

Intelligent Decorative Images Design Based on Improved GAN and Stitch Data

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Abstract: With the growing demand for personalized decoration, traditional manual design methods are inefficient and lack adaptability. This study proposes an intelligent design model for decorative images by integrating stitch data into an improved Generative Adversarial Network (GAN). The model converts stitch data into adjustable parameters that control style and texture, enhancing generation guidance through a dual-discriminator mechanism, stitch-style loss, and a gradient penalty. Convolutional Neural Networks (CNNs) are incorporated for multi-level feature extraction. On the EmbroideryArt-10k and PatternTexture-8k datasets, the model achieved rapid convergence (loss 0 after 500 epochs), high recognition integrity (98.7%), and F1 scores up to 0.92. The model improves design efficiency and offers a new approach to intelligent, personalized decorative image design. In summary, the model not only improves the efficiency of decorative image design but also offers new ideas for the intelligence and personalization of decorative image design, with important theoretical and practical significance.

Keywords: Decorative image design; adversarial network design; parameterized model; convolutional neural networks (CNN); stitch data.

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1. Introduction

The demand for personalized and high-quality decorative images is growing (Yüksel et al., 2025; Nyboer, 2024). Traditional design, reliant on manual skill, is inefficient and lacks adaptability (Al-Zebari, 2024; Shi et al., 2024). While computer vision and CNNs show promise, they often fall short in handling multidimensional, nonlinear design tasks. Generative Adversarial Networks (GANs) have proven powerful in image generation (Kitole and Sesabo, 2024). Stitch data, rich in texture and structural information, offers precise guidance for decorative design. However, how to effectively integrate stitch data with GAN models to achieve intelligent design of multidimensional nonlinear decorative images remains an urgent problem (Li et al., 2024; Lome, 2024). Therefore, a high-performance parametric decorative image intelligent design model based on an improved GAN and stitch data is designed. The model introduces a dual-discriminator mechanism to jointly ensure macro- and micro-level image quality and integrates a CNN module into the generator to capture complex textures and patterns. The gradient penalty is adopted to improve training stability and convergence speed. Style loss and stitch feature matching are incorporated to enhance consistency with real stitch data in texture and pattern, further aligning generated images with the target style. This research overcomes the limitations of traditional design methods, offering new ideas and technical support for intelligent, personalized decorative image design, thereby contributing to the industry's sustainable development. To address these challenges, this study investigates whether the integration of stitch data into a GAN framework improves the quality and stylistic accuracy of generated decorative images compared to baseline GAN models, whether the proposed dual discriminator mechanism enhances the structural fidelity and fine-detail preservation of generated embroidery-style images, and whether the incorporation of a CNN module into the generator improves convergence stability and the representation of complex textures and patterns. To answer these questions, an intelligent design model (IGCM) is developed that combines an improved GAN with stitch data. The model introduces a dual-discriminator mechanism, stitch-style loss, gradient penalty, and CNN-based feature extraction, with the effectiveness of these components evaluated using quantitative metrics and comparative experiments on specialized datasets. The study is situated within a theoretical framework that integrates computational aesthetics, generative adversarial learning theory, and parametric design theory. Central to this framework is the concept of a "multi-dimensional nonlinear decorative field," formally defined as a high-dimensional feature space in which decorative elements (texture, pattern, stitch structure, and spatial arrangement) interact nonlinearly to produce emergent aesthetic properties. This field is characterized by three dimensions: (1) textural dimension: capturing surface

granularity and stitch density variations. (2) structural dimension: encoding geometric arrangement and pattern hierarchy. (3) stylistic dimension: representing high-level artistic attributes such as embroidery tradition and compositional balance. The nonlinearity arises from the interdependent relationships among these dimensions, in which changes in one dimension nonlinearly influence the perceptual and aesthetic outcomes of the others. By formalizing this concept, the study provides a theoretical foundation for understanding how decorative image generation can be modeled as a learning problem within a structured, parameterizable field, rather than as an ad hoc architectural engineering task.

2. Related Works

Recently, significant progress has been made in the field of intelligent design of decorative images. Scholars and research institutions are dedicated to exploring efficient and intelligent design algorithms to meet the growing demand for personalized decoration. Early research primarily focused on rule-based methods that automatically generate decorative images using preset rules and templates, but their fixed rule sets limit adaptability to diverse design scenarios (Zhang and Wang, 2024). Zhong and Jing (2025) proposed an innovative design method based on a two-layer clustering user behavior analysis algorithm for digital soft decoration display, improving user satisfaction and experience through more accurate demand prediction and personalized design. Kahraman et al. (2024) introduced a theoretical framework and conceptual model for integrating AI into interior design education. Comparative experiments showed significant improvement in design efficiency and a 22% increase in functional innovation capability. Vijendran et al. (2024) applied CNN and GAN methods to extract, analyze, and synthesize geometric features from artistic images, thereby enhancing performance in tasks such as style transfer and image classification. GANs are widely used in image design and data augmentation due to their powerful feature learning capabilities. Chen et al. (2023) proposed an improved model based on GAN and contextual attention to address issues like blurring, texture distortion, and low resolution in image restoration, yielding more realistic and clearer results. Yue et al. (2023) combined a GAN with an LSTM network to process image streams and quickly locate abnormal targets in controlled airspace by predicting future images, thereby overcoming vulnerabilities to network attacks in automatic correlation monitoring. The method achieved an average detection accuracy of 92.3%, with 11.9% false positives and 6.2% false negatives.

Parametric models express variables and constraints in the design process as parameters, enabling automation and intelligence. Their application in decorative image design is gaining attention. Chi et al. (2025) designed a parametric model that uses body dimensions from scanners and designer-identified features to automate personalized shirt pattern design and significantly improve efficiency. Guo et al. (2024) built a CNN-based parametric model to couple gradients of the loss function with respect to multiple parameters in elastic full-wave inversion, alleviating local minima and reducing dependence on the initial model. CNN is a feedforward neural network that efficiently processes images through layered local perception units. Related research includes Yuan et al. (2023), who used a hybrid CNN model on CT images to denoise, effectively preserving details while reducing noise. Arkin et al. (2023) proposed an innovative CNN-based method optimized with a moving-window transformer, improving detection speed and image quality. Xie et al. (2024) introduced a region-oriented network to address slow inference speed, enhancing performance and accuracy.

In summary, while significant progress has been made in intelligent decorative image design, existing methods still face limitations in terms of innovation and practicality for multi-dimensional, nonlinear design problems. Therefore, this study improves GAN by integrating CNN and introducing a dual-discriminator mechanism, a stitch-style loss function, and a gradient penalty term, aiming for technical breakthroughs. The improved GAN handles complex decorative image design tasks, with stitch data providing finer guidance and support. The research aims to provide a practical and efficient design method for multi-dimensional nonlinear decorative images, promoting further development in the field.

