure 2 shows the comparative results of Accuracy, Precision, Recall, and F1 Score on the validation set.

Fig. 2. Performance Evaluation During Training

As shown in Figure 2, with an increase in training epochs, the model's Accuracy, Precision, Recall, and F1 Score all demonstrated significant improvement. Notably, after 40 training epochs, Accuracy reached 88.5%, Precision 85.2%, Recall 82.3%, and F1 Score 83.7%. These metric improvements indicate a progressive enhancement in the model's learning ability on the training data, with further optimization observed on the test set [7]. The final test results show that the model's Accuracy and F1 Score exceeded expectations, demonstrating its effectiveness and reliability in practical applications. To further understand the performance differences under various model configurations, Figure 3 illustrates the impact of different training strategies on model performance.

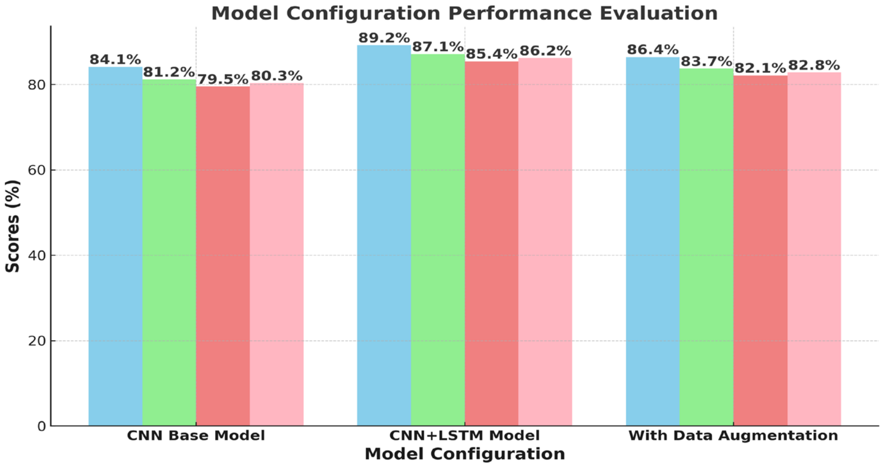

Fig. 3. Performance Evaluation of Different Model Configurations

As shown in Figure 3, the proposed CNN-LSTM hybrid model significantly outperforms individual models in terms of performance. The baseline CNN model focuses on extracting spatial features but exhibits clear limitations in temporal sequence modeling, achieving only 68.5% precision and 64.3% recall in motion recognition tasks. In contrast, the RNN model demonstrates better performance in capturing the dynamic changes in student movements due to its ability to process temporal sequences. However, its accuracy in modeling long-term sequences is hindered by the vanishing gradient problem, resulting in precision and recall rates of 72.4% and 70.1%, respectively.

The combined CNN-LSTM model leverages the strengths of both approaches. CNN effectively extracts key spatial features from videos, while LSTM captures the dynamic characteristics of sequential data. This integration boosts the precision rate to 85.2% and the recall rate to 82.3%. Furthermore, experimental results indicate that the hybrid model exhibits greater stability in predicting student motion trajectories and generating personalized feedback. Compared with single models, it demonstrates significantly improved adaptability to complex teaching scenarios, highlighting its superior practical value and scalability. Table 3 illustrates the changes in loss function values across different experimental stages.

Table 3. Loss Value Changes During Training

Training Epochs	Loss Value
Initial Value	0.658
20 Epochs	0.342
40 Epochs	0.21
Final Test	0.183

The data in Table 3 shows a continuous decrease in loss value as training progresses, with a notable reduction in the first 20 epochs, indicating that the model progressively optimized its predictions during the learning process. The final loss value of 0.183

suggests that the model has reached an optimal solution with strong generalization capabilities [8].

