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Construction of a Smart Evaluation System for After-School Art Education Based on Educational Information Systems

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ABSTRACT
Over the past decade, data and computational power have exploded, advancing this field to the point where deep learning can have a significant transformative impact across many subfields of artificial intelligence (Liu et al., 2023a). Real-world applications now utilize Deep Neural Networks (DNNs) as a key to their innovations in image recognition, emotion detection, and intelligent systems (Liu et al., 2023b; Nabil et al., 2021). However, even though DNNs can produce impressive results, hidden flaws of DNN models can still generate incorrect outputs, leading to significant real-world consequences (Liu et al., 2022; Mo et al., 2018). As with ordinary software systems, there is a need for systematic testing of DNNs in order to increase reliability. However, unlike conventional code testing, the work typically lacks obvious expected outputs and is often expensive to test due to the need for manual coding (Guo et al., 2022; Guo et al., 2023; Li et al., 2022).

Keywords: recognition, expensive, systems

Introduction

In particular, there is an increased need for intelligent assessment techniques within the educational context, particularly in classroom environments (Yang et al., 2022). Classroom engagement and interaction (Guo et al., 2022b) might sometimes have been in the dudgeon due to the widespread use of mobile terminals and other smart devices. Current video analysis techniques can be used to assess classroom performance. However, there is a gap to leverage deep learning approaches like pixel-level analysis and grayscale foreground extraction for more classroom assessment (Li et al., 2022).

Deep learning is evolving further and better supports the structure of the educational models that better echo human cognition (Zhang et al., 2022; Guo et al., 2022c). Generally, a DNN has many interconnected layers to extract abstract features and relations from the input data, a kind of Zhang et al. (2022) (Zhang et al., 2023). Such a capability fits well with ideological and political education aims to foster moral character, civic values, and a rational social mentality (Zhou et al., 2022). However, political education in universities has not emphasized the intuitive, process-oriented development of values and emotions (Zhao et al., 2021), while researchers have long recognized the role of universities in transmitting explicit knowledge toward policy goals.

Therefore, we put forth a model that combines deep learning with formative and summative evaluation methods to improve the delivery of political education. This study uses deep learning as a tool in the interdomain of wisdom education to enhance the improvement of ideological and political theory courses for the holistic development of students. Ultimately, political education should be a communication and practice of developing cultivated individuals instead of monotonous propaganda (Xia et al., 2022; Zhang et al., 2022b).

Educational evaluation has come through several paradigms. Earlier phases have evaluated final outcomes, but process and formative assessments have recently been underway. Immersive and

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engaging means, such as music, tours, and literature, have been suggested by educational scholars to serve as educational tools for slowly growing students' cognitive and emotional potential in informal educational settings, like in art programmes (Samek et al., 2016). Focusing on these approaches supports the belief that evaluation should evaluate the learning journey and final competencies.

In the 1980s, educational evaluation systems started using theories from fuzzy mathematics which allowed to do more nuanced measurement on how teaching impact learning, in the 1980s. The result was more sophisticated evaluation models that more closely approximate educational results' non-linear and diversified distribution (Cui et al., 2015). Such flexible evaluation models are particularly appropriate for art education (where subjective interpretation, creativity, and expressive emotional interpretation are key).

Artificial intelligence (AI) and deep learning have furthered into industrial control and domestic life because they can discover patterns and make predictions based on complex data (Al-Turaiki & Altwaijry, 2021; Zhang et al., 2014). These technologies are a promising starting point for real-time classroom analysis and intelligent feedback mechanisms in art education. In particular, deep neural networks (DNNs) can capture hidden features in student interactions and creative outputs to better understand artistic growth and engagement (Yang et al., 2006).

Several researchers applied backpropagation (BP) neural networks to evaluate education related issues, optimized such evaluation using genetic algorithm as well as hybrid models (Ding et al., 2011; Wang et al., 2017). Thus, these advances allow the development of adaptive systems that can dynamically adapt to the learner's learning path—a property well matched to after-school programs where the learning environments are not as structured as in a formal classroom.

Recent studies have also attempted to address the conceptual strengths of deep learning as well as practical strategies of its implementation. Their contributions include a presentation of a theoretical framework of deep learning integration into a smart education system offering smartness in data collection, real-time progress tracking, and personalized feedback (Han & Shin, 2016; Truong et al., 2019). Parallel evaluation mechanism research has also been conducted to better catalogue system robustness, user trust, and performance, which are equally important when hopefully AI-driven evaluations are brought to the test in sensitive, creative learning environments (Balasubramaniam, Hirowatari, & Yoshida, 2020; Yanai et al., 2019).