3. Methodology

3.1. Construction of Decorative Image Design Model Based On GAN and Stitch Data

With the continuous improvement in people's quality of life, the demand for decorative images is increasingly diverse and personalized. Traditional decorative image design relies on manual designer creation, which is time-consuming, labor-intensive, and ill-suited to large-scale customization (Liu, 2024; Chen et al., 2024). Therefore, a decorative image design model based on GAN and stitch data is built. The model employs a GAN framework and incorporates stitch data to enable intelligent, personalized processing of decorative image design. The stitch data contains unique aesthetic elements from various embroidery and knitting techniques, including delicate lines, intricate patterns, and diverse textures. These elements are transformed into high-quality image data through precise digital processing, providing a solid foundation for the subsequent design process. The basic embroidery trajectory of the stitch is shown in Fig. 1.

In Fig. 1, the basic stitch is flat-stitch embroidery with horizontal straight trajectories, evenly distributed stitches, and consistent stitch lengths. Back stitch embroidery: Presenting a continuous line trajectory, with half of the first stitch retracted to form tightly connected lines. Lock edge embroidery: It is done along the edge trajectory of a circular pattern, with stitches piercing from the outside into the inside, forming a chain-like structure. Satin embroidery: Parallel and tightly arranged stitches in a square area, with consistent direction, covering the entire square area. The French knot embroidery: Composed of multiple strands interwoven to form three-dimensional and full nodes. Chain embroidery: Composed of continuous circular stitches forming a chain-like trajectory, with each loop of uniform size (Hu et al., 2024). As a key element in decorative image design, stitch data carries rich connotations and unique characteristics, enabling the generation of professional content, enhancing detail authenticity and significantly improving style controllability. GAN is a deep learning model consisting of two networks: a generator and a discriminator. The encoded stitch features are embedded in the generator as conditional inputs, directly influencing the parameterized image generation process and ensuring that the output conforms to the composition and texture rules of embroidery art. The generator is responsible for designing fake data that is as close

to real data as possible, while the discriminator is responsible for distinguishing between real data and the fake data generated by the generator. The two continuously optimize during the confrontation process. Ultimately, the generator can generate highly realistic data (Zhang et al., 2022). Ultimately, the generator designs high-quality samples to deceive the discriminator into determining them as real data, thereby designing high-quality data (Liu et al., 2025). The function of the GAN is given by Eq. (1).

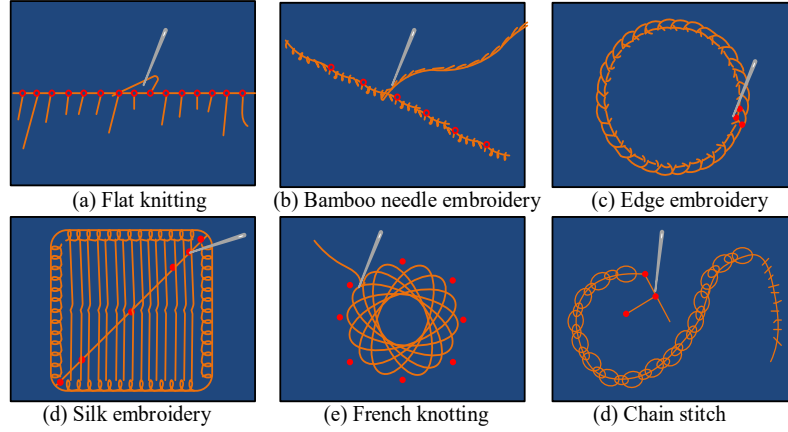


Fig. 1. Basic embroidery track of stitch

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (1)$$

In Eq. (1), $p_{data}(x)$ signifies the distribution of real data. $p_z(z)$ signifies the distribution of the input noise variable. $G(z)$ is a sample designed for the generator. $D(x)$ signifies the probability that the discriminator output sample is true. E represents the expected value operation. x represents real image data samples. The calculation of the discriminator reaching the optimal state after training iterations is shown in Eq. (2).

$$D_G^*(x) = \frac{P_{data}(x)}{P_G(x) + P_{data}(x)} \quad (2)$$

In Eq. (2), $P_G(x)$ represents the design data distribution. The generator is designed to convert stitch data into decorative images with unique aesthetic features. The stitch style loss function based on feature matching is shown in Eq. (3).

$$L_{style} = \| Gram(\phi(x)) - Gram(\phi(G(z))) \|_2^2 \quad (3)$$

In Eq. (3), L_{style} represents the loss of stitch style, which is used to ensure that the design image matches the texture and pattern features of the stitch data. ϕ represents the pre-trained feature output. $Gram$ represents a matrix calculation used to capture correlations between features. The gradient penalty loss function is shown in Eq. (4).

$$L_{GP} = E_{\hat{x} \sim p_{\hat{x}}} [(\| \nabla_{\hat{x}} D(\hat{x}) \|_2 - 1)^2] \quad (4)$$

In Eq. (4), L_{GP} represents the gradient penalty loss, which is used to improve training stability. $\hat{x}$ represents the interpolated sample obtained by linear interpolation between the real and design images. $p_{\hat{x}}$ represents the distribution of interpolated samples. $\nabla_{\hat{x}} D(\hat{x})$ represents the gradient of the discriminator on the interpolated sample. The local detail discriminator focuses on capturing local details, emphasizing the smoothness of lines, the delicacy of textures, and the accuracy of stitch elements, ensuring that the designed image also meets high-quality standards at the micro level (Octadion et al., 2025). To further improve the quality and diversity of design images, the key stitch elements are parameterized. The research simplifies complex image information into a set of controllable parameters, capturing the geometric features, texture changes, and arrangement patterns of stitch elements using parameterized models, thereby accurately describing the image content. By adjusting these parameters, the style, texture, and detail representation of the design image can be flexibly controlled. The geometric invariant moment calculation constructed using pixel feature region reconstruction technology is shown in Eq. (5).

$$Dif(C_1, C_2) = \frac{\min_{v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E}}{w[(v_i, v_j) + F_E]} \quad (5)$$

In Eq. (5), C_1, C_2 is the decorative image area to be compared. $w[(v_i, v_j) + F_E]$ is the weight function. $F_E = \frac{\ln I}{\ln D}$ and I represents complexity. D is the spatial dimension. To further improve the controllability, editability, and design efficiency of the generated results, an intelligent generation model based on GAN and stitch data is deeply integrated. A parameterized modeling method is introduced to construct a responsive and dynamically adjustable design mechanism. The core of parameterized modeling design is compiling the project itself as a function. Unlike traditional 3D modeling techniques, parameterized modeling technology enables the generation, development, modification, and transformation of form and structure by varying parameters, thereby enabling the rapid design and dynamic editing of visual models (Lo Turco et al., 2023).

