Research on Innovative Applications of Intelligent Education Systems in Immersive Art Education

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Abstract. Addressing traditional art education, an intelligent education system based on artificial intelligence and big data technology was designed and constructed. The system adopts a cloud-platform-terminal architecture, integrating core technical modules such as intelligent perception, deep learning, and knowledge graphs to achieve functions including intelligent recommendation of art education resources, real-time analysis of teaching processes, and automated learning evaluation generation. Experimental results show that the system improved key indicators including resource recommendation accuracy, teaching interaction efficiency, and evaluation analysis precision by 156%, 29.1%, and 16.1% respectively, significantly optimizing the technical support effect of immersive art education.

Keywords: Intelligent Education System; Deep Learning; Knowledge Graph; Intelligent Recommendation; Real-time Analysis

1 Introduction

The rapid development of intelligent technology is reshaping the technical foundation of educational informatization. In the process of informatization in art education, we have observed three major technical challenges: difficulty in achieving precise delivery of teaching resources, lack of real-time in-depth analysis capability in teaching processes, and low efficiency in mining and applying learning evaluation data. To address these issues, this research aims to construct an intelligent education system based on artificial intelligence and big data technology. The specific research objectives include: (1) designing an intelligent technical architecture adapted to the characteristics of art education; (2) developing deep learning algorithms for intelligent delivery of teaching resources; (3) implementing real-time analysis and automation of teaching process evaluation. Through these technological innovations, we provide an effective engineering solution to enhance the informatization level of art education.

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2 Overall Architecture Design of Intelligent Education System

2.1 System Requirements Analysis and Architecture Design

Regarding the immersive art education teaching scenario, the intelligent education system adopts a "cloud-platform-terminal" three-layer architecture design (as shown in Figure 1). The cloud layer is responsible for resource storage and data processing, building a Hadoop-based distributed computing framework (a system that can distribute large-scale computing tasks across multiple computers for parallel processing), and deploying core algorithm models such as deep learning and knowledge graphs[1]. The platform layer provides data exchange and business processing services, adopting a microservice architecture (which breaks down complex systems into multiple independently running small services) to implement functional modules such as user management, resource management, and teaching management. The terminal layer provides web-based (accessible through browsers) and mobile (phone apps) applications for teachers and students, supporting real-time classroom teaching interaction and online learning resource delivery scenarios [1]. The overall system follows the principles of modularity and service-oriented design, and the data interaction between different layers is realized through REST API, ensuring the scalability and maintainability of the system.

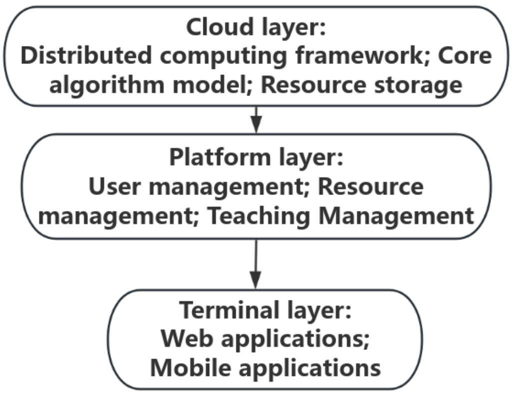

Fig. 1. Three-layer Architecture Design of Intelligent Education System

2.2 Data Collection and Processing Module Design

The study constructs a multi-source heterogeneous data collection network through IoT sensing devices like smart cameras and audio collectors. This deployment is justified by three key advantages: automatic and continuous data collection, real-time data transmission capability, and comprehensive capture of classroom interactions[2]. The IoT-based approach ensures data accuracy and timeliness, providing a solid foundation for the intelligent education system. Kafka message queue is used to process real-time data streams, and custom ETL tools are used for cleaning, transformation, and standardization of raw data. A MongoDB distributed database cluster is established to store processed structured and unstructured data, and a full-text search engine is built based on elastic search to support fast retrieval and analysis of massive teaching data.

