# Combining Creative Adversarial Networks with Art Design Models and Machine Vision Feedback Optimization

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**Abstract.** In the field of art and design, different artistic styles endow works with unique charm and expressive power. Computer-aided design (CAD) model processing in art and design refers to the stage of using computer technology to process CAD models in art and design works. The traditional CAD model processing methods mainly include rule-based optimization, parametric design, etc. However, these methods often struggle to achieve ideal results when faced with complex and diverse art and design works. This article proposes an art and design CAD model processing and machine vision feedback optimization method based on Generative Adversarial Networks (GAN). This method combines an image sparse encoding algorithm to repair and optimize art images, guiding the optimization direction of the model. Through experimental verification and subjective assessment by observers, the results show that this method is significantly superior to traditional design methods in terms of image restoration accuracy, quantity of erroneous pixels, and user satisfaction. This method improves the quality of restoration and creation and provides new impetus for the progress of art and design.

**Keywords:** Generative Adversarial Networks; Art and Design; CAD; Machine Vision
**DOI:** https://doi.org/10.14733/cadaps.2024.S16.103-116

## 1 INTRODUCTION

Nowadays, people are in a digital and visual era, and images have become an indispensable part of people's daily lives and work. In the field of art design, the quality and processing effect of images are directly related to the visual effect and expressive force of works. Colored painting art is an art form with a profound historical heritage and rich cultural connotations. Computer-aided design (CAD) has provided new possibilities for creating and applying painting art. Alotaibi [1] explored a method for translating painting art images into images based on Deep Generative Adversarial Networks (GANs) to achieve automated painting design. It adopts an improved deep generative adversarial network, Pix2Pix GAN, for CAD design of color art image-to-image translation. The task of the generator is to generate a target image (i.e., a painted artwork) based on the input source image. The task of the discriminator is to determine whether the generated image is genuine. Through training, the generator will learn to convert the source image into a painted artwork similar to the target image. In order to train the Pix2Pix GAN model, we need to prepare a large number of datasets of painted art images. These datasets can include colored artworks with different styles and themes, such as oil paintings, watercolors, printmaking, etc. In addition, we also need to preprocess the dataset, such as unifying image size and normalizing pixel values, to ensure that the painting art. By applying this method, we can automatically generate various styles of painted art, providing artists with more creative space and inspiration sources. Every artistic design work involves a lot of image processing and operation. The purpose of these treatments and operations is to make the design work more in line with the designer's creativity but also more in line with the audience's visual aesthetics.

Traditional CAD art visual design methods often require a large amount of manual involvement and experience accumulation. Generative Adversarial Networks (GANs) have provided new ideas for solving this problem. Behzadi et al. [2] proposed a scheme for implementing CAD art visual design using Conditional. The learning target image of the generator is fixed and random during the migration network process of the discriminator. The noise labels have a certain impact on the conditional generation adversarial of deep learning. Through training, the generator will learn to generate images that are similar to real target images. In the plan, we first collect a large number of image datasets of art and visual design works, including paintings, sculptures, architecture, etc., with different styles and themes. Then, we use Conditional GAN for training so that the model can learn the patterns and features of artistic visual design. By applying this solution, we can provide artists with more creative space and inspiration sources and meet the needs of modern design. In addition, this scheme can also be applied to other types of image generation tasks, such as face synthesis, image restoration, etc., and has broad application prospects. The traditional CAD model processing method of art design is difficult to achieve the ideal effect in the face of complex and diverse art design works. In the fields of art and design, innovation and exploration are eternal themes. With the continuous progress of technology, especially the development of artificial intelligence, more and more innovative methods are being introduced into these fields, among them. Dai et al. [3] explored a new method for reverse design of structural art colors using conditional GAN to find multiple solutions. Conditional GAN is a special type of GAN that can combine conditional information to generate target images. In our approach, we will use conditional GAN for the reverse design of structural art colors. Specifically, we will input a source image and a set of target colors and then use conditional GAN to generate a new image that is similar to the source image but with the target color. The generator will use Convolutional Neural Networks (CNN) to extract features from the source image and use conditional information to control the application of colors. The discriminator will use similar techniques to compare the differences between generated images and real images. Through training, the generator will learn to generate new images that are similar to the source image but have the target color. In this context, how to process artistic images more accurately and efficiently is the focus of academic and artistic circles.

