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AI-generated content construction in digital exhibition halls and practical study of image processing algorithms in educational reforms

Shige Ren[1,✉]

[1] College of Art and Media, Chongqing Metropolitan College of Science and Technology, Chongqing, 401320, China

ABSTRACT

With the rapid development of science and technology, the traditional mode of teaching is inefficient and difficult to flexibly respond to the needs of knowledge updating, and generating content and applications based on AI has become an important way to solve this problem. According to the form of interaction in the digital exhibition hall, the article proposes SinGAN model and uses the multi-head self-attention mechanism to coordinate the overall features and detailed features in the generated adversarial network image, and to deal with the large range of dependencies in the image. The proposed AI-generated content and SinGAN image processing method are applied in the teaching of practical courses using the course "Digital Electronics Technology and Application" of a university in Guangdong Province, which specializes in electronic information and engineering, as an experimental object. The experiment shows that the percentage of content with a content quality score of 0.6 to 1.0 reaches 75.7%. As the course progresses, the keyword coverage rate reaches 0.996, and AI-generated content is efficiently applied in the course. The student performance of the experimental class with AI-generated content and image processing method teaching mode and the regular class with traditional teaching mode were 80.75 and 67.91 respectively, and the sample t-test for the significance of the student performance of the two classes was P=0.006, which showed a significant difference in the students' performance between the two teaching modes. Students' satisfaction with the new teaching mode is high, indicating that the AI-generated content and image processing methods proposed in the article have been well applied in education reform.

Keywords: digital exhibition hall, AI generated content, SinGAN, image processing

1. Introduction

In recent years, the rapid development of artificial intelligence (AI) technology has demonstrated great potential in different fields. Among them, the application of AI in the field of education has attracted

✉ Corresponding author.
E-mail address: xxiguaner@163.com (S. Ren).

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widespread attention [1-2]. The combination of AI and education is regarded as an important way to promote educational reform and innovation, and it brings great changes and challenges to teaching and learning [3-5]. The traditional teaching mode is led by teachers and passively accepted by students. In the new era, the integration of AI and education will have a profound impact on the way, content and assessment of education [6-8].

Artificial intelligence can provide support for education in many aspects, personalized learning experience is an important performance of AI education, through the analysis of students' learning behavior and performance, AI systems can design personalized learning plans and teaching resources for students according to their interests, abilities and learning styles and other individual differences [9-12]. This means that each student can learn according to his/her own needs and level, which can improve the learning effect and satisfy individual needs. At the same time, AI also provides teachers with effective teaching aids [13-15]. Teachers can obtain students' learning data and feedback information through AI systems, quickly understand students' learning status and provide individualized guidance. Although AI technology has many beneficial applications in education and learning, we also need to be vigilant about the problems [16-19]. AI technology does not replace the role of teachers, teachers are still the main force of education and teaching, and the application of AI technology needs to ensure that no harmful information is transmitted to the direction of students [20-22].

The SinGAN network proposed in this paper consists of a fully convolved GAN pyramid, where each layer is responsible for learning the patch distribution of an image at different scales. And the practice of self-attention mechanism is used to perform attention operations on multiple sets of different features of the same dimension. The self-attention mechanism is fused with the multi-attention mechanism. Residual normalization is performed on this basis, which consists of a residual layer and a normalization layer. The role of the residual layer is to add the original inputs with the inputs processed by the multi-head self-attention mechanism to avoid problems such as gradient vanishing, gradient explosion, and network degradation; the layer normalization replaces the defects of BatchNorm with LayerNorm. LayerNorm avoids the defects of BatchNorm by calculating the mean and variance for individual samples in each batch, which allows the model to be extraction of features from other samples in a batch.

2. AI-generated content and image generation methods for digital exhibition halls

2.1. *Interactive forms in digital exhibition halls*

The form of information exchange with image, text, and numerical value transmitted between the exhibits and the experiencer is the so-called data interaction form, and there are three kinds of input methods: direct input, selective input, and information reading. Direct input is the most common, is the use of human direct information through the key or touch screen version of the input to the device, due to manual input, error is higher, so for the accuracy of the input information requires the experience of the second confirmation; selective input generally refers to the interactive process to provide the experience of the menu options, through the menu options for the form of choice; information reading is mainly through the professional equipment on the barcode or two-dimensional code that has been pre-set information. The information reading is mainly done by scanning the barcode or two-dimensional code that has been preset with good information by professional equipment.

Image interaction is the interaction with visual display as the ultimate purpose, and the interaction form of presenting the preset information through professional display equipment. Image interaction can input and analyze images through PC, and decide different interaction modes through different image displays, so as to produce different preset effects according to the specific interaction modes between the experiencer and the display device. With the increasing sophistication of hardware in recent years, the computational methods of image interaction are also constantly updated, ensuring the accurate recognition of images while also exploring and innovating in display design. Voice interaction is to make the experiencer interact with the exhibits through the propagation of voice, and the interaction between the experiencer and the exhibits is carried out through the cooperation of voice recognition mechanism and voice feedback mechanism. On the one hand, this form of interaction design has higher requirements for the exhibits themselves, and on the other hand, the words of the experiencer are random and unpredictable, which leads to the extremely high requirements for the ability of voice interaction equipment, and even requires the intervention of AI function. At present, the form of voice recognition is not able to fully meet the requirements, the support for the technology is not yet fully mature, is still limited to the application of the specified voice for exhibit interaction, but the future of the voice interaction exhibition form can be expected.