3.2. Optimization Design of Decorative Image Intelligent Design Model Based on Improved GAN

The intelligent design model for decorative images, which relies on GANs and stitch data, performs well at image feature extraction and style transfer. However, when dealing with complex and varied stitch combinations, it is prone to problems such as texture blur and pattern confusion. Meanwhile, due to the diversity and complexity of stitch data, the model is prone to overfitting, leading to a lack of innovation and diversity in the generated decorative images. CNNs have powerful image feature extraction capabilities for processing complex image data. Therefore, the study combines CNN with GAN to propose an intelligent design model for decorative images. The model enhances the detailed representation of GAN in the image design process through the efficient feature-extraction capability of CNN, while improving the model's stability and adaptability to complex scenes (Wu and Kyungsun, 2024; Li et al., 2024). When the CNN model is running, the input layer receives multidimensional nonlinear landscape data and passes it to the hidden layer. The model uses convolution and pooling operations to extract hierarchical features and reduce the dimensionality of the input data. The fully connected layer performs cross-channel fusion over abstract features, and the SoftMax classifier maps the resulting representation to class probability distributions. In CNNs, max pooling can preserve local maximum features in the nonlinear decorrelated signal feature map. The study adopts the max pooling method, as presented in Eq. (6).

$$p^{l(i,t)} = \max_{(j-1)w+1 \leq t \leq jw} \{ \hat{o}^{l(i,t)} \} \quad (6)$$

In Eq. (6), $p^{l(i,t)}$ signifies the output value of the t -th neuron in the i -th feature map of the l -layer after passing through the pooling layer. $\hat{o}^{l(i,t)}$ signifies the output value of the t -th neuron in the i -th feature map of the l -layer after being activated by the function. To improve the efficiency of parameterized model construction and achieve an integrated design, a template block region-matching method is used to optimize the CNN structure. The proposed IGCM model involves several critical hyperparameters that influence training stability and generation quality. A sensitivity analysis is conducted to assess the model's robustness to variations in the three most critical hyperparameters: learning rate, style loss weight, and gradient penalty coefficient. For each parameter, variations of $\pm 50\%$ from the selected value are tested while holding others constant. Table 1 presents the key hyperparameters and their selected values, along with the rationale for each choice.

Table 1 illustrates the hyperparameter selection and rationale. To further optimize the nonlinear decoration modeling effect, the study introduces virtual environment spatial visual modeling technology, combined with pixel level distribution characteristics and multidimensional similarity measurement methods, and constructs a spatial region feature matching Eq. as presented in Eq. (7) (He et al., 2025; Mokayed et al., 2023).

$$F = \tilde{p}(x, y) = p(x, y) \left(\frac{v(x)}{v(y)} \right)^{1/2} \quad (7)$$

In Eq. (7), F is the spatial region feature matching model. $\tilde{p}(x, y)$ is the normalized feature distribution. In model construction, creating the target logic must decompose the model creation into a series of steps to design the target model (Islam et al., 2023). The quantitative evaluation of key feature-point parameters in the adjacent regions of the target contour is given by Eq. (8).

$$\text{NLM}[g(i)] = \sum_{j \in \Omega} w(i, j) g(j) \quad (8)$$

In Eq. (8), $w(i, j)$ is the characteristic function. $g(j)$ represents the feature value at pixel j . The second-order moment of multi-dimensional nonlinear decorative image design is shown in Eq. (9).

$$\mu_{pq} = \sum_{m=1}^M \sum_{n=1}^N (x - \bar{x})^p (y - \bar{y})^q f(x, y) \quad (9)$$

In Eq. (9), x is the horizontal axis of the pixel in the decorative image. y signifies the vertical axis of the pixels in the decorative image. (x, y) signifies the feature value at pixel (x, y) in the decorative image. By training and adjusting the model, a decorative image design model architecture based on an improved GAN and stitch data is ultimately developed, as shown in Fig. 2.

In Fig. 2, the decorative image design model based on an improved GAN and stitch data takes random noise as input, gradually constructs images through a parameterized modeling process, and guides the generation path with stitch semantic information to ensure that the output results comply with professional design standards. In terms of the discrimination mechanism, the global feature discriminator evaluates macro-level style consistency and color coordination to ensure overall visual quality. The local detail discriminator focuses on the rationality of the stitch structure, the precision of the line texture, and the clarity of the edges to enhance the realism of embroidered decorative elements. Mechanisms such as multi-scale adversarial training, style loss function, and gradient penalty are introduced. The model introduces regularization terms to avoid overfitting and improve its generalization, thereby enabling efficient design and processing of various types of decorative images.

Table 1. Key hyperparameters and selection rationale

Hyperparameter	Selected value	Justification
Learning rate (G)	0.0002	Standard for GAN training; lower rates (0.0001) slow convergence, and higher rates (0.0005) cause mode collapse
Learning rate (D)	0.0001	Set lower than G to maintain discriminator stability; empirically found to balance adversarial dynamics
Gradient penalty λ	10.0	Recommended value from WGAN-GP literature (Gulrajani et al., 2017); values between 5-15 yielded similar performance
Style loss weight α	0.5	Determined via grid search (0.1, 0.3, 0.5, 0.7, 0.9); 0.5 balanced style transfer and content preservation
Batch size	16	Limited by GPU memory (80GB); smaller batches (8) increased gradient variance; larger (32) exceeded memory capacity
Latent dimension z	128	Common practice for image generation; tested 64, 128, 256; 128 provided best trade-off between diversity and quality
CNN (generator)	depth	12 layers
		Selected via ablation; 8 layers insufficient for complex texture capture; 16 layers increased overfitting

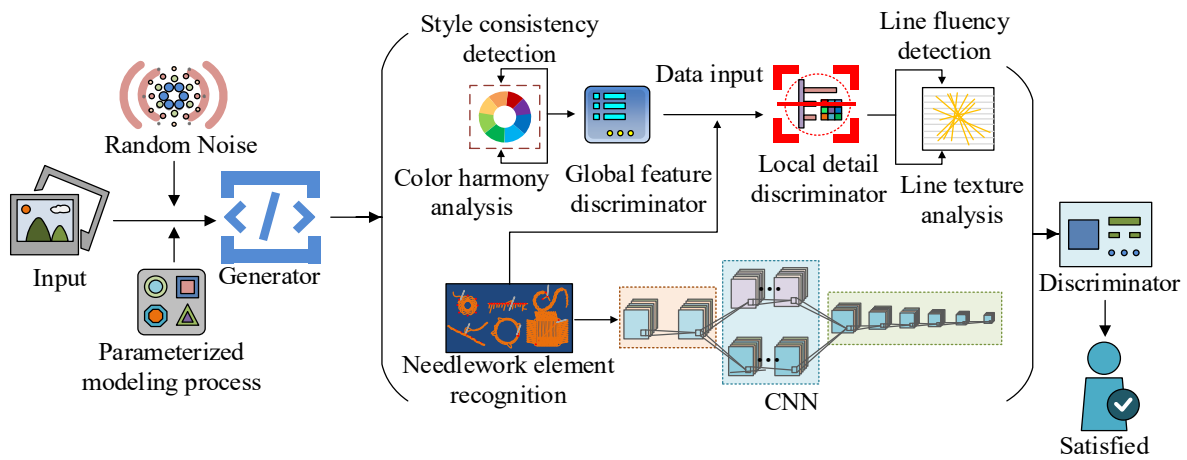


Fig. 2. Decorated image generation model based on improved GAN and stitch data

In Fig. 2, the decorative image design model based on an improved GAN and stitch data takes random noise as input, gradually constructs images through a parameterized modeling process, and guides the generation path with stitch semantic information to ensure that the output results comply with professional design standards. In terms of the discrimination mechanism, the global feature discriminator evaluates macro-level style consistency and color coordination to ensure overall visual quality. The local detail discriminator focuses on the rationality of the stitch structure, the precision of the line texture, and the clarity of the edges to enhance the realism of embroidered decorative elements. Mechanisms such as multi-scale adversarial training, style loss function, and gradient penalty are introduced. The model introduces regularization terms to avoid overfitting and improve its generalization, thereby enabling efficient design and processing of various types of decorative images.