Paper-cutting art is a traditional art form with a long history and unique charm. Computer-aided design (CAD) has brought new possibilities to the art of Paper Cuttings. Fei et al. [4] proposed a comprehensive CAD design method for Paper Cuttings structures based on a generative antagonism network (GAN) and realized automatic Paper Cuttings design. This method can learn the characteristics of various paper-cutting designs and generate structures similar to real paper-cutting works. Through the combination of Paper cutting works generated by physical cutting and other types of art design, we can get works of art with unique charm. This method has brought new possibilities for paper-cutting art and provided more creative space and inspiration for artists. This paper uses a Conditional GAN to design the Paper-cutting structure. The model consists of a generator and a discriminator. The task of the generator is to generate the corresponding Paper cutting structure according to the given random noise and labels (such as animals, flowers, etc.). The task of the discriminator is to determine whether the generated structure is genuine. Through training, the generator will learn to generate a structure similar to the real Paper cutting works. Some paper-cutting structures are generated using the trained model, and these structures are physically cut to get the actual paper-cutting works. Finally, we combine these Paper Cuttings works with other types of art design to get unique works of art.

Computer art vision tasks have wide applications in many fields, including image generation, style transfer, image restoration, and so on. However, selecting the appropriate optimizer algorithm to improve the performance of computer art vision tasks is an important issue. Hassan et al. [5] explored this issue and proposed a method using an adaptive optimizer. The optimizer is one of the important algorithms used to train neural networks. Different optimizer algorithms have different characteristics and applicable scenarios. In computer art vision tasks, selecting the appropriate optimizer can improve training speed and model performance. The experimental results show that using an adaptive optimizer can significantly improve training speed and model performance. Compared with traditional fixed learning rate optimizers, adaptive optimizers can converge faster and produce better results. In addition, the adaptive optimizer can automatically adjust hyperparameters to better adapt to different tasks and datasets. By comparing the similarity of the target images, the training generator conducted noise group analysis on the learning results. Extract target identification curves from the random noise environment impact results. The result has been widely applied in the similarity of target images. providing artists with more creative space and inspiration sources. Optimal Transport has been introduced as a mathematical method in the fields of machine learning and computer vision. The main idea of optimal transportation is to find the minimum cost transfer scheme between two probability distributions, which can help us map one distribution to another. In art visual image processing, optimal transportation can be used for tasks such as feature extraction, style transfer, and image restoration. Kamsu et al. [6] proposed a generative adversarial network model based on optimal transportation (OT-GAN) for processing and analyzing artistic visual images. This model introduces optimal transportation into the generator and discriminator, optimizing the similarity between generated images and real images by minimizing transportation costs.

Constrained crystal DCGAN constrained optimization algorithms. This model task is to generate corresponding crystal structure art visual images based on given random noise and constraint conditions. The task of the discriminator is to determine whether the generated structural image is authentic. Long et al. [7] proposed a constrained crystal depth convolutional generative adversarial network for visual feedback in crystal structure art. This network can automatically generate various types of crystal structure images and has high generation ability and translation accuracy. By applying this network, we can provide artists with more creative space and inspiration sources, and meet the needs of modern design. In addition, this network can also be applied to other types of image generation tasks, such as face synthesis, image restoration, etc., and has broad application prospects. Porous media is a material with a complex internal structure and a wide range of applications. The structure and function of porous media have a significant impact on their performance and effectiveness in fields such as architecture, art, and biomedical engineering. Therefore, how to control the artistic architecture of porous media has become a challenging issue. Machine learning, the controlled synthesis of artistic architectures, received widespread attention. Nguyen et al. [8] proposed a controlled synthesis method for constructing porous media art architecture using GAN and RL. This method is based on a deep learning framework and combines the advantages of GAN and RL to achieve efficient control and optimization of porous media structures. By interacting with the generator to learn the optimal strategy, a more suitable porous media model can be obtained. In the algorithm, we define a reward function of the generated model and the degree to which it meets the requirements. Through continuous iteration and optimization, the RL algorithm will learn to control the behavior of the generator to obtain the optimal porous medium model. These research results represent the contributions, showcasing the integration of advanced technologies such as deep learning, computer vision, and virtual reality with art and design, promoting the innovation of the field of art and design.