The form of interaction with exhibits through the body movements of the experiencer to realize the form of outputting specific commands is called action interaction. In the design process of action interaction, designers use specific equipment to mobilize the means of science and technology, so as to realize the interaction between the exhibits or display scenes, which can fully mobilize the interest of the audience, and then achieve better display results. Such as interactive puzzle is through the real shooting action, induction to the wall with gravity capture to realize the product interaction puzzle.

In the design of automobile exhibition hall, through the motion capture technology, let the experience stand in front of the interactive screen, through the simulation of driving to control the direction of the car corresponding to the screen to move and speed changes. In the motion interaction design, the fun research is the focus of the designer to consider, so that the experience in the process of visiting not only satisfied with the visual experience, but more importantly, fully understand and feel the experience of the display products.

2.2. Single Graph Generation Networks

2.2.1. Single Graph Generation Networks . The goal of Single Image Generative Networks is to learn an unconditional generative model that captures the internal statistical information of a single training image. This task is structurally similar to a traditional GAN setup, with the difference that here the training samples are patches of individual images rather than entire image samples from a database.SinGAN is one such model, which is a model that can learn enough information from individual images and then use this information to generate new high-quality, diverse new samples similar to, but not identical to, the original image. The network structure of SinGAN consists of a set of convolutional pyramids containing GANs, each layer of which is responsible for learning the distribution of patches at different scales of the image. Such a structure allows the generation of new samples of arbitrary size and different vertical to horizontal scales, which are not only variable but will maintain the global structure of the input sample and the detailed texture in the sample, etc. In SinGAN the statistics of complex image structures are captured at many different scales.SinGAN is able to do the internal learning of a single image from a single image and performs the unconditional generation. It is the first network that learns internally from a single image and generates images that are difficult to distinguish by human detection methods, and it also has the ability to be used in a wide range of image processing tasks, such as super-resolution, painting image generation, image rationalization, and so on.

2.2.2. Network training process. The generation of new sample images starts at the coarsest scale and then passes sequentially through all the generators up to the finest scale, with the models in this chapter inputting new random noise at each scale. All generators and discriminators feel the same way, so structures of decreasing size are captured as the generation process proceeds. At the coarsest scale, the only input to the generative network is random noise, and the generation of new samples has no dependence on other inputs at this level, i.e., it can be shown that the model is indeed an unconditional generative network, as expressed by the formula, i.e., G_N maps the spatial Gaussian white noise Z_N to the image samples X_N.

$$X_N = G_N\left(Z_N\right) \tag{1}$$

The effective feeler field for each layer of the scale is typically half the height of the sample image input to that layer, and for each layer of G_N it generates an image whose general layout is similar to the global structure of the original sample. The generator G_n for $(n < N)$ in each finer scale adds details to the input image of the previous layer that were not generated by the generator of the previous size. With the exception of the bottom layer, which has only noise Z_n input, the input data for the generators G_n in each layer consists of the generated image from the previous layer at the coarser scale after upsampling:

$$X_n = G_n\left(Z_n, \left(X_{n+1}\right)\uparrow^r\right) n < N \tag{2}$$

All generators in the network have a similar architecture, the Resnet network structure, where random noise Z_n is added to the image $\left(X_{N+1}\right)\uparrow^r$ and then fed into the convolutional layers. This ensures that the samples fed into the generator network have random noise in them, so that the network does not ignore the condition of random inputs, and the samples generated by this method will remain random. This method of generation involving randomness is often used. The role of the convolutional layers in this network is to generate missing details in $\left(X_{N+1}\right)\uparrow^r$ that were not generated on the previous scales. The operations performed in G_n for each layer can be viewed in equation (3).

$$X_n = \left(X_{n+1}\right)\uparrow^r + \left(\psi_n\left(\left(Z_n + \left(X_{n+1}\right)\uparrow^r\right)\right.\right. \tag{3}$$

Equation (3) ψ_n is a fully convolutional network consisting of five 3×3 -size Conv layers, a single BatchNorm layer, and a single LeakyReLU layer. The BatchNorm layer changes the distribution of values passing through the layer to a standard normal distribution with mean 0 and variance 1 by means of normalization, which essentially changes the increasingly skewed distribution of the data passing through the network to a more standard distribution. In essence, it is to change the distribution of the data after the neural network is more and more skewed into a more standard distribution, through this operation can make the input value distribution in the nonlinear function of the more sensitive intervals, the use of normalized input values can be better activation of the function, so that a slight change in the value of the input will make the loss function will change greatly, in other words, such an operation can make the gradient value becomes larger, to avoid the occurrence of the gradient disappearance, at the same time, the gradient value becomes larger is equivalent to the network learning. How to converge faster, that is, through the BatchNorm layer can make the network training faster. The activation function Leaky ReLU is very similar to ReLU, Leaky ReLU performs better in solving the neuron death problem, for ReLU, the value of the part of it that is less than 0 is set to 0, while the value of the input in Leaky ReLU that is negative is still set to negative after it and still has a gradient, although the gradient value is small, the ReLU function and the LeakyReLU function are shown in Figure 1.

In practice, the α in Leaky ReLU is usually taken as 0.01, the advantage of Leaky ReLU is that in back propagation, when using Leaky ReLU activation function, the gradient can still be computed for values less than zero, but when using ReLU activation function, these values are all zero and the gradient can not be computed, which can make the negative part of the information will not be lost.