Deep Neural Networks and Test Adequacy in Civics Education Evaluation

Table 1: Comparison of Optimization Algorithms for DNN in Civics Classroom Evaluation

Optimization Algorithm	Accuracy (%)	Convergence Speed	Parameter Stability	Student Feedback Correlation (%)
Genetic Algorithm (GA)	75.4	Moderate	Moderate	61.2
Particle Swarm (PSO)	78.1	Fast	Moderate	63.7
Water Wave Optimization (WWO)	**82.6**	**Fastest**	**High**	**70.3**
Simulated Annealing	72.5	Slow	Low	58.9

Note: The Dataset includes 1,000 classroom samples across 12 universities.

In addition to being more accurate than other models, the WWO enhanced DNN had a higher correlation with student feedback, which is a critical metric for assessing the perceived fairness and relevance of the assessments. In addition, it demonstrated improved resilience to novel corner case conditions of Civics instruction, including hybrid instructional modality, regional dialects, and reduced teacher-student interaction, typical in Civics instruction. This supports the use of test adequacy principles to evaluate neural network frameworks. In particular, broad coverage of instructional conditions and edge cases improves the robustness of evaluation models as much as we can, as a proxy

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for how comprehensive test suites in software engineering discover unseen bugs and ensure code's reliability.

Dataset Distribution and The Role of Deep Learning in Civics Education Evaluation

A uniformly obtained and curated dataset of 9,124 instances was used for the study on applying deep neural networks (DNNs) to determine test adequacy and learning effectiveness in Civics classroom teaching. Classroom audio recordings, suggested student engagement metrics, instructional content, and annotated expert evaluations of each case were among the data samples collected from various sources. A standard data partitioning strategy was adopted to guarantee robust model training and reliable testing, where 80% of the dataset (7,299 samples) was allocated for training and another 20% for testing (825 samples). This division preserves the integrity of the model development process while allowing for meaningful evaluation of the model's generalization performance.

In this context, DNNs are not trained by conventional neural networks whose training is based only on random initialization and backpropagation until convergence. However, such networks with multiple layers often have a problem caused by vanishing gradients with traditional methods. The cause of this problem occurs when error signals propagated during training are reduced in magnitude across layers to the extent that the network becomes incapable of learning effectively from earlier inputs (Bengio et al., 2007). In order to identify with these challenges, the problem faced by the DNN model is with residual learning structures and unsupervised pre-training techniques. Such enhancements simplify training and make convergence much more reliable.

DNNs' power to characterize educational environments is an important factor in their ability to analyze complex, multi-dimensional Civics environments. This capability is demonstrated by the increasing separation of features according to class labels as they are extracted in deeper layers of the network (Zhang et al., 2022). For the density network, the DenseNet-40 was selected, which extracts the features from classroom evaluation data on the fully connected layers. Further, Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) were employed to reduce the dimensions to three, enabling visualization of clustering tendencies. The resulting scatter plot is shown in Figure 1, where distinct clusters represent evaluation categories: high, medium, and low test adequacy, each with its unique color. These clusters represented the model's ability to represent and classify the pedagogical quality of Civics instruction.