GAN, as an emerging deep-learning technology, has shown strong potential in the field of image processing. GAN introduces the idea of adversarial training to make the generated images more realistic, providing a new solution for artistic image processing. However, there are still some challenges when dealing with complex art and design works using a single GAN model. In order to improve the effectiveness of art image processing, this article proposes a method combining GAN for art design CAD model processing and machine vision feedback optimization. This method integrates image sparse encoding algorithms to fully utilize the sparsity of the image itself and achieve restoration and optimization of artistic images. At the same time, a machine vision feedback mechanism is introduced to compare the processed image with the original image, guiding the optimization direction of the model and improving the satisfaction of the processing results. I hope that through this study, new insights and ideas can be brought to the field of art image processing, providing more efficient and convenient image-processing tools for art and design workers. The innovation and contribution of this article lie in:

This article combines GAN with art and design CAD model processing to propose a new framework for art image processing. The research introduced image sparse encoding algorithm to fully explore the sparsity of images and achieve efficient restoration and optimization of artistic images; This study also innovatively introduces a machine vision feedback mechanism to provide accurate guidance for model optimization, improve the quality of processing results and user satisfaction.

The structure of this article is as follows: First, introduce the research status of GAN, art and design CAD model processing, and image sparse encoding algorithms; Secondly, elaborate on the art and design CAD model processing and machine vision feedback optimization methods combined with GAN, including the model architecture, training process, and optimization strategies; Next, a comprehensive performance assessment of the proposed method will be conducted through the experimental section, demonstrating its processing effectiveness in different scenarios; Finally, summarize the entire article and explore future research directions.

## 2 RELATED THEORIES AND RESEARCH STATUS

Machine learning and computer vision technology have made significant progress in many fields. Especially in the field of art, these technologies provide new possibilities for the digital processing, recognition, and interpretation of artworks. Nicholas et al. [9] explored how to integrate art images to achieve machine vision feedback. Real-time multi-resolution scanning is a digital image processing technique that extracts features of an image at different resolutions by performing multi-resolution analysis on the image. This technology can effectively capture the details and structure of images at different scales, providing rich feature information for subsequent machine learning. In this article, we will combine real-time multi-resolution scanning with machine learning to construct an integrated machine vision feedback system. The system first uses real-time multi-resolution scanning technology to extract multi-scale features from the input art images and then inputs the extracted features into a machine-learning model for training and prediction. Art images are a visual art form with unique charm and expressive power. However, traditional CAD art image design methods often require a lot of manual involvement and experience accumulation, making it modern design. Deep learning and Generative Adversarial Networks (GANs) have provided new ideas for solving this problem. In art image processing, topology refers to the way various parts of an image are connected. Optimizing the topological structure of artistic images can help designers better understand and modify the composition of the images. Parrott et al. [10] proposed a new GAN model called the Art Image Topology Optimization Network (AITON) to achieve this goal. The AITON model includes a generator and a discriminator. The input of the generator is the original art image and processed topology information, and the output is the optimized art image. The input of the discriminator is the original artistic image, optimized artistic image, and processed topological structure information, and the output is the similarity between the two. During the training process, we use a mixed loss function that includes a content loss and a structure loss. Content loss is used to maintain the similarity between the optimized art image and the original art image in terms of content, while structural loss is used to maintain the consistency between the optimized art image and the given topological structure. We also introduced art-based design enhancement technology. Specifically, we add an aesthetic feature extraction layer at the input of the generator, which can enhance random noise based on given aesthetic features. In this way, we can enhance and optimize the aesthetic features of the generated images during the training process, in order to achieve more attractive and expressive artistic image design. In the field of architecture, machine learning can help us better understand the performance of building materials, predict their behavior, and optimize their design. Peng et al. [11] explore how to use machine learning techniques to achieve constrained multi-objective design of artistic and ornamental building materials in order to improve the artistic and functional aspects of architecture. Constrained multi-objective design is a design method that considers multiple conflicting design objectives and attempts to find the optimal solution to satisfy all objectives. In the field of architecture, this may involve multiple considerations, such as the strength, weight, durability, and cost of building materials. Machine learning can help us automate this design process. Specifically, we can use a machine learning method that satisfies all design objectives. By inputting a large amount of building material data and corresponding design requirements, this algorithm can learn how to predict the behavior of building materials and generate the optimal design solution that meets specific constraints.