4. Results

4.1. Performance Testing of Intelligent Design Model for Decorative Images

To test the performance of the intelligent design model for decorative images, the designed encryption model is referred to as IGCM. The study takes the Embroidery Artwork-10k Dataset (EmbroideryArt-10k) and the Pattern and Texture-8k Dataset (PatternTexture-8k) for testing. Sample images from the dataset are shown in Fig. 3.

Table 2 contains the computer hardware configuration used in the experiment, including key parameters such as processor model, memory size, storage device type, and network connection speed. The Style-based GAN with Adaptive Discriminator Augmentation (SGAN-ADA) (Sahar et al., 2025) and the Diffusion-GAN Hybrid Model (DGAN) (Wenming et al., 2022) are compared with the IGCM adaptive data augmentation. Recognition integrity is defined as the proportion of generated decorative images that are correctly classified by a pre-trained classifier (ResNet-50) as belonging to the intended style category, reflecting the model's ability to produce stylistically accurate outputs. Design contribution is defined as the ratio of novel design elements (e.g., stitch patterns, texture combinations) present in generated images that do not directly replicate any single training sample, measuring the model's capacity for creative generation. The study compares the image recognition integrity using different methods, and the results are shown in Fig. 4.



Fig. 3. Example image of the dataset (<https://hyper.ai/datasets>)

The basic hardware environment settings are shown in Table 2.

Table 2. Basic hardware environment for the experiment

Hardware Component	Specification	Software Component	Version and Details
Compute GPU	NVIDIA A100 PCIe 80GB (1 unit)	Operating System	Ubuntu 20.04.6 LTS (64-bit)
CPU	AMD EPYC 7742 (64 cores/128 threads) @ 2.25GHz	GPU Driver & SDK	NVIDIA Driver 535.86.05, CUDA 11.8, cuDNN 8.6.0
System Memory	512 GB DDR4 ECC RAM	Deep Learning Framework	PyTorch 2.0.1 (+ TorchVision)
Primary Storage	2 TB NVMe SSD (Samsung 980 Pro)	Programming Language	Python 3.9.18
Data Storage	10 TB SATA SSD (Crucial MX500)	Key Libraries	NumPy 1.24.3, OpenCV 4.8.1, Pillow 10.0.1, Matplotlib 3.7.2, Seaborn 0.12.2, Scikit-learn 1.3.0

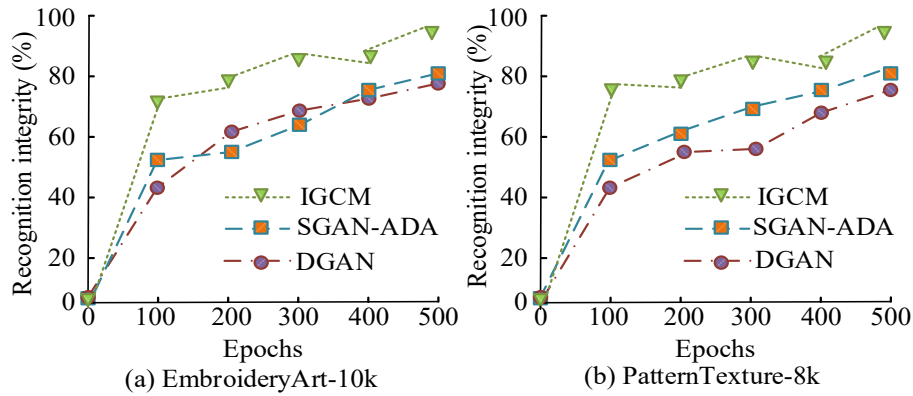


Fig. 4. Image recognition integrity of different methods

As shown in Fig. 4(a) on the EmbroideryArt-10k dataset, after 500 epochs, the IGCM achieved an image recognition accuracy of 98.73%. After 500 epochs, the image recognition integrity of SGAN-ADA was only 84.37%. After 500 epochs, the image recognition integrity of DGAN was only 83.68%. According to Fig. 4(b), on the PatternTexture-8k dataset, the

image recognition integrity of IGCM reached 97.79% after 500 epochs. After 500 epochs, the image recognition integrity of DGAN was 83.57%. After 500 epochs, the image recognition integrity of SGAN-ADA was 83.16%. Overall, the IGCM model has better encryption performance. To supplement the quantitative results in Fig. 4, Fig. 5 demonstrates representative decorative images generated by three contrast models (IGCM, SGAN-ADA, and DGAN) under identical input conditions.

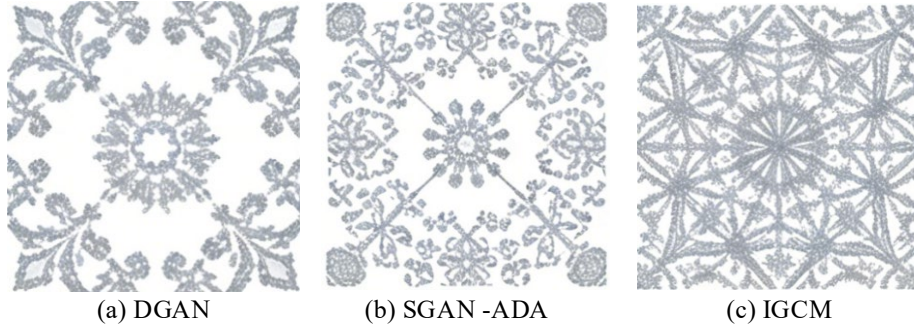


Fig. 5. Real data chart

In Fig. 5(a), DGAN exhibits chaotic, blurred, and incomplete characteristics. Fig. 5(b) shows that the SGAN-ADA structure is recognizable yet indistinct. Fig. 5(c) reveals IGCM with clear edges and rich details. The study compares the F1 scores of different methods, using the Micro-F1 score on the y-axis and model iteration times on the x-axis, as shown in Fig. 6. The F1 score is defined as the harmonic mean of precision and recall, providing a balanced metric for classification performance. For multi-classification problems across decorative style categories, micro-averaging is used to aggregate predictions across all categories.

