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Computer-Aided Design AND APPLICATIONS

Innovative Ceramic Pattern Design and CAD Interactive Editing Method Driven by GAN Technology

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Abstract. This study aims to investigate the novel utilization of the Generative Antagonistic Network (GAN) in designing ceramic patterns, integrating it with computer-aided design (CAD) technology to facilitate an interactive editing approach for enhancing design efficiency and fostering creativity. Initially, this paper examines the constraints inherent in conventional ceramic pattern design methods, notably the protracted design cycles and constrained innovative scope. The design training and generation process of ceramic patterns has a high degree of pattern novelty in learning. In the CAD art editing process of building and designing authentic ceramics, designers construct a complete and authentic design scheme through the learning process of generating identification. The research results indicate that the construction process of CAD interactive design methods can significantly improve design efficiency. Designers can easily adjust layout patterns and edit creative previews.

Keywords: Ceramic Pattern Design; Gan Technology; Interactive Editing of CAD; Innovative; Design Efficiency
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1 INTRODUCTION

Most of the raw materials for ceramic product production come from natural mineral rocks, which have a wide variety and obvious regional distribution. In the process of ceramic product production, the most important thing is the design of ceramic formulas. This formula design method, which highly relies on practitioners' professional experience and knowledge and is uncertain, is not conducive to the modern ceramic industry's modernization and intelligent development needs. Ceramic formula refers to the analysis of the chemical composition and percentage ratio of existing ceramic products based on their raw materials and glazes [1]. An analytical method is an optimization problem with a simple objective function and a clear expression, which can directly obtain the optimal solution through mathematical calculations. When the objective function of an optimization problem is complex or uncertain, it is impossible to obtain the optimal solution through direct mathematical calculations. Ceramic formula design refers to selecting the required production raw materials and determining the percentage content ratio of various raw materials based on the existing ceramic formula [2]. In terms of ceramic pattern interaction, our 3D printing technology provides unprecedented creative freedom. Personalized ceramic products can be customized according to user preferences and needs, or the practicality of the product can be enhanced by printing ceramic components with specific functions. As science and technology advance, and artistic creation methods diversify, the conventional approach to designing ceramic patterns falls short of meeting modern market demands for personalization and innovation [3].

Digital images play a crucial role in diagnosing and recording the preservation status of cultural relics. Quantitative analysis methods not only improve work efficiency, but also enable users to interactively design, analyze, and manage ceramic patterns on a unified platform. However, the current description and communication of image information, especially through explanatory filters, often carries a strong subjectivity [4]. This interactivity not only enhances the user experience but also enables users to customize analysis results based on their own needs and interests. In our research, we tested various advanced algorithms that can accurately separate unique features in ceramic patterns and create binary masks for subsequent statistical analysis and polygonization. To this end, the entire processing flow was integrated into a Geographic Information System (GIS) application. In terms of ceramic pattern interaction, this method allows users to interact with images through an intuitive interface. This method not only promotes the interactive design of ceramic patterns but also semi-automatically identifies and polygonizes regions that correspond to specific features. Through this method, it is possible to objectively analyze and understand the key features of ceramic patterns, such as structure, texture, and colour. In addition, considering that our approach aims to build an efficient protection recovery model, we are committed to generating useful graphical documents that can be used for design, statistics, and interactive analysis in a short period. Real-time adjustment of parameters and options to optimize feature recognition and polygonization results [5].