In artistic creation, composition is one of the key factors for the success of a work. For artists, choosing the right composition is a daunting task that requires a lot of practice and trial and error. However, with the development of technology, machine learning algorithms have provided artists with new tools to help them make better decisions in the creative process. Salimbeni et al. [12] introduced painting, which can help artists better compose in three-dimensional space. This machine learning application is developed based on a deep learning convolutional neural network (CNN) model. This model has been trained on a large number of Giorgio Morandi still-life datasets to identify and classify various composition elements and techniques. By inputting a still-life image, the application can analyze the composition elements in the image, such as shape, color, texture, etc., and output corresponding analysis reports and suggestions. Artists can import their sketches or drawings into the application to obtain feedback and suggestions about their composition elements. In addition, the application can also be used in teaching and art research fields to help scholars and students better understand Giorgio Morandi's composition skills and style. Art image restoration is an important task in image processing, aimed at restoring the original image from degraded images. Artistic image representation is the process of transforming images into a form suitable for computer processing, and sparse encoding is an effective method for artistic image representation. Graph Laplacian regularization is an effective sparse encoding regularization method. Sha et al. [13] explored how to use sparse encoding graph Laplacian regularization for art image restoration and representation. We conducted experiments using standard image processing datasets and evaluated our method using metrics.

The blended learning model can combine traditional classroom teaching with online learning, providing learners with more flexible and diverse learning methods while also bringing new opportunities and challenges to digital art teaching design. Wang [14] explores the application of digital art teaching design from the following aspects. Through practical case analysis, it is found that there are significant advantages in digital art teaching design. Firstly, the blended learning mode can combine traditional classroom teaching with online learning, improving students' learning effectiveness and efficiency. Secondly, online learning spaces can provide abundant learning resources and diverse learning methods, meeting the personalized needs and learning interests of students. Finally, online learning spaces can promote students' self-directed and cooperative learning and improve their overall quality and ability level, which has broad application prospects in digital art teaching design. By constructing online learning spaces, designing digital art courses, implementing blended learning models, and conducting practical case studies, the effectiveness and quality of digital art teaching can be improved. The restoration of artistic materials is an important task aimed at protecting and restoring cultural heritage and making it as close to its original state as possible. The development of machine learning technology has provided new possibilities for the restoration of artistic materials. Wang et al. [15] explored how to use machine learning techniques for repairing and designing artistic materials. Machine learning technology can help us automate and optimize the repair process of artistic materials. Among them, deep learning technology can be used to identify and classify the degree of damage to art materials and propose corresponding repair plans. By training a CNN model, we can generate corresponding repaired images based on the input art material images.