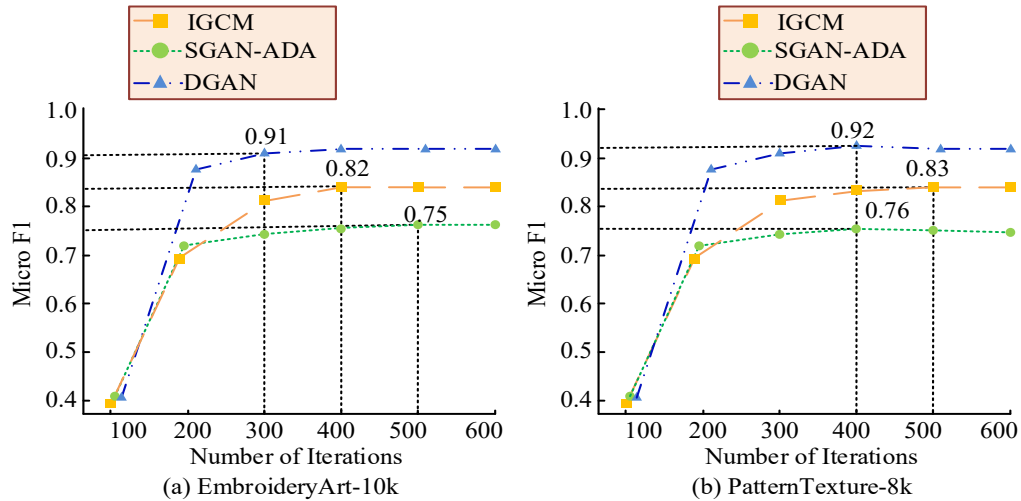


Fig. 6. The F1 scores of different methods

According to Fig. 6(a) on the EmbroideryArt-10k dataset, the IGCM model achieved the highest F1 score, reaching 0.91 after more than 300 iterations. The SGAN-ADA model ranked second, peaking at 0.82 after more than 400 iterations. The DGAN had the lowest F1 score and reached the highest point of 0.75 after more than 500 iterations. According to Fig. 6(b) on the PatternTexture-8k dataset, the IGCM model achieved the highest F1 score, reaching 0.92 after more than 400 iterations. The SGAN-ADA model ranked second, peaking at 0.83 after more than 500 iterations. The DGAN had the lowest F1 score and reached the highest point of 0.76 after more than 500 iterations. The IGCM model has higher speed and accuracy in decorative image recognition. To assess the statistical significance of the observed differences, one-way ANOVA was conducted on the F1 scores across the three models (IGCM, SGAN-ADA, DGAN) on both datasets. On the EmbroideryArt-10k dataset, the ANOVA yielded $F(2, 27) = 14.32$, $p < 0.001$, indicating significant differences among the three models. Post hoc Tukey HSD tests revealed that IGCM significantly outperformed both SGAN-ADA ($p < 0.01$) and DGAN ($p < 0.001$), whereas the difference between SGAN-ADA and DGAN was not statistically significant ($p = 0.18$). Similar results were obtained on the PatternTexture-8k dataset, with $F(2, 27) = 12.87$, $p < 0.001$. These results confirm that the improvements introduced in IGCM lead to statistically significant performance gains. To supplement the quantitative results shown in Fig. 6, Fig. 7 presents representative decorative images generated by three contrastive models (IGCM, SGAN-ADA, and DGAN) under identical input conditions.

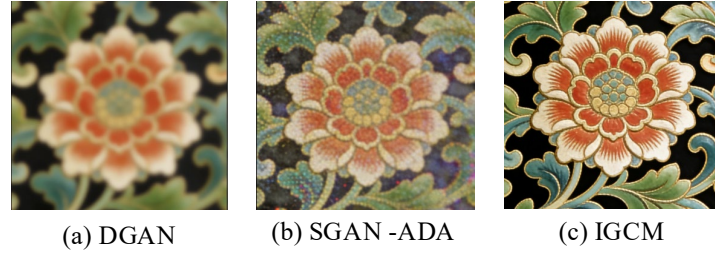


Fig. 7. Real data samples of F1 metrics

As shown in Fig. 7(a), DGAN exhibits chaotic images with frequent misclassification. Fig. 7(b) demonstrates that SGAN-ADA produces blurry images with sporadic errors and low confidence scores. Fig. 7(c) indicates that IGCM achieves clear image classification with high confidence accuracy.

4.2. Practical Application Effect of Intelligent Design Model for Decorative Images

To complement the perceptual evaluation, quantitative metrics were employed to assess the visual quality of generated decorative images. The Fréchet Inception Distance (FID) and Structural Similarity Index Measure (SSIM) were computed between generated images and real images from the test sets. Lower FID indicates higher fidelity, while higher SSIM reflects better structural preservation. The results are summarized in Table 3.

Table 3. Quantitative evaluation of generated image quality (FID and SSIM)

Model	EmbroideryArt-10k		PatternTexture-8k	
	FID	SSIM	FID	SSIM
/				
GCM	-	0.84	28.9	0.87
SGAN-ADA	45.7	0.76	41.2	0.79
DGAN	52.3	0.71	48.6	0.74

As shown in Table 3, on both datasets, IGCM achieved the lowest FID and highest SSIM among the three models. Compared to SGAN-ADA, IGCM reduced FID by 29.1% on EmbroideryArt-10k and 29.9% on PatternTexture-8k, while improving SSIM by 10.5% and 10.1%, respectively. These quantitative results indicate that IGCM generates images with higher fidelity and better structural similarity to real decorative images, corroborating the perceptual improvements observed in the user satisfaction analysis. To evaluate the practical applicability of the proposed model, a user satisfaction study was conducted with 200 volunteers (80 professional designers, 40 design educators, and 80 advanced design students). Participants rated images generated by IGCM, SGAN-ADA, and DGAN across four cost conditions (CNY 150, 200, 250, and 300) using a 5-point Likert scale covering visual quality, stylistic accuracy, design efficiency, and overall satisfaction. Presentation order was counterbalanced to avoid bias. The mean satisfaction score was compared using repeated-measures ANOVA with a Bonferroni correction ($p < 0.05$). The results are presented in Fig. 8.