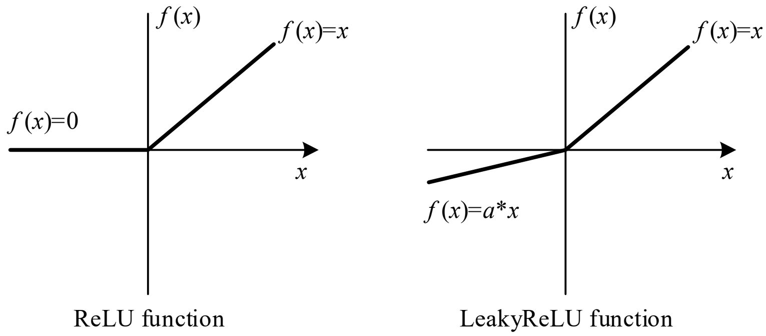

Fig. 1. ReLU function and LeakyReLU function

Since the generator in this paper is fully convolutional, it is possible in this paper to generate images of arbitrary size and aspect ratio by varying the size of the noisy map in the input network when generating test samples.

2.3. Image generation method based on Transformer encoder architecture

2.3.1. Multi-pronged self-attention mechanisms. In order to make the generative adversarial network can coordinate the overall features and detailed features in the image and deal with the large range of dependencies in the image, this paper uses the multi-head self-attention mechanism to solve this problem. The attention mechanism can be described as a function mapping from a query to a set of key-value pairs, where query Q, key K and value V are vectors, d_k is the dimension of key K, and the output of the attention mechanism is a weighted sum of different values V, and the weights are obtained by dot-multiplying between query Q and key K, dividing it by a scale factor $\sqrt{d_k}$, and finally connecting to the softmax function. The specific expression formula for the ordinary attention mechanism is shown in equation (4).

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

In this paper, we adopt the approach of self-attention mechanism. The core idea of the self-attention mechanism is that it does the attention mechanism to itself, i.e., $Q=K=V$. The use of the self-attention mechanism to the output $o^{\langle t\rangle}$ of the convolutional layer in the t nd moment enables the model output to also take into account the other contents in the image at low resolution at the same time in the case of possessing a restricted range of sensory fields, and handles the large range of dependencies very well. After using the self-attention mechanism, Eq. (4) is updated to Eq. (5), where $d_{o^{\langle t\rangle}}$ is the dimension of vector $o^{\langle t\rangle}$.

$$\begin{aligned} self\_Att\left(o^{\langle t\rangle}\right) &= Attention\left(o^{\langle t\rangle},o^{\langle t\rangle},o^{\langle t\rangle}\right) \\ &= soft\max\left(\frac{o^{\langle t\rangle}o^{\langle t\rangle}T}{\sqrt{d_{o^{\langle t\rangle}}}}\right)o^{\langle t\rangle} \end{aligned} \tag{5}$$

The single attention mechanism only needs to do one attention operation on query Q, key K and value V; the specific operation of the multi-attention mechanism is to do multiple linear mappings on query Q, key K and value V to get multiple groups QW, QK and QV, which are regarded as the updated query Q, key K and value V, and the attention mechanism is used on each group QW, QK, QV, and finally the merged result is linearly mapped to to get the final update result. The architecture of the multi-head attention mechanism is shown in Fig. 2, and the specific formulas are shown in Eq. (6) and Eq. (7).

$$MultiHead(Q,K,V) = Concat(head_1,\dots,head_m)W^O \tag{6}$$

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{7}$$

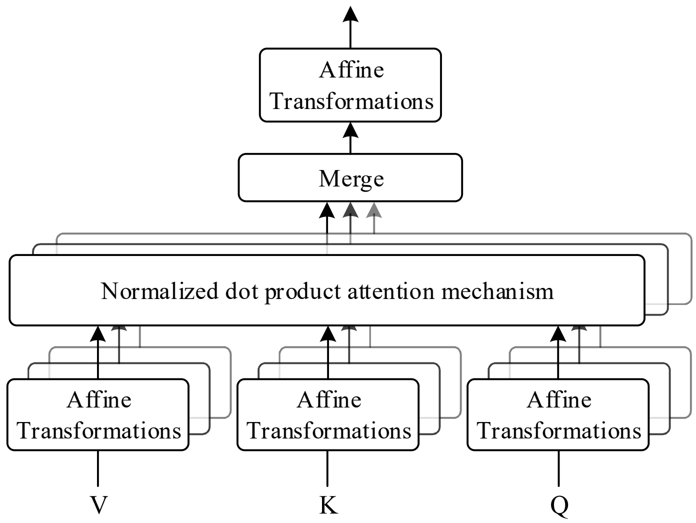

Fig. 2. Multi-head attention mechanism

where the linear projection parameters are matrices $W_i^Q \in \mathbb{R}^{d_{model}*d_k}$, $W_i^K \in \mathbb{R}^{d_{model}*d_k}$, $W_i^V \in \mathbb{R}^{d_{model}*d_v}$, $W^O \in \mathbb{R}^{hd_v*d_{model}}$, d_k are the dimensions of key k, d_v is the dimension of value v, h is the number of attention operations, and d_{model} is the dimension of the merged operant object. Multiple linear mapping of Q, K and V can get multiple sets of features obtained from different angles in the same dimension, compared with the operation of attention operation on only one set of features alone, attention operation on multiple sets of different features in the same dimension makes the model more well-considered and robust in performance. After fusing the self-attention mechanism with the multi-attention mechanism, Eqs. (4) and (5) are updated to Eqs. (8) and (9).

$$\begin{aligned} self\_MultiAtt\left(o^{\langle t\rangle}\right) &= MultiHead\left(o^{\langle t\rangle}, o^{\langle t\rangle}, o^{\langle t\rangle}\right) \\ &= Concat(head_1,\dots,head_m)W^O \end{aligned} \tag{8}$$

$$head_i = Attention\left(o^{\langle t\rangle}W_i^Q, o^{\langle t\rangle}W_i^K, o^{\langle t\rangle}W_i^V\right) \tag{9}$$