Artificial intelligence has shown tremendous potential in various fields. Especially in the field of art, artificial intelligence has become an important tool for creative design. This article will explore how to use artificial intelligence for creative design of wick process patterns, and combine sustainable design concepts to achieve the combination of environmental protection and art. The wick process is an ancient and exquisite manufacturing technique that produces pattern effects through the burning of the wick. However, the traditional wick manufacturing process is cumbersome and requires a large amount of manual operation. To address this issue, Wang et al. [16] utilized artificial intelligence technology to automate and optimize the production of lamp core process patterns. Firstly, we use deep learning techniques to train the model to automatically generate wick process patterns based on input parameters. These parameters can include color, shape, size, etc. By adjusting these parameters, we can obtain different styles of wick process patterns. Secondly, we combine the concept of sustainable design and use environmentally friendly materials to achieve the production of lamp core technology. For example, we can use biodegradable materials to replace traditional plastic materials, thereby reducing environmental pollution. In addition, it reduces dependence on fossil fuels. Art images are a precious cultural heritage, often subject to various damages and noise due to historical, environmental, and other factors. In order to protect and repair these images, an effective image restoration and denoising method is needed. Deep learning, as a powerful tool, has been widely applied in image restoration and denoising tasks. However, traditional deep learning methods may not achieve optimal results for complex and scarce data such as art images. Therefore, Xu et al. [17] proposed a prior method for art image restoration and denoising based on deep sparse representation. Deep sparse representation is a method that combines deep learning and sparse representation. It learns the sparse representation of data by training deep neural networks, thereby mining the inherent rules and prior knowledge in the data. In the task of art image restoration and denoising, deep sparse representation can learn the sparse dictionary of the image and use the sparsity in the dictionary to denoise and restore the image.

## 3 CAD MODEL CONSTRUCTION OF ART DESIGN AND OPTIMIZATION OF MACHINE VISION FEEDBACK

Art and design CAD model processing refers to the stage of using computer technology to process CAD models in art and design works, aiming to improve the quality and visual effects of the work. The traditional CAD model processing methods mainly include rule-based optimization, parametric design, etc. However, these methods often struggle to achieve ideal results when faced with complex and diverse art and design works. With the development of deep learning technology, neural network-based CAD model processing methods are gradually receiving attention. These methods achieve accurate processing and optimization of complex works by learning the data distribution and feature representation of a large quantity of art and design works. At present, research in this field mainly focuses on network architecture design, feature extraction and representation learning, optimization algorithms, and other aspects.

Image sparse encoding algorithm is a method of encoding and representation that utilizes the sparsity of images. The sparsity of an image refers to the fact that most pixels in the image have zero or near zero values, with only a few pixels having larger values. By mining and utilizing this sparsity, image sparse encoding algorithms can achieve efficient processing and compression of images. In the field of image processing, sparse encoding algorithms have been used for tasks such as image denoising, image compression, and image restoration. For example, image denoising methods based on sparse representation can effectively remove noise by learning the sparse representation of the image; The image compression method based on sparse encoding can significantly reduce storage space and transmission bandwidth while ensuring image quality. Traditional art and design methods often require a lot of manual operation and professional knowledge, while the introduction of CAD technology greatly improves design efficiency and creative freedom. GAN and other deep learning algorithms have demonstrated strong capabilities in image generation, restoration, and reconstruction tasks. Based on this background, this section aims to propose an improved art and design CAD modeling method that combines GAN, sparse encoding algorithm, and machine vision technology to solve the repair and reconstruction problems encountered in traditional methods.

In the field of art and design, different artistic styles endow works with unique charm and expressive power. In order to achieve the learning and transfer of artistic style, this section utilizes the powerful generation ability of GAN to construct an artistic style learning module. Firstly, collect a large amount of image data from different art styles and preprocess and annotate them. Then, using the conditional GAN architecture, the artistic style is used as the conditional input to guide the generator in generating images with corresponding artistic styles. Through adversarial training of the discriminator, the generator gradually learned how to generate realistic images based on a given artistic style. The neural network model for learning art style is shown in Figure 1.