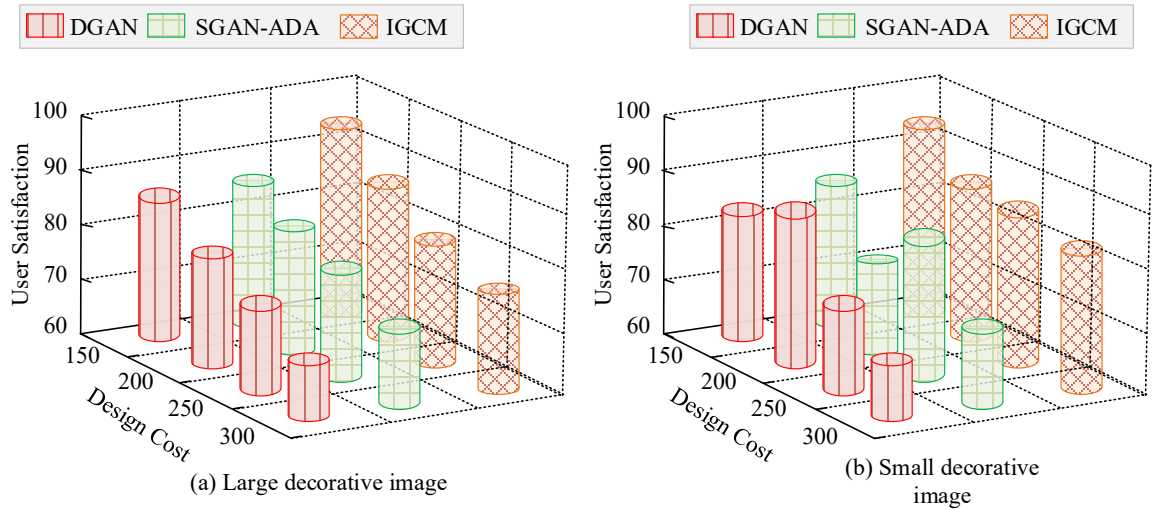


Fig. 8. User satisfaction statistical chart

According to Fig. 8(a), when designing large decorative images, user satisfaction decreases with increasing design cost. IGCM achieves the highest satisfaction rate, 92%, at a cost of CNY 150, which drops to 76% at CNY 300. For SGAN-ADA,

the highest satisfaction is 88% at CNY 150, falling to 72% at CNY 300. DGAN reaches 86% satisfaction at CNY 150, declining to 68% at CNY 300. As shown in Fig. 8(b), a similar downward trend in satisfaction is observed for small decorative images as costs rise. IGCM achieves 93% satisfaction at CNY 150, then decreases to 82% at CNY 300. SGAN-ADA reaches 87% at CNY 150 and 75% at CNY 300. DGAN achieves 82% at CNY 150, falling to 66% at CNY 300. Overall, the IGCM model maintains relatively higher user satisfaction across different cost levels. To supplement the quantitative results shown in Fig. 8, Fig. 9 presents representative decorative images generated by three contrast models (IGCM, SGAN-ADA, and DGAN) under identical input conditions.

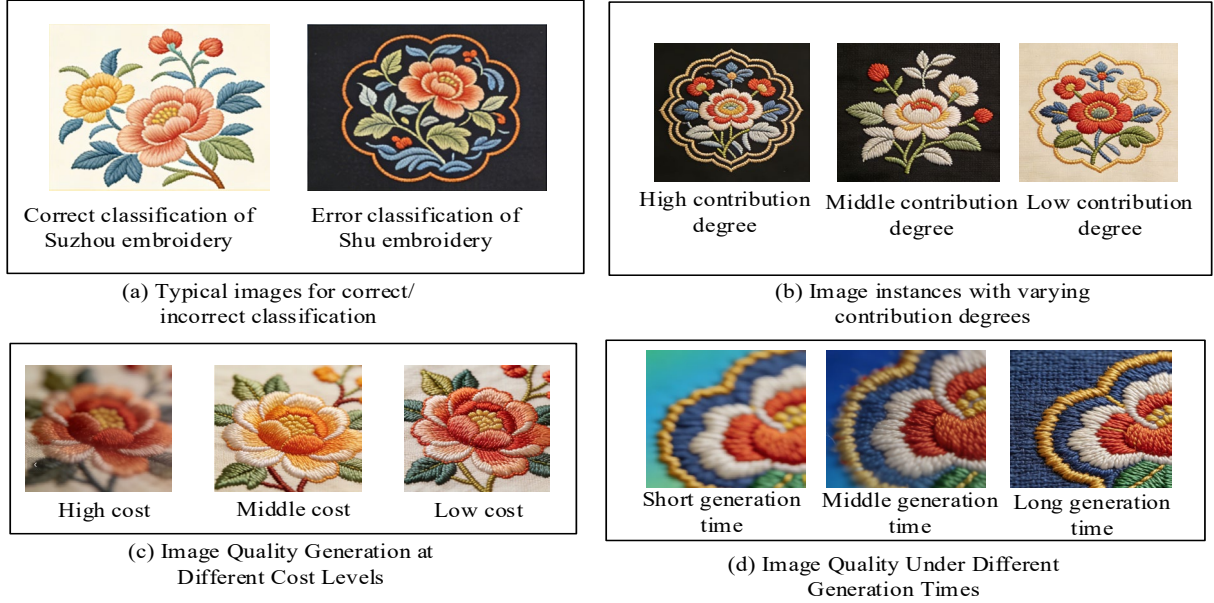


Fig. 9. Representative decorative image

Fig. 9(a) presents typical images with correct/incorrect classifications. Fig. 9(b) displays image instances with varying contribution levels. Fig. 9(c) illustrates quality differences in images generated under different cost levels. Fig. 9(d) shows the evolution of image quality across different generation time periods.

4.3. Ablation Research Contributed by Each Module

To isolate and quantify the contribution of each architectural component, a series of ablation experiments was conducted on the EmbroideryArt-10k dataset. Starting from a baseline GAN model, components were incrementally added: (1) stitch data embedding (Stitch), (2) dual discriminator mechanism (Dual-D), (3) style loss function (StyleLoss), (4) gradient penalty (GP), and (5) CNN integration (CNN). Each variant was trained under identical conditions, and performance was evaluated using FID, SSIM, recognition integrity (Rec-Int), and F1 score.

Table 4. Ablation study results on EmbroideryArt-10k dataset

Model Configuration	FID ↓	SSIM ↑	Rec-Int (%) ↑	F1 Score ↑
Baseline GAN	68.3	0.62	82.4	0.68
+ Stitch	54.7	0.71	87.6	0.75
+ Stitch + Dual-D	48.2	0.76	91.2	0.81
+ Stitch + Dual-D + StyleLoss	41.5	0.79	93.8	0.85
+ Stitch + Dual-D + StyleLoss + GP	37.8	0.81	95.4	0.88
IGCM (Full)	32.4	0.84	98.7	0.91

As shown in Table 4, all modules contribute positively to model performance. The stitch pattern data embedding demonstrates the most significant improvement, reducing FID by 19.9% compared to the baseline model, indicating that domain-specific aesthetic knowledge encoded in stitch patterns provides critical guidance for decorative image generation. The dual discriminator mechanism further enhances structural fidelity, with SSIM improving from 0.71 to 0.76 and the F1 score increasing by 0.06, confirming that separating global and local discrimination effectively preserves macroscopic composition and microscopic stitch details. The style loss function improves stylistic consistency, elevating recognition accuracy from 91.2% to 93.8%, while the feature-matching mechanism ensures alignment with target embroidery styles. The gradient penalty enhances training stability and convergence quality, resulting in an additional 3.7-point reduction in FID and a 1.6% improvement in recognition integrity. CNN integration delivers the final performance boost, particularly in texture representation, contributing the largest FID reduction (5.4 points) among the three components. Overall, the complete

IGCM model achieves cumulative improvements across all metrics, validating the synergistic effects of component integration. To quantify the macro and micro image quality and design realism of IGCM, the study recorded the global feature discriminator output probabilities for 500 randomly selected generated images from each model. Design realism was assessed using (1) FID to measure distribution similarity with real images, and design expertise ratings were evaluated by 20 professional designers (10 with over 5 years of experience) who scored 100 randomly selected images from each model on a 5-point scale (1 = clearly synthesized, and 5 = indistinguishable from real embroidery). The analysis results are presented in Table 5.