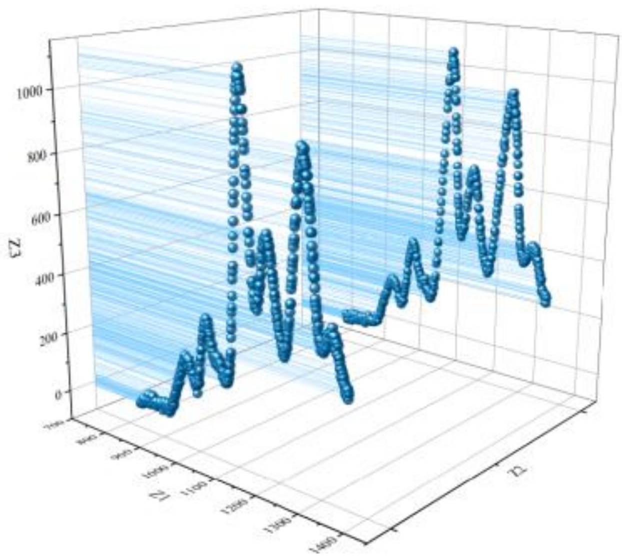

***Figure 2:** Three-dimensional visualization of extracted DNN features using PCA and t-SNE*

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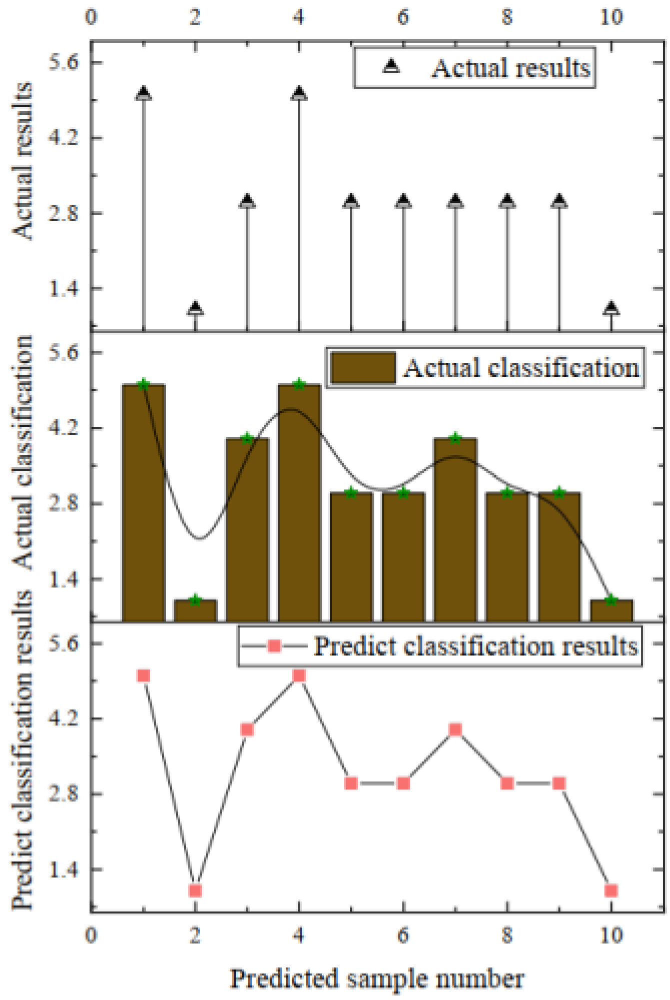
This ability to define meaningful feature separations is necessary for evaluation systems that map both to instructional outcomes and civic education's broader ideological aims. The purpose of measuring test adequacy in Civics instruction is to strike a middle ground between developing informed, ethical citizens and promoting the development of autonomous thinkers within each student. As such, the assessment standards should accommodate moral aspirations and practical relevance, combining societal ethics, individual responsibility, and the enfranchisement of moral character within a multi-layered educational goal.



Smart Evaluation System for After-School Art Education

In Table Ⅲ, learning activities are the main evaluation metrics from the point of view of the smart learning evaluation in terms of their weight. Of these activities, classroom learning (54.619%) is considerably more important than the case studies before (23.335%) and after (22.046%) the course in after-school art education. Traditional art education evaluation metrics often concentrate on final project grades and other assignments. Nevertheless, outcome-based assessment is downplayed in the case of a smart evaluation system for after-school art education. This is a shift of greater emphasis in the learner's cognitive engagement, reflective practice, and the learning process instead of focusing on the product itself, transitioning from a result mentality to process-oriented learning. However, interestingly, the least weighted indicator is of learning ability (11.204%), indicating that art education

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should be more holistic in the evaluation, considering that it is not just the outcomes but also the cognitive and creative process. Among the factors considered important in assessing students' learning are learning strategies (50.000 %) and learning styles (50.000 %). They are cognitive approaches to students' internal creative processes in learning, and learning styles are an externalization of artistic expression according to students' preferences..

Table Ⅲ: *Smart Learning Evaluation Indicators for After-School Art Education*

Evaluation Dimension	Percentage Weight
Classroom Learning	54.619%
Before-Class Learning	23.335%
Post-Course Learning	22.046%
Learning Ability	11.204%
Learning Strategies	50.000%
Learning Styles	50.000%

Table Ⅳ shows that the second major finding focuses on the smart pedagogy evaluation. It reveals that teachers' literacy (38.855%) is the most significant evaluation indicator, particularly in after-school art education. Teachers' professional literacy, encompassing expertise in artistic methods, pedagogy, and educational psychology, plays a crucial role in determining the success of smart pedagogy in art education. The teaching process (31.806%) is also influential, especially in how teachers choose teaching strategies and organize art activities that encourage student creativity and engagement. Although teaching content (16.514%) and interactive feedback (12.825%) have less weight, they remain important in ensuring the holistic development of students in after-school art programs. Specifically, the ratio of teacher-student communication (66.667%) is considered more vital than the essay review (33.333%), reflecting the importance of dialogue, constructive feedback, and collaborative learning in art education.