3D printing technology, as a revolutionary force in modern manufacturing, has penetrated many industries, including fashion and ceramic art. 3D printing technology will play a more important role in the fields of fashion and ceramic art. In the field of ceramic art, 3D printing technology has also brought revolutionary changes to the design and interaction of ceramic patterns. By precisely controlling printing parameters and materials, designers can create ceramic works with complex details and multi-colour surface textures. With an understanding of the interaction design between fashion elements and ceramic patterns, explore how to integrate these elements together to create a unique and charming 3D-printed fashion prototype [6]. This interactivity not only enhances the creative ability of designers but also enables consumers to more intuitively feel the unique charm of ceramic works. In the fashion industry, 3D printing technology provides unprecedented creative space for fashion and textile designers, enabling them to create unique 3D printed clothing, fabrics, and fashion accessories. A module partitioning method based on axiomatic theory was proposed for the modular creation experience of ceramic shape design. A teapot was selected for example analysis and design, achieving an interactive modular creation experience of ceramic shape design. The paper proposes to combine ceramic creation experience with virtual technology, conduct in-depth research on traditional ceramic product manufacturing processes, and combine modular theory with user demand analysis methods. The necessity of virtual experience research on ceramics has been determined through the current status of digital research on ceramic culture. Multiple methods of manual moulding have been studied, and the virtual ceramic experience method based on the drawing moulding method has been systematically developed [7]. Analyze the interaction process of each functional page, and output the interaction prototype and interface design scheme of the system. The construction of a 3D-based virtual pottery experience system is of great significance in addressing the limitations of traditional pottery experiences. Using the Kano model analysis method to determine user requirements, and based on this, studying the specific functional module content of the system, sorting out the information architecture of the system. The paper constructs an interactive system design model based on ceramic art production and verifies the feasibility of modular design of ceramic shapes. Theoretical research and design of the paper, functional testing of the system, design of the system testing process and evaluation table of system functional elements, and summary and analysis of the system functional modules based on user feedback data, providing direction for system optimization. Based on determining the system functions, using a 3D engine combined with C # language, complete the writing of functional operation scripts to achieve interactive effects. The design and implementation of a virtual ceramic experience system provide a new research direction for the development and dissemination of traditional ceramic culture. Using 3D modelling software to construct a realistic casting scene model, enhances the user's sense of realism and immersion. Not only can it break the limitations of traditional pottery in terms of venue, materials, technology, etc., and provide users with a good experience, but it can also promote the inheritance of ceramic culture.

This article comprises six sections. The introductory section outlines the research background, current state, content, and methodologies. Section two provides an overview of the fundamental principles and applications of GAN technology and CAD interactive editing. Section three delves into the specifics of implementing innovative ceramic pattern designs. Section four details the practical aspects of the CAD interactive editing approach. Section five presents the system's implementation and performance evaluation findings. Lastly, section six recapitulates the research outcomes and anticipates future research avenues.

The primary innovations encompass: (1) The utilization of GAN technology in ceramic pattern design to elevate design innovation and efficiency; (2) By integrating CAD's interactive editing capabilities, personalized customization of ceramic patterns is achieved; (3) The efficacy and practicality of the proposed approach are substantiated through empirical validation.

2 RELATED WORK

View-based 3D model retrieval has become an important research and application field, especially in ceramic pattern interactive design, where its potential value is increasingly prominent. In this context, the study aimed to explore the application effect of deep learning features in view-based 3D model retrieval, especially in ceramic pattern interaction design, through systematic evaluation. Gao et al. [8] explored the application effect of deep learning features in view-based 3D model retrieval. Specifically, it focuses on the application of these features in ceramic pattern interaction design, evaluating their performance in pattern recognition, matching, and retrieval by simulating different interaction scenarios and conditions. The experimental results show that deep learning features perform well in 3D model retrieval of ceramic pattern interactive design, consistently outperforming all traditional manual features. The results of Hu et al. [9] indicate that the performance of multi-view deep learning features is better than that of single-view deep learning, with lower computational complexity. This discovery provides a new method for the interactive design of ceramic patterns, which can further improve the accuracy and efficiency of pattern recognition by integrating information from multiple angles.

Especially in the specific field of ceramic pattern interactive design, its potential application value is increasingly prominent. Although deep learning has achieved significant results in the field of computer vision, it is still effective in 3D model retrieval. Considering that there is currently no comprehensive evaluation benchmark for the application of deep learning features in this field, Hu et al. [10] conducted a systematic study. In terms of performance, deep learning always performs well in both noiseless and noisy environments, and its robustness far exceeds that of manually crafted features. Li et al. [11] conducted innovative research on ceramic cultural relic restoration methods using the non-contact, high-precision, and high-efficiency features of 3D laser scanning, 3D model reconstruction, 3D printing, and other technologies in 3D digitization technology, aiming to improve the efficiency of ceramic cultural relic restoration. Secondly, a retrieval database for the form of ceramic cultural relics was constructed, and a brief analysis was conducted on the development characteristics of ceramic cultural relics styles in various dynasties. Before restoration, the missing model reconstruction plan can be determined by searching for similar objects, the style of the dynasty, and the geometric features of the damaged area. Presenting a more complete restoration effect, providing a substantial digital restoration archive for subsequent data research and utilization. After obtaining and processing the 3D model data, combined with traditional visual experience comparison and computer algorithm matching, research on fragment alignment and stitching methods. Using 3D laser scanning technology to collect data on damaged cultural relics while protecting them from damage. Subsequently, a model reconstruction method based on matching surface extraction was proposed and its feasibility was verified through examples. In order to guide the restoration process of 3D digitization, permanently preserve cultural relic data, and expand the utilization space of cultural relic restoration resources. It has sorted out the full process restoration management plan for ceramic cultural relics based on three-dimensional digital technology, and standardized and improved the restoration practice work. Finally, 3D printing technology is used to print out the reconstructed model, which is then bonded and fixed with the original fragments. Texture and colour mapping are applied to all 3D fragment models to improve the integrity of the restoration. This discovery is of great significance for the interactive design of ceramic patterns, as multi-view deep learning features can more comprehensively capture the details and features of ceramic patterns, thereby improving retrieval accuracy and user experience. The 3D model retrieval algorithm usually includes two core steps: feature extraction and similarity measurement, where robust features are key to ensuring accurate measurement of similarity. Especially in the application of ceramic pattern interactive design, it is still in the initial exploration stage. In addition, Murugesan et al. [12] also conducted in-depth research on multi-view deep learning network architecture. Through detailed comparison, we found that deep learning features are superior to handcrafted features in multiple aspects.