Table 5. Evaluation of macro and micro image quality and design realism

Model	Macro Quality (Global Score)	Micro Quality (Local Score)	FID	Design Professionalism Score (1-5)
IGCM	0.92 ± 0.03	0.89 ± 0.04	32.4	4.21 ± 0.38
SGAN-ADA	0.78 ± 0.05	0.71 ± 0.06	45.7	3.45 ± 0.52
DGAN	0.65 ± 0.07	0.58 ± 0.08	52.3	2.87 ± 0.61

As shown in Table 5, different models exhibit significant differences in macro and micro image quality, as well as in design professionalism scores. The IGCM model outperforms all other models across all metrics, achieving higher global and local quality scores and the lowest FID, indicating greater similarity between the generated and real images. The design professionalism score further highlights IGCM's advantages in visual appeal and practicality, reinforcing its leading position in relevant tasks.

5. Discussion

This study proposes an intelligent decorative image design model (IGCM) based on an improved GAN and stitches data to address inefficiency, slow iteration, and lack of personalization in traditional methods. Enhancements include a dual-discriminator CNN module, a gradient penalty, a style loss, and stitch feature matching. Tested on EmbroideryArt-10k and PatternTexture-8k, IGCM achieved near-zero loss after 500 and 480 epochs, with completeness of 98.73% and 97.79%, and F1 scores of 0.91 and 0.92, respectively. Compared with prior methods [9,10, and 11], IGCM shows superior efficiency, convergence, detail generation, and personalization. Limitations include occasional errors in complex scenarios and declining satisfaction under high design costs. Future work will focus on improving robustness, cost efficiency, and energy sustainability.

From a practice-oriented perspective, for design studios and decorative product companies, the proposed model enables AI-assisted rapid prototyping, reducing manual design time from days to minutes. The integration of stitch data and parametric control supports cost-aware generative workflows, enabling predefined quality-efficiency trade-offs. High user satisfaction across cost levels suggests that automated generation complements rather than replaces human expertise, freeing designers for high-value creative refinement. Industrial design managers can integrate the IGCM model into existing workflows across three stages. During the ideation process, the model enables rapid prototyping, allowing junior designers to generate dozens of style variants in a matter of hours rather than days. For cost optimization, parametric control allows managers to preset cost thresholds (low-cost variants for mass-market products, high-cost variants for premium collections), reducing manual estimation and rework. For resource allocation, automated generation handles routine tasks, freeing experienced designers to focus on creative direction and quality assurance. Implementation requires a modest upfront investment (2-3 weeks for integration and 1-2 days of training per designer), after which design iteration time can be reduced by an estimated 60-70%.

Several limitations should be acknowledged. First, standardized generative evaluation metrics remain underdeveloped; perceptual quality and artistic merit are difficult to quantify objectively. Second, while an ablation study was added in Section 4.3, interactions among components warrant further investigation. Third, dataset diversity is limited. Experiments were conducted only on two embroidery-focused datasets, leaving performance on other decorative domains (ceramics, wood carvings, and metalwork) and cultural motifs unexplored. Fourth, the risk of overfitting cannot be dismissed given the model's capacity (7.8M parameters) relative to the dataset sizes (10,000 and 8,000 images). Fifth, cost sensitivity revealed in the user satisfaction analysis indicates that acceptance declines as design costs increase, necessitating further economic analysis. These limitations suggest that general applicability requires validation on more diverse datasets and evaluation frameworks.

6. Conclusion

This study proposed an intelligent design model (IGCM) for decorative images based on an improved GAN and stitch data, integrating stitch guidance, dual discriminators, CNN-based feature extraction, and parametric control. On EmbroideryArt-10k and PatternTexture-8k datasets, IGCM achieved rapid convergence (loss to 0 after 500 epochs), recognition integrity of 98.7%, F1 scores up to 0.92, FID of 32.4, and SSIM of 0.84. Ablation studies confirmed positive contributions from each component, and user satisfaction remained high across varying cost levels. Limitations include limited dataset diversity, potential overfitting, and a lack of standardized generative metrics. Future work will extend the model to broader decorative domains and cultural motifs while improving computational efficiency. Beyond these empirical results, the study offers three broader insights. First, domain-specific aesthetic knowledge can be encoded as learnable parameters, shifting design AI from data-driven generation toward knowledge-guided creation. Second, the dual discriminator reveals that high-quality design requires simultaneous attention to holistic composition and micro-level detail, challenging monolithic quality metrics. Third,

parametric control enables cost-aware generative design, allowing designers to navigate quality-efficiency trade-offs with economic constraints in mind.

From a managerial perspective, this paper suggests three changes in decision-making for design studio and decorative product company managers. First, they can adopt the IGCM model for rapid prototyping, reducing initial concept generation from days to hours. Second, the parametric control mechanism enables cost-aware generative workflows, allowing managers to set cost thresholds to align with production budgets (low-cost variants for mass-market products and high-cost variants for premium collections). Third, resource allocation can be restructured by assigning routine design tasks to AI-assisted workflows, freeing experienced designers to focus on high-value creative direction and quality assurance. These changes, supported by empirical evidence, provide a pathway for integrating AI-generated decorative images into professional design practice.