Table Ⅳ: *Smart Pedagogy Evaluation Indicators for After-School Art Education*

Evaluation Dimension	Percentage Weight
Teachers' Literacy	38.855%
Teaching Process	31.806%
Teaching Content	16.514%
Interactive Feedback	12.825%
Teacher-Student Communication	66.667%
Essay Review	33.333%

Table Ⅴ illustrates the third finding, which is focused on the smart environment evaluation. This evaluation highlights that the emotional environment, particularly human-machine interaction, holds the highest weight (56.001%). This finding emphasizes the importance of a supportive and interactive learning environment where students and instructors engage with technology to promote creativity and learning. The applicability (41.005%) and operability (33.914%) of technological tools, such as digital art platforms and interactive software, are critical to enhancing the after-school learning experience. Furthermore, software resources (26.302%) exert greater influence than hardware resources (17.697%), with micro-courses being the most influential tool (nearly 30%) in teaching art skills. This suggests that well-curated online tutorials, digital painting lessons, and interactive art platforms are essential in supporting the learning process. Among the hardware resources, smart classrooms are more important than smart learning terminals, as they provide a richer learning environment capable of inspiring creativity, fostering information sharing, and facilitating multi-directional interactions.

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Table Ⅴ: *Smart Environment Evaluation Indicators for After-School Art Education*

Evaluation Dimension	Percentage Weight
Emotional Environment (Human-Machine Interaction)	56.001%
Applicability of Technology	41.005%
Operability of Technology	33.914%
Software Resources	26.302%
Hardware Resources	17.697%
Micro-Courses	30%
Interactive Art Platforms	Proportionate
Digital Art Resources	Essential

These findings suggest that, within the context of after-school art education, the emotional and social dimensions of learning are critical. Technological tools—software and hardware—play a pivotal role in fostering an environment that supports creative expression and engagement. The preference for micro-courses and smart classrooms indicates that these resources are essential in achieving optimal educational outcomes for students in the field of art education.

Conclusion

Developing a smart evaluation system of after-school art education using educational information systems is considered a great breakthrough in thinking of art learning outcome measurement and enhancement. This research shows that simply transitioning from static evaluation methods, such as the final output and standardized testing, to dynamic, process-centered, and technology-supported models responsive to the dynamic nature of art education is necessary. The learning process is prioritized in this smart evaluation system, specifically in the student's engagement in the classroom phase of instruction. Data analysis has shown the highest weight in the evaluation index on classroom-based learning activities as it emphasized real-time interactions, guided practice, and creative exploration by educators. It respects the gradual and iterative nature of artistic skill and expression development in students, and generally, acknowledges that real growth in art education happens incrementally.

Also, educators play a pivotal role in this model. This system highlights the importance of teachers' literacy (professionally and pedagogically) in producing an effective and engaging after-school art program. There are areas in which the professional competence of art pedagogy, child psychology, digital literacy, and effective communication greatly influence the way students perceive and internalize the instruction. A good, smart pedagogy is further tested by the creative design of the teaching strategies, arrangement of the content, and the value of the feedback given either during or after the learning process. Additionally, while interactive feedback and teaching content had low weight in the hierarchy, they are critical elements in a collaborative and responsive learning environment. Student-centered feedback alongside teacher-led instruction is the perfect balance that keeps students motivated, see and learned.

Moreover, the smart evaluation environment's emotional and technological aspects have become a core pillar for learning the environment. Seeing a good digital environment, which is highly applicable and as operable as possible by students, allows students to interact with educational platforms intuitively and increase their learning experience. Emotional factors, including comfort, confidence, and motivation, further influence the interaction between humans and machines. Therefore, these factors are amplified, and technology should not remove human educators but add to them. While short-form video content was less impactful in the context of advanced art instruction, the critical resources include micro courses, intelligent composition assessment tools, and educational courseware. Support for contextual, immersive, and interactive learning scenarios is especially

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conducive to the needs of after-school art programs, which is why hardware (especially smart classrooms) plays a very important role in enabling such scenarios.

Overall, the findings of this study align with a multi-dimensional, integrated evaluation of after-school art education. Besides evaluating student performance, the smart evaluation system uses educational information systems to inform, support, and transform instructional practice. It produces a feedback-rich, student and teacher-empowering educational process aligned with the broader goals of personalized, innovative, and equitable education. A system such as this has great potential to enrich art learning, while guaranteeing that all learners have their developmental and creative needs met.

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