In the process of ceramic pattern design, layout is not only the key to aesthetics but also directly related to the readability and interactivity of the pattern. By introducing a self-attention module, the labels and geometric parameters of these elements are jointly optimized to ensure that the generated layout conforms to design rules and is creative. To address this issue, Tian [13] developed an innovative differentiable wireframe rendering layer. In ceramic pattern design, this is particularly important because the position, size, and rotation angle of each element (such as flowers, leaves, or textures) can affect the overall visual effect and user experience of the pattern. Ceramics is one of the excellent traditional cultures in China. Ancient ceramic products, as art pieces, have been extensively tested and summarized by craftsmen to enhance the aesthetic appeal of ceramic products. Xu et al. [14] elaborated on the current research status of particle swarm optimization algorithms both domestically and internationally, the emergence of ceramic formula problems, and the significance of using intelligent optimization algorithms to solve ceramic formula problems. Due to the good concurrency, robustness, and adaptability of intelligent computing methods, they have achieved good results in solving complex and high-dimensional optimization problems. Common intelligent computing methods include genetic algorithms, particle swarm optimization algorithms, etc. Solving the ceramic formula problem, which involves selecting ingredient ratios based on raw materials and target formulas to minimize chemical composition errors, is essentially a typical optimization problem. Unlike ancient times where ceramic ingredients were used as ceramic formulas, modern ceramic formulas are chemical formulas composed of chemical compositions. Adaptive changes are made to the inertia weight of each particle in the particle population. As the fitness value of the particle approaches the global optimal value, it can be determined that the particle needs to explore its neighbouring areas more. Based on the historical experience and flight conditions of particle flight processes, a new adaptive inertia weight strategy is designed by introducing global range values. The improved particle swarm optimization algorithm incorporating adaptive inertia weight and nonlinear asynchronous learning factor strategy will be applied to the ceramic formulation problem. By using the linear weighted sum method to transform the ceramic formulation problem from a multi-objective problem to a single-objective problem, it is combined with the Critic method to assign weights to different chemical compositions. Prove that LayoutGAN can not only generate high-quality ceramic pattern layouts but also adapt to different styles and requirements of design tasks.

In the field of ceramic pattern design, transferring the colour style of a unique colour image to another ceramic object to create a unique colour scheme is a challenging and creative task.

Therefore, Xu and Zheng [15] proposed an innovative colour network model specifically designed for the interactive design of ceramic patterns. The target network focuses on describing the surface and morphology of ceramic objects to be coloured, such as ceramic plates, ceramic vases, or ceramic sculptures, in order to generate appropriate colour schemes for these objects. This mapping process is not just about simple colour copying. Colour sequence (ensuring colour distribution on ceramic objects is similar to the reference image), adjacency (ensuring natural and harmonious transitions between adjacent colours), concentration (ensuring appropriate distribution density of colours on ceramic objects), and subspace size (ensuring reasonable distribution range of colours in dimensions such as hue, saturation, and brightness). Transform the problem of reusing colour pattern features into a mapping process from the source network to the target network. However, it takes into account the characteristics of ceramic materials, surface textures, lighting effects, and cultural and aesthetic factors of ceramic patterns. This allows designers to easily input reference images and select ceramic objects, and then the system automatically generates a series of colour schemes that meet the requirements. In order to ensure high colour consistency between the generated colour scheme and the original reference image, four key indicators were designed to measure the consistency between the two networks. It can continuously optimize and adjust the optimal combination of four indicators to ensure that the generated colour scheme meets both the colour style of the reference image and the aesthetic requirements of ceramic pattern design. To verify the feasibility and effectiveness of this colour network model, we conducted a series of colour combination graphic design tasks and applied the generated colour scheme to the actual ceramic pattern design. In addition, we have also introduced the comprehensive aesthetic evaluation of designers as an important feedback mechanism. By having professional designers rate and comment on the generated colour scheme.