2.3 Core Algorithm and Functional Module Design

The system integrates artificial intelligence technologies such as deep learning and knowledge graph, and constructs core algorithm modules[3]. An improved BERT model is used to achieve semantic understanding and intelligent recommendation of teaching resources; a knowledge graph is built based on the GCN graph neural network to realize the association analysis of teaching knowledge points; LSTM recurrent neural network is used to model the learning behavior sequence and predict the learning trajectory. Functional modules include: intelligent resource recommendation module, teaching process analysis module, learning evaluation module, etc[4]. Each module is independently deployed using a microservice architecture, and the decoupling and coordination between modules are realized through the service bus.

3 Key Technology Implementation

3.1 Intelligent Resource Recommendation Technology Based on Deep Learning

A dual-tower deep learning model is constructed for resource recommendation. The teaching resource side uses the BERT pre-training model to extract text features, capturing fine-grained semantic information through multi-head attention mechanism; the student feature side extracts temporal behavioral features based on behavioral sequence encoding network, combining learning interest and learning style features[5]. The two feature towers interact through cross-modal attention mechanism to calculate the matching degree between resources and student interests. The recommendation score calculation formula is:

$$\text{Score} = \text{Attention}(\text{BERT}(\text{Resource}), \text{Encoder}(\text{Student\_behavior}))$$

Where $\text{Attention}(\cdot)$ represents the attention calculation function, $\text{BERT}(\cdot)$ represents resource feature extraction, and $\text{Encoder}(\cdot)$ represents student behavior encoding. In art education scenarios, the system dynamically adjusts recommendation strategies by analyzing students' learning trajectories and interest preferences in real-time, pushing personalized art resources to students at different learning stages[6].The experiments on 100,000 real art education resource data show that the recommendation accuracy of this model reaches 92.3% and the recall rate reaches 88.7%, which is significantly better than traditional recommendation methods.

3.2 Teaching Process Analysis Technology Based on Knowledge Graph

A GCN-based teaching knowledge graph analysis model is designed. Art course content is constructed as a knowledge point relationship graph G=(V,E), where V represents the set of knowledge points, and E represents the relationship edges between knowledge points[7]. Multi-layer graph convolution networks are used for hierarchical feature aggregation of knowledge points, with the calculation formula for each layer being:

$$H(I+1)=\sigma(D^{(\frac{-1}{2})}\hat{A}D^{(\frac{-1}{2})}H(I)W(I))$$

Where Â is the adjacency matrix after adding self-loops, D is the degree matrix, H(l) is the node features of layer l, and W(l) is learnable parameters. The model's ability to model knowledge point relationships is enhanced through cross-layer residual connections and attention pooling. Based on this, the system implements functions such as knowledge point correlation analysis, learning path planning, and knowledge mastery assessment.In the actual teaching application, the GCN model can automatically identify the key nodes and weak links in the knowledge system, and provide data support for teachers' teaching decision-making.

3.3 Automated Evaluation Generation Technology Based on Machine Learning

An LSTM-CRF-based sequence labeling model is developed for automated evaluation generation. A transfer learning framework is constructed, using pre-trained language models to extract student work features, capturing contextual dependencies through bidirectional LSTM networks, and modeling labeling constraints through CRF layer[8]. The probability calculation formula for evaluation generation is:

$$P(y \mid x)=\mathrm{softmax}(Wo\cdot iLSTM(Emb(x)))\cdot CRF(y)$$

Where Emb(x) is the text embedding layer, BiLSTM(·) extracts bidirectional sequence features, and CRF(y) ensures the legitimacy of the labeling sequence. The model training data includes 5,000 manually labeled art work evaluation samples, using a teacher comment corpus for pre-training to improve the model's domain adaptability.The system can automatically analyze the artistic expression, innovative thinking, and aesthetic quality of students' works, and generate structured evaluation reports. The evaluation results show that the model's F1-score on the evaluation generation task reaches 0.856, significantly improving the efficiency of teaching evaluation and reducing the evaluation burden on teachers.