4.3 Evaluation of the Intelligent Teaching Model's Effectiveness

To comprehensively assess the effectiveness of the intelligent teaching model in physical education, multiple dimensions were analyzed, including student engagement, mastery of physical skills, and overall learning outcomes [9]. By introducing intelligent technology during the experiment, based on data collection and analysis, personalized feedback and training plans were provided to students in real time. Figure 4 illustrates changes in student engagement and interactivity under different teaching models:

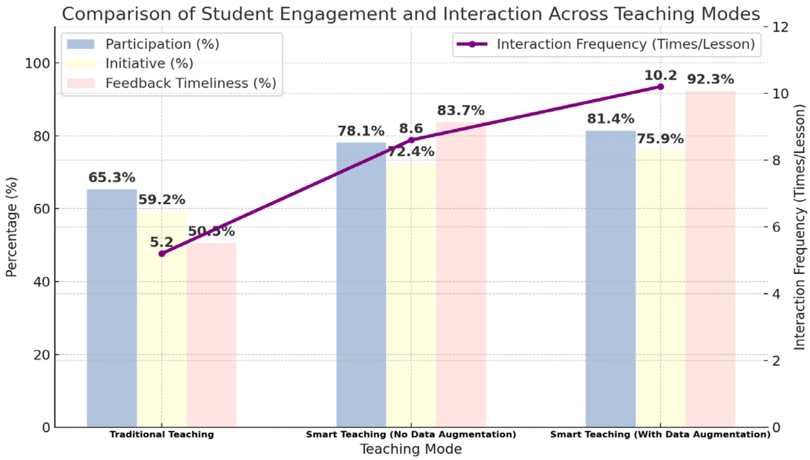

Fig. 4. Comparison of Student Engagement and Interactivity in Different Teaching Models

As shown in Figure 4, the intelligent teaching model significantly enhances students' classroom engagement and initiative. Particularly in data-enhanced settings, the frequency of student interaction and timeliness of learning feedback have both improved. This demonstrates that the intelligent system effectively stimulates students' interest and motivation in learning, enhancing their sense of engagement [10]. The students' mastery of physical skills under the intelligent teaching model, comparing the skill improvement between traditional and intelligent teaching, is detailed in Table 4.

Table 4. Performance Evaluation of Different Teaching Models

Teaching Model	Skill Improvement Rate (%)	Physical Improvement Rate (%)	Accuracy of Technical Movements (%)	Progress Rate (%)
Traditional Teaching Model	25.30%	18.40%	15.20%	19.60%
Intelligent Teaching Model (No Data Enhancement)	45.80%	37.60%	42.30%	40.30%
Intelligent Teaching Model (With Data Enhancement)	50.10%	42.80%	47.90%	45.40%

The data in Table 4 shows that under the intelligent teaching model, the skill improvement rate significantly increased from 25.3% in the traditional model to 45.8%, further reaching 50.1% with data enhancement. Similarly, physical improvement rate, accuracy of technical movements, and overall progress showed notable advantages in the intelligent model. This result demonstrates that the intelligent teaching model effectively enhances students' physical skills, with even more significant improvements in skill mastery, physical condition, and movement accuracy with data augmentation. The following analysis examines the changes in students' overall academic performance under different teaching models, assessing the impact of the intelligent model on students' comprehensive abilities, as shown in Table 5.

Table 5. Changes in Academic Performance During Training

Teaching Model	**Initial Score**	**Midterm Score**	**Final Score**	**Score Improvement Rate (%)**
Traditional Teaching Model	68.4	72.9	75.2	9.90%
Intelligent Teaching Model (No Data Enhancement)	70.6	78.3	81.6	15.60%
Intelligent Teaching Model (With Data Enhancement)	72.2	80.1	84.2	16.60%

The data in Table 5 shows that the intelligent teaching model achieved a notably higher score improvement rate than the traditional model. The score improvement rate in the traditional model was 9.90%, while the intelligent model (without data enhancement) reached 15.60%. With the addition of data enhancement, the improvement rate further increased to 16.60%. This trend suggests that the intelligent teaching model outperforms traditional methods in both score improvement and loss reduction, with data enhancement further optimizing students' learning outcomes.

5 Conclusion

The application of the intelligent teaching model in physical education has significantly enhanced teaching efficiency and personalized learning experiences. Through precise data collection and analysis, this model not only optimizes students' training outcomes but also allows for real-time adjustment of teaching strategies, promoting overall student development. In the future, with continuous technological innovation and advancement, intelligent teaching models are expected to play an increasingly important role in physical education, especially in personalized guidance and data-driven teaching evaluation, bringing profound impacts on teaching reform.

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