2.3.2. Normalization of residuals. The residual normalization layer is composed of a residual layer and a normalization layer. The role of the residual layer is to add the original inputs with the inputs processed by the multi-head self-attention mechanism to avoid problems such as gradient vanishing, gradient explosion, and network degradation; the layer normalization avoids the defects of the ordinary BatchNorm. Although BatchNorm is a very effective tool in training neural networks, its defect is that the calculation of BatchNorm needs to rely on the data in the batch, and different batches will calculate different mean and variance, which leads to the model to have a lower bound on the size of the data batch, stipulating that the size of the data batch used in the model must be large enough so that the batch samples can be sufficiently representative of the overall characteristics of the samples. The LayerNorm avoids the shortcomings of the BatchNorm by calculating the mean and variance for individual samples in each batch, allowing the model to extract features while being free from the interference of other samples in a batch.The formulas for the LayerNorm are shown in Equation (10)-Equation (12), and the difference between the LayerNorm and the BatchNorm is illustrated in Figure

1. BatchNorm is shown in Fig. 3. Where x is the input, i denotes the dimension of the batch, and j denotes the dimension of the features, which are very small values.

$$\mu_i = \frac{1}{m} \Sigma_{j=1}^{m} x_{ij} \tag{10}$$

$$\sigma_i^2 = \frac{1}{m} \Sigma_{j=1}^{m} \left(x_{ij} - \mu_i \right)^2 \tag{11}$$

$$\hat{x}_{ij} = \frac{x_{ij} - \mu_i}{\sqrt{\sigma_i^2 + \epsilon}} \tag{12}$$

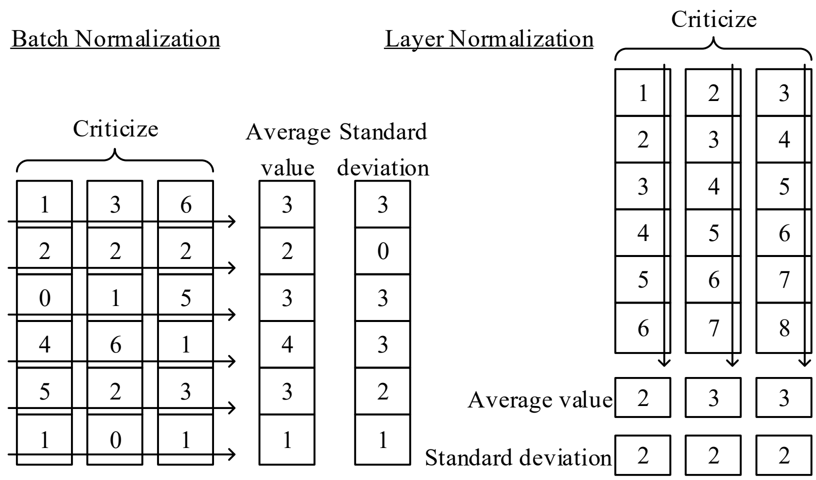

Fig. 3. Difference between BatchNorm and LayerNorm

3. Practical application of AI-generated content and image processing methods in teaching and learning

3.1. Experiments with AI-generated content in the curriculum

In order to verify the quality and effectiveness of AI-generated content in teaching practice, actual teaching experiments can be conducted. For the assessment of teaching effectiveness, the following assessment indicators can be selected. First, the content quality score is evaluated using the open-source tool Natural Language Data Package, which evaluates the generation quality score of a single sentence or multiple sentences (e.g., whole documents and paragraphs) by the function that comes with the tool. Second, keyword coverage is used using the TF-IDF method. Firstly, the frequency of occurrence of each word in the content (TF) is calculated, after that the inverse frequency of the word in the content set (IDF) is calculated, and finally the two are multiplied to get the weight of the word, and the word with higher weight is the keyword, and the algorithm tends to filter out the common words and keep the important words. The keyword coverage can be derived from the occurrence of the keyword in the content.

3.1.1. Content quality and score. In order to assess the quality of AI-generated content in the digital showroom, the percentage of the number of generated content quality scores using the proposed in this paper is shown in Figure 4.

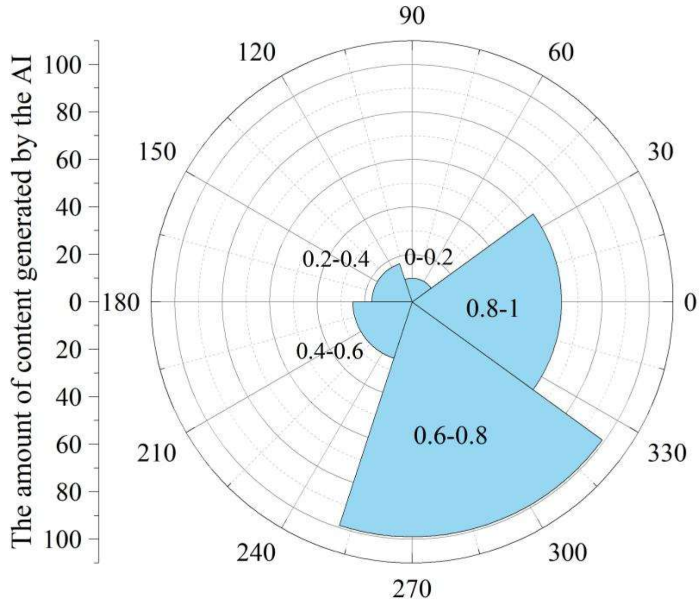

Fig. 4. The proportion of generated content

As can be seen from Figure 4, the content with higher quality score is extracted in a higher proportion, it is the content with 0.6 to 1.0 quality score that accounts for 75.7%, more than half of the content, to realize the efficient generation of content.