3 INNOVATIVE METHODS OF CERAMIC PATTERN DESIGN

3.1 Limitations of Traditional Ceramic Pattern Design Methods

Nevertheless, this approach exhibits evident constraints, as outlined in Table 1:

Limitations	*Specific content*
Long design cycle	Traditional manual drawing takes a long time, and the whole design process takes a long time from conception to completion, which leads to low efficiency and cannot meet the rapidly changing needs of the modern market.
Low efficiency	In the process of manual drawing, modification and adjustment are relatively cumbersome, which further reduces the design efficiency and affects the speed of product listing.
Design innovation is limited.	Designers' imagination and painting skills become the bottleneck of innovation, and it is difficult to achieve subversive new designs, and it is easy to fall into the framework of tradition and convention.
Breakthrough innovation is difficult.	Because of relying on personal experience and skills, traditional methods make it difficult to achieve large-scale and systematic innovation, which limits the diversity and novelty of ceramic pattern design.
High design cost	Manual drawing requires a lot of manpower and time costs, and high-quality materials and tools also increase the cost.
Uncertainty of market acceptance	The results of traditional design methods do not necessarily meet the modern aesthetic or market demand, and there are market risks, so it is difficult to guarantee the market acceptance of each design.

Table 1: Limitations of traditional ceramic pattern design methods.

3.2 Application of GAN in Ceramic Pattern Design

GAN technology has brought revolutionary changes to ceramic pattern design. By training the generator and discriminator to learn, GAN can generate new patterns with similar but not exactly the same style as real ceramic patterns. Not only does this approach significantly enhance design efficiency, but it also produces highly original and artistic patterns. Furthermore, GAN technology facilitates the transfer and amalgamation of various styles, allowing for the seamless integration of diverse ceramic pattern elements to craft distinctive design pieces.

3.3 Realization of Innovative Ceramic Pattern Design

The specific steps to achieve innovative ceramic pattern design include 1) Gathering and preprocessing a vast collection of ceramic pattern datasets for training GAN models. 2) Establishing and training the generator and discriminator networks, enabling the generator to produce novel patterns resembling authentic ceramic designs through iterative adversarial learning. 3) Utilizing the trained GAN model to create unique ceramic patterns. Additionally, within this segment, we forecast the likelihood of potential colours for each pixel and introduce an automatic colourization technique that employs the network architecture depicted in Figure 1.

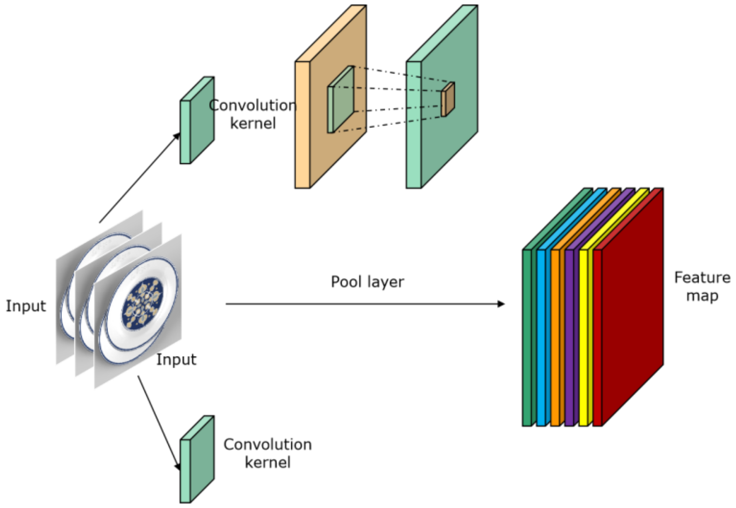


Figure 1: Network structure of the algorithm.

The generator's loss function is frequently represented as the reciprocal of the discriminator's ability to discern generated data accurately. In layman's terms, the generator strives to increase the discriminator's error rate in distinguishing its output. When dealing with binary classification tasks that utilize cross-entropy loss, the equation takes the form of:

$$L_G = -E_{z\sim p_z(z)}\left[\log D(G(z))\right] \tag{1}$$

Let $G(z)$ represent the sample produced by the generator, $D(x)$ denote the discriminator's outputted probability that the sample x is authentic and z signify random noise drawn from the prior noise distribution $p_z(z)$.

The discriminator's loss function typically measures the disparity between its discrimination accuracy on real data and its accuracy on fake data produced by the generator. In essence, the discriminator strives to minimize the likelihood of mistakenly identifying generated samples as real. The mathematical expression for this is:

$$L_D = -E_{x\sim pdata(x)}\left[\log\left(D(x)\right)\right] - E_{z\sim p_z(z)}\left[\log\left(1 - D(G(z))\right)\right] \tag{2}$$

Let $p_{data}(x)$ represent the probability distribution of genuine data.