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

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References

- Al-Zebari, A. (2024). Ensemble convolutional neural networks and transformer-based segmentation methods for achieving accurate sclera segmentation in eye images. *Signal Image and Video Processing*, 18(2), 1879-1891. DOI: 10.1007/s11760-023-02891-7.
- Arkin, E., Yadikar, N., Xu, X., Aysa, A., and Ubul, K. (2023). A survey: object detection methods from CNN to transformer. *Multimedia Tools and Applications*, 82(14), 21353-21383. DOI: 10.1007/s11042-023-14999-4.
- Chen, J., Shao, Z., Cen, C., and Li, J. (2024). HyNet: A novel hybrid deep learning approach for efficient interior design texture retrieval. *Multimedia Tools and Applications*, 83(9), 28125-28145. DOI: 10.1007/s11042-023-16579-0.
- Chen, Y., Xia, R., Yang, K., and Zou, K. (2023). DGCA: high resolution image inpainting via DR-GAN and contextual attention. *Multimedia Tools and Applications*, 82(30), 47751-47771. DOI: 10.1007/s11042-023-15313-0.
- Chi, C., Zeng, X., Bruniaux, P., and Tartare, G. (2025). An intelligent recommendation system for personalised parametric garment patterns by integrating designer's knowledge and 3D body measurements. *Ergonomics*, 68(3), 317-337. DOI: 10.1080/00140139.2024.2338787.
- Guo, K., Zong, Z., Yang, J., and Tan, Y. (2024). Parametric elastic full waveform inversion with convolutional neural network. *Acta Geophysica*, 72(2), 673-687. DOI: 10.1007/s11600-023-01123-3.
- He, Y., Xu, X., and Yu, X. (2025). Automatic identification of AI-generated ceramic art images using convolutions-based neural networks models. *International Journal of Information and Communication Technology*, 26(15), 1-24. DOI: 10.1504/IJICT.2025.146371.
- Hu, X., Yang, C., and Fang, F. (2024). Msebgan: Multi-stitch embroidery synthesis via region-aware texture generation. *IEEE Transactions on Visualization and Computer Graphics*, 31(9), 5334-5347. DOI: 10.1109/TVCG.2024.3447351.
- Islam, A., Othman, F., Sakib, N., and Babu, H. M. H. (2023). Prevention of Shoulder-Surfing Attack Using Shifting Condition with the Digraph Substitution Rules. *Artificial Intelligence and Applications*, 1(1), 58-68. DOI: 10.47852/bonviewAIA2202289.
- Kahraman, M. U., Şekerci, Y., Develier, M., and Koyuncu, F. (2024). Integrating artificial intelligence in interior design education: concept development. *Journal of Computational Design*, 5(1), 31-60. DOI: 10.51214/jcd.2024.050103.
- Kitole, F. A. and Sesabo, J. K. (2024). The heterogeneity of socioeconomic factors affecting poverty reduction in Tanzania: A multidimensional statistical inquiry. *Society*, 61(5), 560-574. DOI: 10.1007/s12115-024-00957-x.
- Li, T., Hui, S., Zhang, S., Wang, H., Zhang, Y., Hui, P., and Li, Y. (2024). Mobile user traffic generation via multi-scale hierarchical GAN. *ACM Transactions on Knowledge Discovery from Data*, 18(8), 1-19. DOI: 10.1145/3664655.
- Li, Y., Zhao, M., Mao, J., Chen, Y., Zheng, L., and Yan, L. (2024). Detection and recognition of Chinese porcelain inlay images of traditional Lingnan architectural decoration based on YOLOv4 technology. *Heritage Science*, 12(1), 137-178. DOI: 10.1186/s40494-024-01227-z.
- Liu, C., Gu, J., Yao, L., and Zhang, Y. (2025). Research on embroidery style migration model based on texture cycle GAN. *International Journal of Clothing Science and Technology*, 37(1), 138-153. DOI: 10.1108/IJCST-04-2023-0062.
- Liu, W. (2024). Optimization of an Innovative Design System for Han Embroidery Dresses Based on Image Matching Method. *International Journal of e-Collaboration*, 20(1), 1-17. DOI: 10.4018/IJeC.357643.
- Lo Turco, M., Tomalini, A., and Bono, J. (2023). Proportions, constraints and semantics for a parametric model. *Nexus Network Journal*, 25(1), 333-340. DOI: 10.1007/s00004-023-00667-7.

- Lome, E. (2024). Stitching a Lineage: Embroidered Coats of Arms in Eighteenth-Century Boston. *Winterthur Portfolio*, 58(1), 9-40. DOI: 10.1086/732828.
- Mokayed, H., Quan, T. Z., Alkhaled, L., and Sivakumar, V. (2023). Real-time human detection and counting system using deep learning computer vision techniques. *Artificial Intelligence and Applications*, 1(4), 221-229. DOI: 10.37256/aia.142023221.
- Nyboer, J. (2024). Critiquing contemporary interior design students. *International Journal of Technology and Design Education*, 34(4), 1579-1602. DOI: 10.1007/s10798-023-09872-4.
- Octadion, O., Yudistira, N., and Kurnianingtyas, D. (2025). Synthesis of batik motifs using a diffusion-generative adversarial network. *Multimedia Tools and Applications*, 84(7), 3407-3438. DOI: 10.1007/s11042-025-20620-9.
- Shi, M., Seo, O. J., Cha, S. H., Xiao, B., and Chi, H. L. (2024). Generative AI-powered architectural exterior conceptual design based on the design intent. *Journal of Computational Design and Engineering*, 11(5), 125-142. DOI: 10.1093/jcde/qwae077.
- Azadi, S., Dixe, S., Leite, J., Borges, J., Queiros, S., and Fonseca, J. (2025). Automatic generation of in-vehicle images: StyleGAN-ADA vs. MSG-GAN. *Computers and Informatics*, 5(1), 23-31. DOI: 10.62189/ci.1261718
- Vijendran, M., Deng, J., Chen, S., Ho, E. S., and Shum, H. P. (2024). Artificial intelligence for geometry-based feature extraction, analysis and synthesis in artistic images: a survey. *Artificial Intelligence Review*, 58(2), 64. DOI: 10.1007/s10462-024-11051-3.
- Wu, Y. and Kyungsun, K. (2024). Automatic generation of traditional patterns and aesthetic quality evaluation technology. *Information Technology and Management*, 25(2), 125-143. DOI: 10.1007/s10799-022-00356-w.
- Wenming Cao, Zhiwen Yu, Hau-San Wong. (2022). GAN-based clustering solution generation and fusion of diffusion. *Systems Science & Control Engineering*, 10(1), 24-42. DOI: 10.1080/21642583.2021.2024100
- Xie, X., Cheng, G., Wang, J., Li, K., Yao, X., and Han, J. (2024). Oriented R-CNN and beyond. *International Journal of Computer Vision*, 132(7), 2420-2442. DOI: 10.1007/s11263-024-01951-z.
- Yuan, J., Zhou, F., Guo, Z., Li, X., and Yu, H. (2023). HCformer: hybrid CNN-transformer for LDCT image denoising. *Journal of Digital Imaging*, 36(5), 2290-2305. DOI: 10.1007/s10278-023-00845-6.
- Yue, M., Zheng, H., Cui, H., and Wu, Z. (2023). Gan-lstm-based ads-b attack detection in the context of air traffic control. *IEEE Internet of Things Journal*, 10(14), 12651-12665. DOI: 10.1109/JIOT.2023.3284562.
- Yüksel, Ş., Gündoğdu, B., and Kaya, N. (2025). Co-design in somewhere: The interpretations of interior design students on future architectural scenarios in metaverse. *Interactive Learning Environments*, 33(1), 260-275. DOI: 10.1080/10494820.2024.2343759.
- Zhang, Y. and Wang, J. (2024). Artistic sense of interior design and space planning based on human machine intelligent interaction. *Intelligent Decision Technologies*, 18(3), 1783-1796. DOI: 10.3233/IDT-240615.
- Zhang, Y., Ong, C. C., Zheng, J., Lie, S. T., and Guo, Z. (2022). Generative design of decorative architectural parts. *The Visual Computer*, 38(4), 1209-1225. DOI: 10.1007/s00371-021-02142-1.
- Zhong, H. and Jing, M. (2025). Digital soft decoration display design microspecialty based on double layer clustering user behavior analysis algorithm. *Intelligent Decision Technologies*, 19(3), 1551-1564. DOI: 10.1177/18724981251314270.



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