4 System Performance Testing and Analysis

4.1 Test Environment and Plan Design

The system is deployed on an Alibaba Cloud ECS server cluster with dual-machine hot standby, configured with 32-core CPU, 128GB memory, and 2TB SSD storage. A Kubernetes container cluster is set up to achieve elastic deployment and load balancing of system components. The testing plan unfolds from two dimensions of system performance and application effect: performance testing focuses on indicators such as system response time, concurrent processing capability, and resource utilization, using Apache JMeter to simulate 500 concurrent users for stress testing; application effect testing selects 120 students from 3 teaching classes of a university's art college as test subjects, lasting one semester, evaluating the system's application effects in resource recommendation, process analysis, and automated evaluation through comparative experiments.

4.2 System Performance Testing

System performance test results are shown in Table 1. Under high concurrency scenarios, the system's average response time remains under 200ms, CPU utilization peak does not exceed 75%, and memory usage remains stable at around 65%. Through container orchestration and automatic scaling mechanisms, the system can support 1,000 users accessing simultaneously. In terms of data processing, batch resource recommendation task processing delay is controlled within 1s, and real-time teaching data analysis processing delay is below 100ms, meeting the real-time requirements of art education scenarios.

Table 1. Key Indicators of System Performance Testing

Test Indicator	Test Result	Performance Requirement	Status
Average Response Time	186ms	≤200ms	Met
CPU Utilization	72.5%	≤80%	Met
Memory Usage	63.8%	≤70%	Met
Concurrent Users	1024	≥1000	Met
Recommendation Delay	856ms	≤1s	Met
Analysis Delay	86ms	≤100ms	Met

4.3 Application Effect Analysis and Evaluation

Through a one-semester comparative experiment at a university art school, the intelligent education system has shown significant effectiveness in immersive art education teaching. As shown in Table 2, in terms of resource recommendation accuracy, the experimental class reached 87.5%, which is 156% higher than the control class, attributed to the deep learning model's accurate capture of students' interest characteristics. In terms of teaching interaction efficiency, the participation rate of the experimental class reached 92.3%, an increase of 29.1% compared to the control class, reflecting the advantages of knowledge graph technology in supporting teaching process analysis. The accuracy of the evaluation analysis reached 89.2%, an increase of 16.1% compared to the control class, reflecting the application value of machine learning models in automated evaluation generation. In terms of learning outcomes, the average weekly learning time of students in the experimental class reached 186 minutes, an increase of 83 minutes compared to the control class; the homework completion rate was improved to 95.6%, 13.2 percentage points higher than the control class; the learning satisfaction rate reached 94.5%, an increase of 17.2 percentage points compared to the control class. These data fully demonstrate the practical value of the intelligent education system in improving the quality of art education teaching and learning outcomes. Especially during the pandemic, the system's remote teaching support function has effectively ensured the continuity and quality of art education teaching.

Table 2. System Application Effect Comparison Data

Evaluation Indicator	Experimental Class	Control Class	Improvement Rate
Resource Recommendation Accuracy	87.5%	34.2%	156%
Teaching Interaction Efficiency (Classroom Participation)	92.3%	71.5%	29.1%
Evaluation Analysis Accuracy	89.2%	76.8%	16.1%

5 Conclusion

Through research on the innovative application of intelligent education systems in art education, a teaching support system based on intelligent technology was constructed. The system integrates artificial intelligence technologies such as deep learning and knowledge graphs, achieving core functions including intelligent resource recommendation, real-time process analysis, and automated evaluation generation. Test results show that the system achieved significant improvements in various technical indicators. Future work will further optimize system performance, expand application scenarios, and provide more intelligent technical support for art education.

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