During the training of a GAN, both the generator and discriminator are typically refined simultaneously. The overall loss, calculated as the harmonic mean of the generator's and discriminator's losses, serves as a benchmark to steer the network's training process:

$$L = \frac{1}{2}\left(L_G + L_D\right) \tag{3}$$

Assuming the model produces a probability distribution denoted as $P(y|x)$ often determined through the Softmax function, the cross entropy loss function can be described as follows:

$$L\left(y, P(y|x)\right) = -\sum_{i=1}^{N} y_i \log\left(P(y_i|x)\right) \tag{4}$$

Let y represent the actual label, x stand for the input data, y_i signify the indicator for the i class within the actual label, and $P(y_i|x)$ denote the likelihood that the model forecasts the i class upon receiving the input x.

In the process of generating, the style and characteristics of the generated pattern can be controlled by adjusting the input parameters of the generator. Figure 2 shows the generation framework of ceramic pattern interactive design.

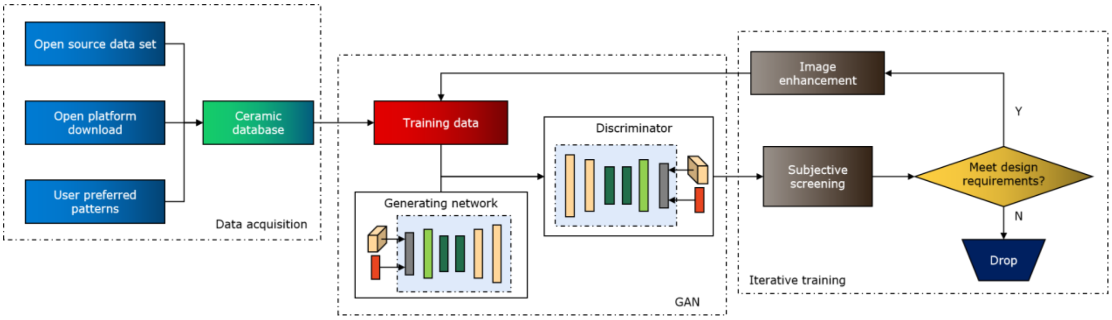


Figure 2: Ceramic pattern interactive design generation framework.

Assuming that an outlier x_i is situated far from all nodes yet in proximity to all j 's, the penalty value assigned to point y_i in the low-dimensional space remains relatively insignificant regardless of its position. Consequently, p_{ij} is defined in the following manner:

$$p_{ij} = \frac{\left|p_{ji} + p_{ij}\right|}{2n} \tag{5}$$

Where n represents the total count of data points, ensuring symmetry and preventing excessively small penalty values.

The multi-image matching approach aims to introduce several intermediary images between the image pairs slated for matching. This strategy serves to minimize the significant intra-class disparities among the image pairs, subsequently enhancing the correlation estimation across the entire dataset. With this rationale, the task of matching ceramic patterns can be framed as follows:

$$\min D_I = \min \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} d' \ \ i,j \tag{6}$$

The multi-image matching map $d' \ \ i,j$ denotes the length of the shortest matching path searched for the image pair I_i, I_j, rather than representing the initialization distance $d \ \ i,j$, which is computed based on the similarity of image pairs.

Establish a maximum confidence threshold designated as ε. Sequentially accumulate the highest probability value from the first-level label classification results towards the preset threshold, $\sum_{j=1}^{k} h_{\theta_2} \ \ Y_j \ \leq \varepsilon$. Subsequently, in conjunction with num_{loc_k}, output the corresponding second-level label category beneath the chosen first-level label. The computation num_{loc_k} is represented as follows:

$$num_{loc_k} = floor\left(\frac{h_{\theta_2} \ \ Y_k}{\sum_{j=1}^{k} h_{\theta_2} \ \ Y_j} \right) * 6 \tag{7}$$

During practical application, a matrix denoted as X is frequently inputted. As a result, q,k,v is converted into a matrix format and documented Q,K,V, while the output can be noted as follows:

$$\text{Attention} \ \ Q,K,V \ \ = \text{softmax}\left(\frac{QKT}{\sqrt{d_k}} \right) V \tag{8}$$

The multi-head combination yields a unified attention mechanism, designed to enhance the model's capacity to focus on various positions, thereby improving its analytical reference ability. Furthermore, within the multi-head framework, the AttentionLayer signifies multiple subspaces and possesses numerous sets of W^Q, W^K, W^V weight matrices.