3.1.2. Changes in coverage. The coverage of the generated content is measured using the keyword coverage, and the change in coverage over time is shown in Figure 5, where 0 to 10 represents the learning progress of the course, and a larger number represents more learning progress of the course.

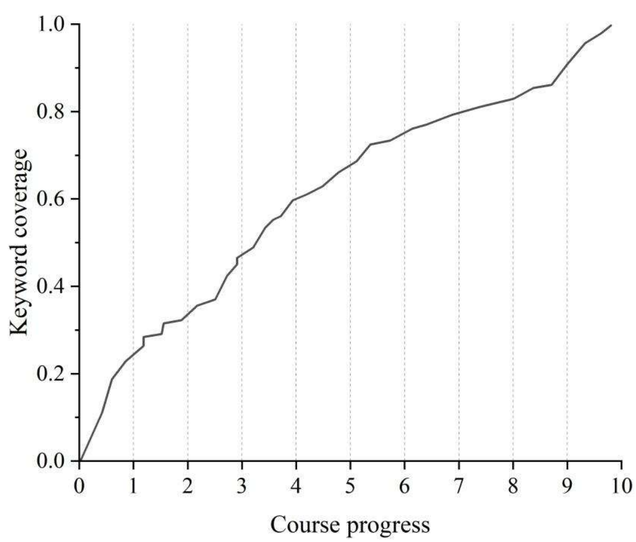

Fig. 5. Coverage area

As the course unfolds, the keyword coverage of the generated content is getting bigger and bigger, and when the course progresses to 10, the keyword coverage reaches 0.996. It can be concluded that after the steps of data collection and pre-processing, key information extraction, content generation content embellishment and so on the content of the natural language processing technology can be realized to generate quickly and efficiently, which provides a new solution for the application of course content generation and automation.

3.2. Comparative Analysis of Learning Achievement

In order to test the practicality of the AI-generated content and SinGAN model-based image generation method proposed in this paper in education reform, it is applied in actual teaching. The students' learning performance in the teaching mode of applying AI-generated content and image processing method and the traditional teaching mode are selected for the comparative study, which are named as the experimental group and the general group respectively. The course taught in this study is Digital Electronic Technology and Application, and the teaching time is the second semester of the 2023-2024 academic year. Because of the slight difference in the way students are evaluated in the two teaching modes, the results of the students in the experimental class and the ordinary class are selected as the end-of-semester examination results. Other influencing factors such as: students' basic level, lecture progress, course study content, reference materials, and final examination paper are all the same.

3.2.1. Objects of study. The research subjects in this chapter are the students of the class of 2023 in the School of Electronic Information and Engineering of a university in Guangdong Province, because the students admitted to our university are regulated by the score line and have strict score regulations, so the students entering the same major do not have a large difference in their learning ability and learning foundation. In order to ensure the scientific validity of the research results, the instructor of the class issued test questions to give the class a pre-study pre-test before the lecture, and the results of the pre-test showed that none of the research subjects had a foundation in the course. Using the AI-generated content and image processing methods proposed in this paper, the selection of experimental teaching mode courses is based on the voluntary choice of students, and the class size is determined by integrating the students who choose the experimental teaching mode of instruction, and the number of participants in the experimental class is finally determined to be 56 people. In order to ensure that the number of students in the experimental class is similar to the number of students in the ordinary class, therefore, the results of students in an ordinary class are randomly selected for comparison, and the number of students is 55.

3.2.2. Research process. The study lasted one semester and two tests were administered to the students in the experimental class and to the students in the regular class.

The first one was a pre-instructional test, in which the same test questions were issued by the classroom teachers, and the 56 students in the experimental class and 55 students in the regular class were given a pre-school test to determine the students' knowledge of the course content as well as their basic level. The results of the tests showed that neither the students in the experimental class nor the students in the regular class had a basic level of knowledge of the course, and there were no cases where they had studied the relevant knowledge in advance.

The second test was conducted at the end of the semester to test the learning outcomes of the students in order to understand the differences in learning outcomes and the impact of the two modes of instruction on student learning.

3.2.3. Data analysis. Through one semester of overall learning, the total performance of the learners in the teaching mode with AI-generated content and image processing methods and the traditional teaching mode were analyzed descriptively, and the distribution of the final grades of the regular class and the experimental class are shown in Fig. 6 and Fig. 7, respectively.