3.4 Experimental Results and Comparative Analysis

To validate the effectiveness of our proposed method, this section conducts experiments and compares them to traditional design methods. The training and test sets are configured at an 8:3 ratio, while the ratio of correct to incorrect images is maintained at 5:2. We select 20% of the entire classified dataset as the validation set. Specifically, the training set comprises 8000 images, the validation set includes 2000 images, and the test set consists of 3000 images. Please refer to Table 2 for a detailed breakdown of the ceramic pattern distribution generated using fractal technology.

	Plum blossom	*(Error) Plum blossom*	*Peach blossom*	*(Error) Peach blossom*
Training set	4000	1600	2000	400
Verification set	1000	400	500	100
Test set	1500	600	750	150

Table 2: Classification distribution of ceramic decorative patterns.

Among these patterns, there are relatively more samples of plum and peach blossoms, while there are fewer samples of error-type plum and peach blossoms. All generated ceramic patterns are processed in a unified size and file format and stored in a designated local folder. After manual screening, we removed invalid data such as black dot images and full white background images. Finally, the obtained dataset is divided into four categories, each containing 1500 or 3000 images, totaling 9000 images. Figure 3 shows examples of various categories, namely plum blossom, peach blossom, (error) plum blossom, and (error) peach blossom.

Figure 3: Partial data set image.

4 REALIZATION OF INTERACTIVE EDITING METHOD OF CAD

4.1 Demand Analysis

During the ceramic pattern design process, designers frequently require real-time modifications and optimizations based on market trends, personal aesthetic preferences, or client feedback. Consequently, developing an efficient interactive editing approach is crucial. Such a method must fulfill several criteria: firstly, an intuitive and user-friendly interface that facilitates easy editing for designers; secondly, support for precise adjustments to both local and global patterns, accommodating personalized design needs; and thirdly, the ability to preview editing effects instantly, allowing designers to adjust and refine their design plans promptly.

4.2 Interactive Editing Function Design

In order to meet the above requirements, this article designs the following interactive editing functions in the CAD system: (1) Providing rich drawing and editing tools, such as brushes, erasers, filling tools, etc., so that designers can perform basic graphic editing operations. (2) Support transformation operations such as scaling, rotation, and translation of patterns to realize global adjustment. (3) Provide advanced editing functions such as colour adjustment and filter effect to enhance the visual effect of the pattern. (4) Support the functions of undo, redo, and historical record, which is convenient for designers to modify and optimize repeatedly.

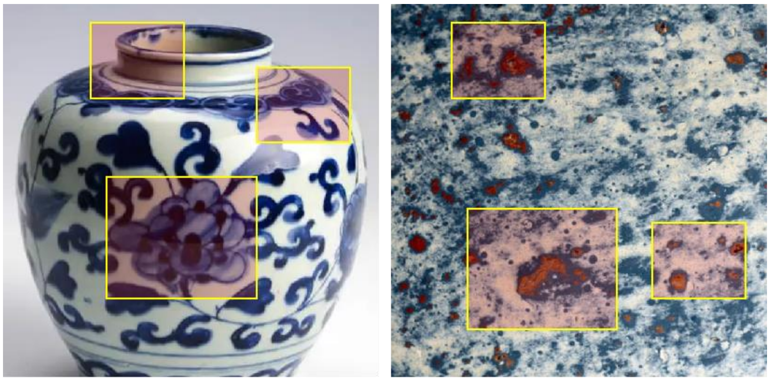
4.3 Editing and Optimization of Ceramic Patterns Based on GAN Technology

In the interactive editing process, this article introduces GAN technology to improve the editing effect further. The specific approach is to use the trained GAN model to transfer and optimize the style of the edited pattern in order to maintain the overall style consistency and artistry of the pattern. In addition, we can also achieve personalized customization of patterns by adjusting the parameters of the GAN model, such as changing the colour, texture, and other features of the patterns.

4.4 User Interface Design and Operation Process

In order to ensure the usability and efficiency of interactive editing, this article designs a concise and intuitive user interface and provides detailed operational process guidance. The user interface includes a menu bar, toolbar, property bar, and drawing area, making it easy for designers to find the editing tools and functions they need quickly. Taking Figure 4 as an example, a comparison was made between the ordinary image shown in (a) and the texture image shown in (b). When examining these two images, a fixed-size rectangular box was used to assist in observation, and different areas of the image were focused by moving this rectangular box. This detailed observation process reveals a significant difference: in (a) figure, when the rectangular box moves to different positions, the changes in the content inside the box are very obvious, reflecting the diversity and complexity of information in ordinary images. In contrast, the two rectangular boxes in (b) maintain a general similarity in their contents no matter where they are moved, indicating that the texture image has an inherent repeatability and regularity.