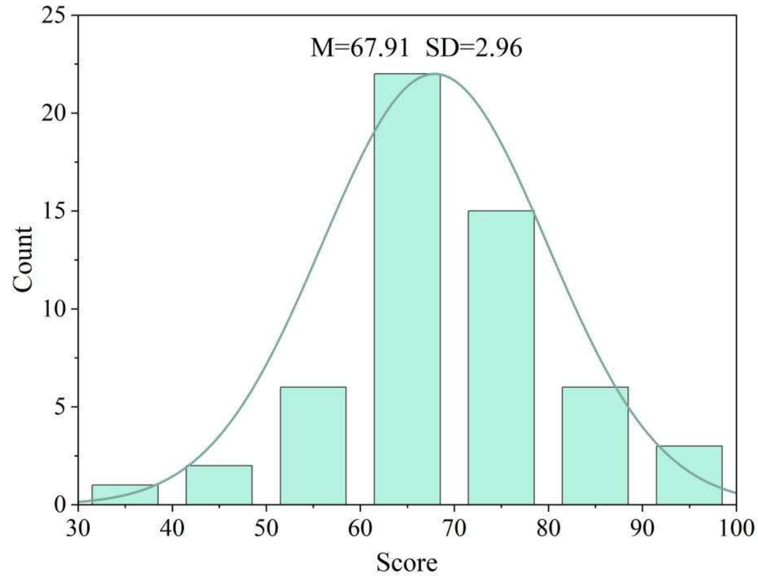

Fig. 6. Regular class final grade distribution map

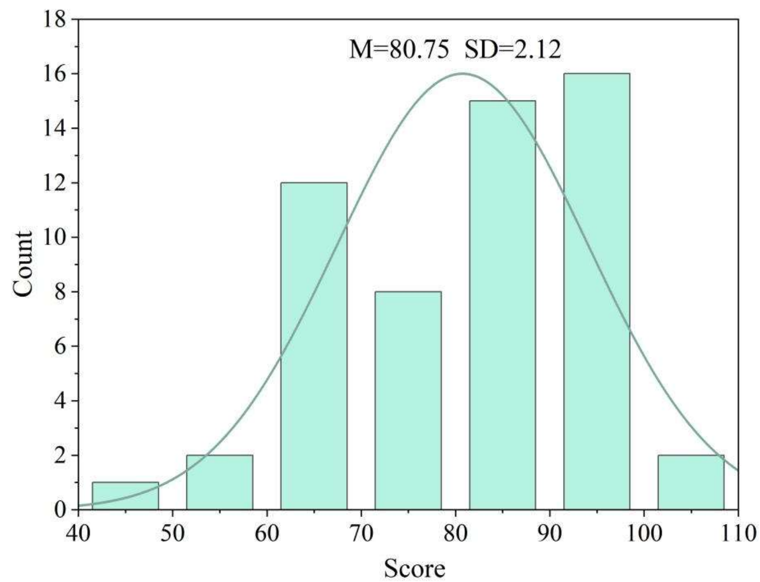

Fig. 7. Experimental class final grade distribution map

The mean score of the students in the experimental class is 80.75, and the mean score of the students in the general class is 67.91. The average score of the experimental class is 12.84 points more than that of the general class, which is significantly higher than that of the general class, and thus it can be seen to a certain extent that the average learning effect of the students in the experimental class is better than that of the students in the general class. The standard deviation of the students in the experimental class is 2.12, and that of the students in the general class is 2.96, which is slightly higher than that of the students in the experimental class, indicating that the individual differences among the students in the experimental class are slightly smaller.

In order to more intuitively compare the data of students in the experimental class with those in the general class, SPSS25.0 was used to draw box plots of the two groups of data, and Figure 8 shows the box plots of students' performance in the general class and the experimental class. The top and bottom of the box each has a line, representing the great value and the small value, the line in the middle of the box represents the median of the students' performance, and the width of the box indicates to a certain extent the degree of fluctuation of the students' performance. It can be seen that the highest score in the experimental class is 100, the lowest score is 49, and the students' scores are concentrated between 69-91, while the highest score in the general class is only 92, the lowest score is 40, and the scores are concentrated between 60-78. It shows that the performance of students in the experimental class has been significantly improved through the teaching reform of AI-generated content and image processing methods.

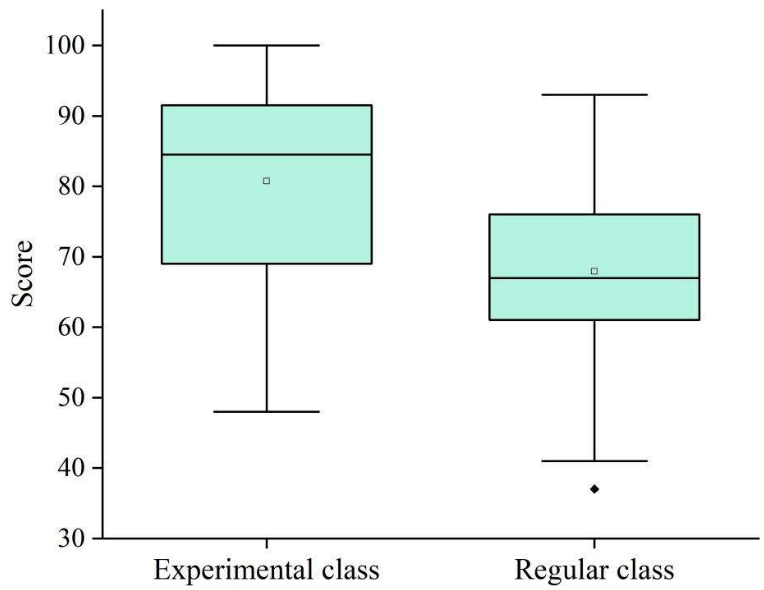

Fig. 8. Regular class and experimental class students results box plots

In order to further test the difference between the experimental teaching mode and the traditional teaching mode to the students' learning effect, the study used the method of independent samples t-test to compare and analyze the data samples of the two groups of students, and the results of the analysis are shown in Table 1.

Table 1. Results of independent sample t test of student learning achievement

Class	N	M	SD	T	P	F
Regular class	55	67.91	2.96	2.546	0.006	0.218
Experimental class	56	80.75	2.12			

From the results of the independent samples t-test, the probability of significance of the students' performance in the two classes P is 0.006<0.05, so it can be concluded that the difference in students' performance between the two teaching modes is significant. It can be shown that the learning effect of the teaching mode with AI generated content and image processing method is better than the traditional teaching mode in the course “Digital Electronics and Applications”.