When focusing on any pixel within the black rectangular box in Figure (b), it is found that its pixel value can be reasonably inferred by observing other pixel values in its adjacent area. This locality feature means that in texture images, the value of a pixel is often closely related to the values of its surrounding pixels and is independent of other regions in the image that are farther away. This phenomenon not only confirms the local characteristics of texture images but also reflects their stationarity; that is, the texture features in the image remain consistent within the local area without significant differences due to small changes in position.



(a) (b)

Figure 4: Comparison diagram of texture and ordinary image.

The operation process starts with opening CAD software, and then goes through the steps of pattern import, basic editing, advanced editing and style optimization, and finally exports the edited pattern file. In the whole process, a real-time preview and feedback mechanism is provided to help designers better grasp the editing effect and direction.

5 SYSTEM IMPLEMENTATION AND PERFORMANCE ASSESSMENT

5.1 System Development Environment and Function Realization

The system development environment is very important to ensure the smooth development and stable operation of the software. In this study, Python is chosen as the main programming language because it is widely used in the fields of data science and machine learning and has rich library and framework support. Specifically, this article uses TensorFlow and Keras frameworks to build and train the GAN model. These frameworks provide advanced API, which makes the development and debugging of the model relatively simple. In terms of development tools, this article uses an interactive development environment such as Jupyter Notebook, which allows us to verify the code step by step and view the results in real time. In addition, in order to build a CAD interactive editing system, this article adopts professional CAD software development kits (SDK), which provide rich APIs to support complex graphical operations and user interface design.

In the aspect of system function realization, the GAN model is first trained by collecting and preprocessing ceramic pattern data sets. The data set processing includes the steps of image size normalization and colour standardization to ensure that the model can learn effective feature representation. Then, the generator and discriminator networks constructed above are adopted, and appropriate loss functions and optimizers are used for training.

In the realization of the interactive editing function of CAD, this article uses the API provided by CAD SDK to realize the functions of importing, exporting, editing and previewing patterns. Furthermore, the trained GAN model is integrated, so that users can preview the pattern effect after style transfer and optimization in real-time during the editing process.

5.2 Simulation Experiment and Performance Assessment

In the aspect of optimization strategy, this article first optimizes the training process of the GAN model, including adjusting the learning rate and increasing the batch size, so as to improve the convergence speed and generation quality of the model. Secondly, in the CAD interactive editing system, the response speed of the user interface and the efficiency of pattern rendering are optimized to ensure that users can edit smoothly.

The data presented in Figure 5 clearly demonstrates that the enhanced GAN model introduced in this article has notably increased the precision of image rendering when compared to the conventional CNN, achieving an improvement of over 30%. More than 30% precision improvement means that the improved GAN model can restore and generate the details and features of ceramic patterns more accurately. Higher rendering accuracy not only improves the quality of design results but also shortens the design cycle. Designers can get high-quality rendering effects faster, thus accelerating the design iteration and innovation process.

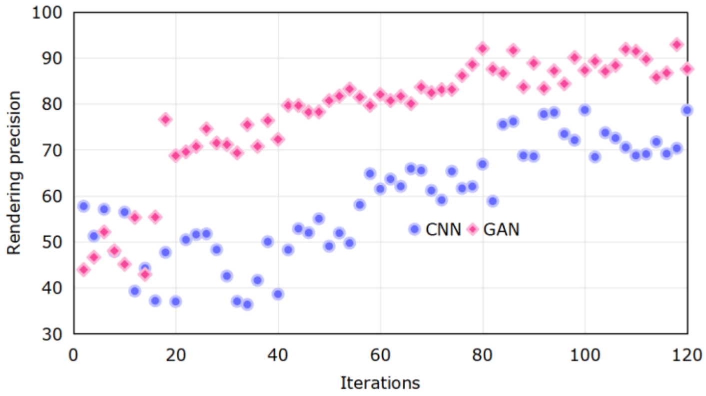


Figure 5: Image rendering accuracy.

From Figure 6, it can be seen that the interactive editing system designed in this article has shown strong advantages in terms of visual comfort and interface response speed.

Figure 7 illustrates the system's pattern rendering time test, revealing that as the pixel count of feature information rises, the processing duration for various techniques also escalates proportionately. However, compared with the traditional CNN model, the interactive editing method of ceramic patterns driven by GAN technology has significant advantages in pattern rendering efficiency.