3.3. *Analysis of satisfaction surveys*

For the actual teaching effect of the designed and developed course using AI to generate content and image processing methods, this paper analyzes the questionnaires and interviews with the students to investigate the students' recognition of the course model and the teaching effect, so as to validate the effectiveness of the actual teaching of the course of applying AI to generate content and image processing methods proposed in this paper. A satisfaction questionnaire about the course content and teaching process was distributed to 56 students participating in the experimental class, and 56 questionnaires were recovered.

3.3.1. Course content satisfaction survey. The course content survey focused on student satisfaction with the AI-generated content and processed images covered in the course Digital Electronics and Applications. The specific survey results are shown in Figure 9.

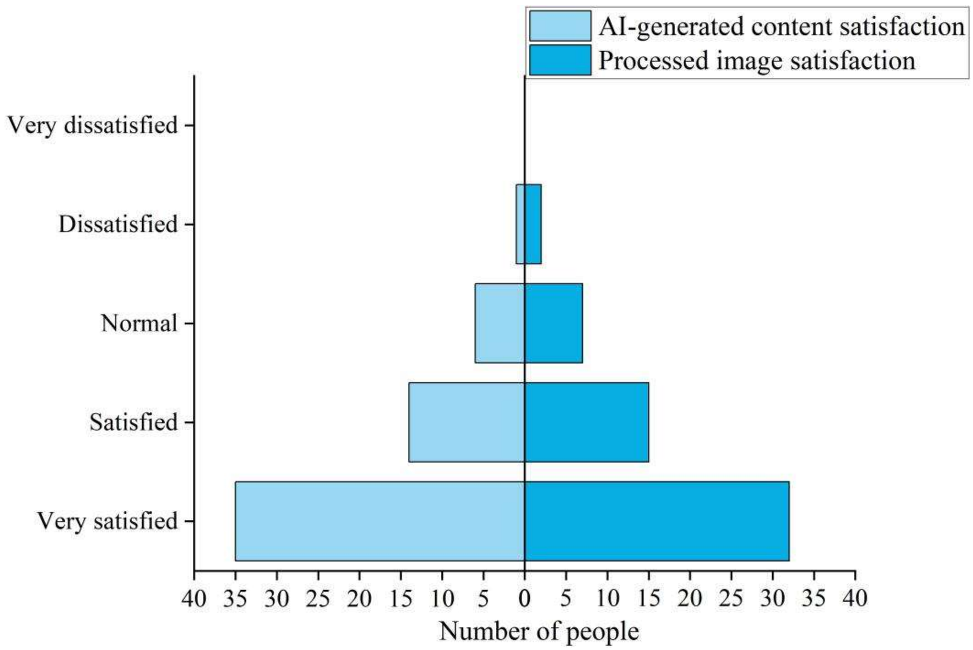

Fig. 9. AI generates content and processes image satisfaction

35 people were "very satisfied" with AI-generated content, accounting for 62.5% of the total, and 14 people were "satisfied", accounting for 25% of the total. The number of "very satisfied" and "satisfied" images was 32 and 15 respectively, indicating that students were more satisfied with the course content, and the AI-generated content was even more satisfied.

3.3.2. Satisfaction Survey on Teaching Effectiveness and Learning Achievement. The survey of the teaching process focused on the students' satisfaction with the "teaching effect" and the three knowledge review methods: "experimental knowledge summary", "mind map knowledge summary" and "mini game knowledge summary". The results of the survey are shown in Figure 10.

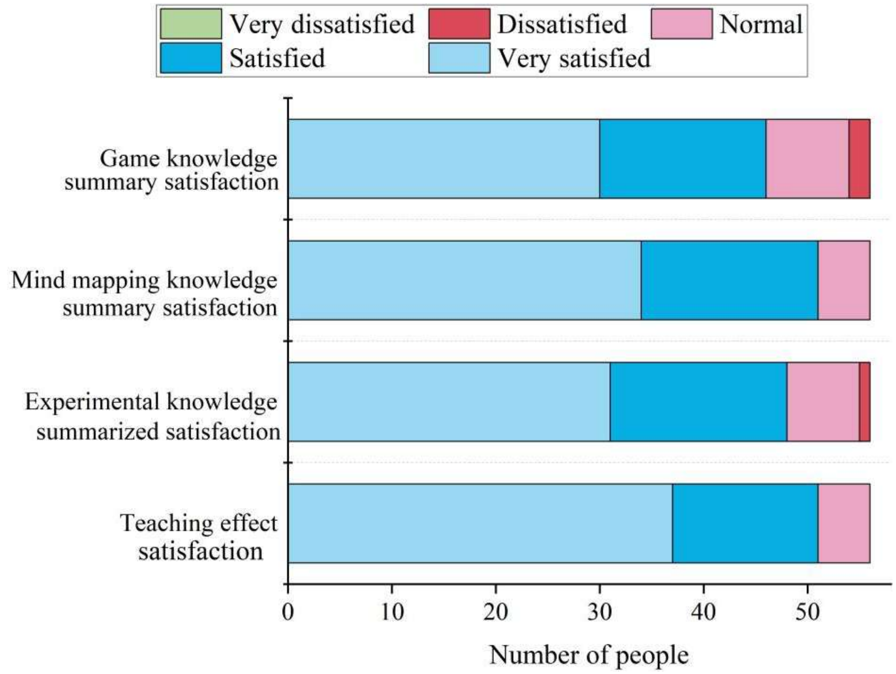

Fig. 10. Survey of teaching effect and learning achievement satisfaction

Overall student satisfaction with teaching effectiveness and learning achievement was high, for teaching effectiveness, 37 out of 56 students were very satisfied, 14 were somewhat satisfied, 5 felt average, and no one felt dissatisfied or very dissatisfied.