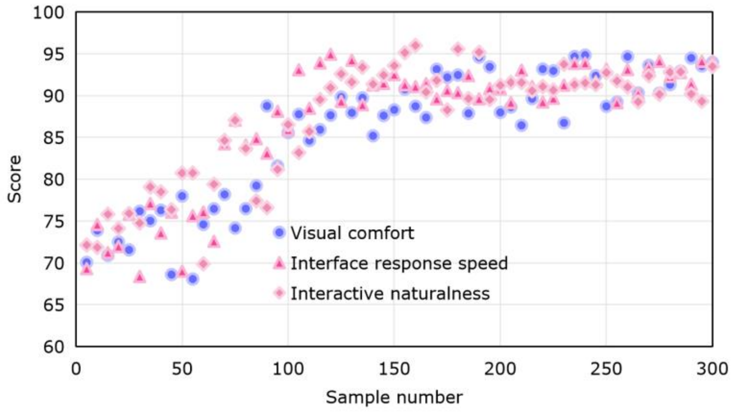


Figure 6: System interactivity score.

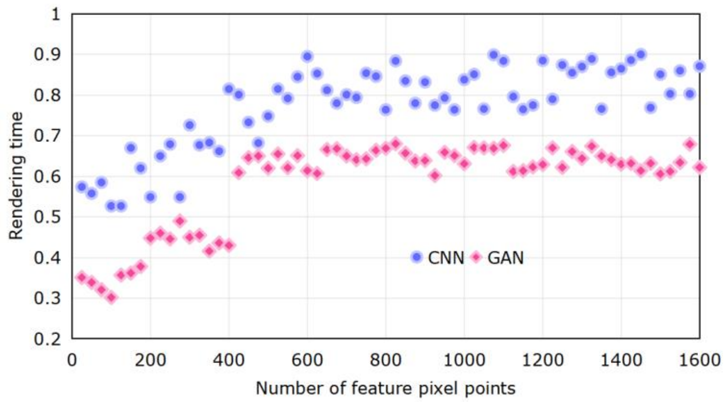


Figure 7: Pattern rendering time.

5.3 User Feedback and Improvement Direction

In the system testing stage, this article invited a group of ceramic pattern designers to experience and provide feedback, as shown in Table 3.

Feedback aspect	*Positive feedback ratio*	*Specific feedback content*	*Improvement suggestion ratio*
Usability	90%	"intuitive operation, quick start"; "Friendly interface, easy to use"	10%
Rich editing functionality	85%	"Providing a variety of editing tools to meet the basic needs"; "Fine adjustment of pattern details."	15%
Innovativeness in generating patterns	80%	"The generated patterns are unique and artistic"; "GAN technology has	20%

		significantly improved the design innovation."	
User interface layout	75%	"The overall layout is reasonable and easy to operate"; "Icons and menu designs are clear and easy to understand."	25%
Overall satisfaction	80%	"The system improves the design efficiency"; "It brings new possibilities for ceramic pattern design."	-

Table 3: User feedback during the system testing phase.

Based on their feedback, it is understood that the system has been recognized for its ease of use, richness of editing functions, and innovation in generating patterns. However, some designers have also proposed some suggestions for improvement, such as adding more style transfer options, optimizing user interface layout, etc. This feedback provides valuable directions for future system iterations.

6 CONCLUSIONS

In this study, GAN technology is successfully applied to ceramic pattern design, and a novel and efficient ceramic pattern design method is realized by combining CAD interactive editing methods. Through a large number of experiments and comparative analysis, the effectiveness and innovation of the proposed method are verified. Specifically, the proposed method can generate highly innovative and artistic ceramic patterns and support designers to make real-time interactive editing and optimization. The research findings positively impact the ceramic pattern design industry. Initially, they enhance design efficiency and foster innovation, empowering designers to craft superior ceramic patterns swiftly. Secondly, through the introduction of an interactive editing capability, designers can now nimbly adapt and refine their designs based on market demands and personal aesthetics. Ultimately, this study breathes fresh creativity and vitality into the ceramic sector, potentially spurring further industry innovation and progress.

Despite notable accomplishments in this study, certain limitations and challenges persist. Considering these obstacles, this article outlines several directions for future research: (1) Exploring more efficient training techniques for the GAN model and lightweight network structures to minimize computing resources and data requirements. (2) Investigating market demand forecasting models to inform ceramic pattern design and optimization better. (3) Integrating cutting-edge technologies, such as virtual reality (VR) or augmented reality (AR), to further enrich designers' interactive experiences and enhance design efficiency. As technology continues to advance and innovative applications emerge, we are confident that ceramic pattern design will embrace further developmental opportunities and market potential.

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