4. Conclusion

The article proposes an unconditional generative model SinGAN, which is trained for a single natural image and optimizes the image generation method based on the Transformer encoder architecture. The AI-generated content and image processing methods proposed in the article are applied in the practical course teaching, and the conclusions are as follows.

1) The average AI generated content quality score in the course application is 0.704, and as the course unfolds, the keyword coverage of the generated content becomes larger and larger, and the final coverage reaches 0.996.

2) The mean values of the students' scores in the experimental class and the regular class are 80.75 and 67.91, respectively, and the standard deviations are 2.12 and 2.96, respectively, indicating that the students' scores in the experimental class have been significantly improved through the application of the teaching mode of AI-generated content and image processing methods.

3) In the questionnaire survey, 59.82% and 66.07% of the students were “very satisfied” with the course content and teaching effect respectively, indicating that the students were highly satisfied with the teaching application of AI content generation and image processing methods.

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References

[1] Fleck, J. (2018). Development and establishment in artificial intelligence. In The Question of Artificial Intelligence (pp. 106-164). Routledge.

[2] Yang, S., Zhao, H., & Luo, W. (2025). The Impact of Artificial Intelligence. Belonging in Culturally Diverse Societies-Official Structures and Personal Customs: Official Structures and Personal Customs, 57.

[3] Doroudi, S. (2023). The intertwined histories of artificial intelligence and education. International Journal of Artificial Intelligence in Education, 33(4), 885-928.

[4] Lu, C. A. (2025). Tracing the Evolution of Artificial Intelligence Education at Stanford University. TechTrends, 1-7.

[5] Qu, J., Zhao, Y., & Xie, Y. (2022). Artificial intelligence leads the reform of education models. Systems Research and Behavioral Science, 39(3), 581-588.

[6] Paek, S., & Kim, N. (2021). Analysis of worldwide research trends on the impact of artificial intelligence in education. Sustainability, 13(14), 7941.

[7] Ezzaim, A., Kharroubi, F., Dahbi, A., Aqqal, A., & Haidine, A. (2022). Artificial intelligence in education-State of the art. International Journal of Computer Engineering and Data Science (IJCEDS), 2(2).

[8] Chiu, T. K. (2021). A holistic approach to the design of artificial intelligence (AI) education for K-12 schools. TechTrends, 65(5), 796-807.

[9] Miller, J. C., Miranda, J. P. P., & Tolentino, J. C. G. (2025). Artificial Intelligence in Physical Education: A Review. Global Innovations in Physical Education and Health, 37-60.

[10] Krasheninnik, I. V., Chorna, A. V., Koniukhov, S. L., Ibrahymova, L., & Serdiuk, I. (2022). Artificial Intelligence in Personalized ICT Learning. International Journal of Computer Science and Network Security, 22(2), 159-166.

[11] Kolchenko, V. (2018). Can modern AI replace teachers? Not so fast! Artificial intelligence and adaptive learning: Personalized education in the AI age. HAPS educator, 22(3), 249-252.

[12] Ravshanovna, K. L., Isoqovich, A. A., & Xasanovich, X. R. (2025). ARTIFICIAL INTELLIGENCE IN ENGLISH CLASSES: REVOLUTIONIZING LANGUAGE LEARNING AND TEACHING. ANALYSIS OF MODERN SCIENCE AND INNOVATION, 1(4), 242-247.

[13] Chen, X., Zou, D., Xie, H., Cheng, G., & Liu, C. (2022). Two decades of artificial intelligence in education. Educational Technology & Society, 25(1), 28-47.

[14] Biswas, R. A., & Molla, A. (2024, August). IMPACT OF ARTIFICIAL INTELLIGENCE ON PERSONALIZED LEARNING. In ARTIFICIAL INTELLIGENCE IN EDUCATION (p. 302).

[15] Ahmad, W., Raj, R., & Shokeen, R. (2025). Reshaping Special Education: Strategic Use of Artificial Intelligence. In Transforming Special Education Through Artificial Intelligence (pp. 1-44). IGI Global.

[16] Uygun, D. (2024). Teachers' perspectives on artificial intelligence in education. Advances in Mobile Learning Educational Research, 4(1), 931-939.

[17] Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. Research and practice in technology enhanced learning, 12(1), 22.

[18] Martínez-Moreno, J., & Petko, D. (2024). What motivates future teachers? The influence of Artificial Intelligence on student teachers' career choice. Computers and Education: Artificial Intelligence, 7, 100296.

[19] Wogu, I. A. P., Misra, S., Olu-Owolabi, E. F., Assibong, P. A., Udoh, O. D., Ogiri, S. O., & Damasevicius, R. (2018).

Artificial intelligence, artificial teachers and the fate of learners in the 21st century education sector: Implications for theory and practice. International Journal of Pure and Applied Mathematics, 119(16), 2245-2259.

[20] Moreno-Guerrero, A. J., López-Belmonte, J., Marín-Marín, J. A., & Soler-Costa, R. (2020). Scientific development of educational artificial intelligence in Web of Science. Future Internet, 12(8), 124.

[21] Opesemowo, O. A. G. (2025). Artificial Intelligence in Mathematics Education: The Pros and Cons. In Encyclopedia of Information Science and Technology, Sixth Edition (pp. 1-18). IGI Global.

[22] du Boulay, B. (2022). Artificial intelligence in education and ethics. In Handbook of open, distance and digital education (pp. 1-16). Singapore: Springer Nature Singapore.