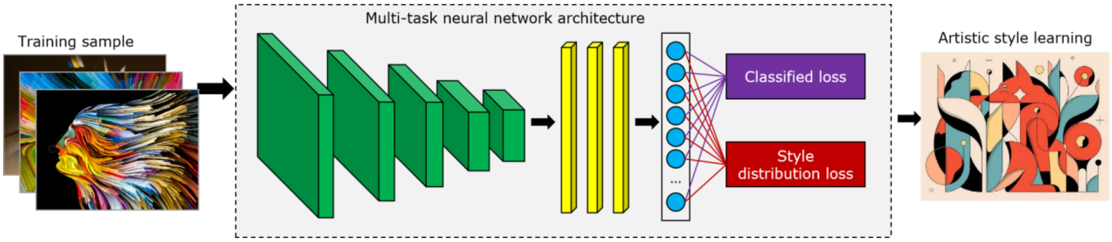



**Figure 1**: Neural network model of artistic style learning.

The core of the art style learning module is the generator network, which receives random noise and art style conditions as inputs and outputs images with corresponding styles. During the training process, a combination of adversarial loss and content loss was used to ensure that the generated images have both the target style and the consistency of the original content. In order to achieve effective classification of artistic styles, sparse encoding algorithms were introduced in the research. Sparse encoding algorithms can learn sparse feature representations in images and maintain the sparsity of features during the encoding process. This sparsity makes the distinction between different art styles more obvious, which helps to improve the accuracy of art style classification. This article first uses the art style learning module to generate a large number of image samples with different styles and extract their features. Then, the sparse encoding algorithm is used to encode these features and obtain the sparse encoding representation of each sample. Next, use these sparse encoding representations to train a multi-class classifier to achieve automatic classification of artistic styles. The flowchart of style classification based on sparse encoding is shown in Figure 2.

By combining GAN and sparse encoding algorithms, accurate learning and classification of artistic styles can be achieved. This provides strong support for the optimization of subsequent art and design CAD models. Specifically, given the signal $s$ and overcomplete dictionary $D$, the sparse representation $x$ with few non-zero elements is found so that:

$$s \approx Dx = d_1 x_1 + \ldots + d_m x_m \tag{1}$$

Among them, $s \in R^n$. The dictionary representation of atoms is:

$$D = \left[d_1, d_2, \ldots, d_m\right] \in R^{n \times m} \tag{2}$$

Sparse representation is:

$$x = \left[x_1, x_2, \ldots, x_m\right]^T \in R^m \tag{3}$$

$$\min_{D,x} \sum_{k=1}^{K} \left\{ \frac{1}{2} \left\| Dx_k - s_k \right\|_2^2 + \lambda R\ x \right\} \tag{4}$$

such as $l_0$ norm and $l_1$ norm. If the fixed dictionary $D$ is used, the coding subproblem is also regarded as a kind of research problem separately:

$$\arg\min \frac{1}{2}\left\|Dx-s\right\|_2^2+\lambda R(x) \tag{5}$$

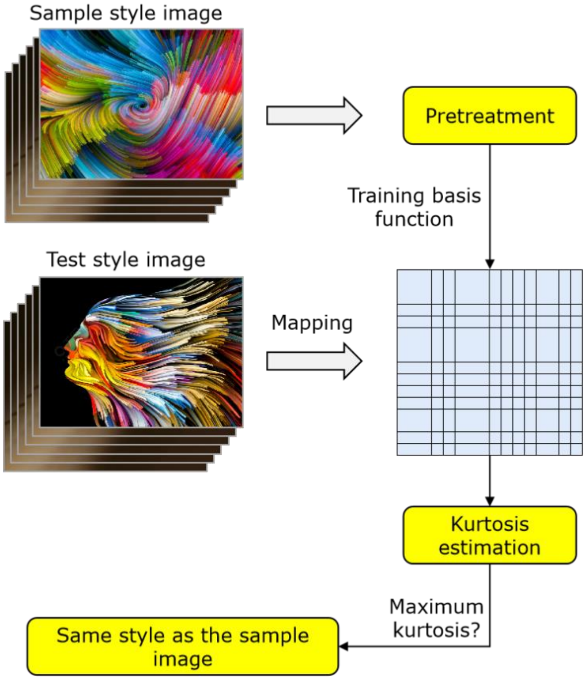



**Figure 2**: Flowchart of sparse encoding algorithm for style classification.

In order to further optimize the art and design CAD model, a machine vision feedback mechanism was introduced in the study. Machine vision, as a non-contact image perception technology, can objectively evaluate image quality and provide accurate feedback information. In the optimization process, the first step is to input the images output by the art and design CAD model into the machine vision system. The machine vision system generates assessment results on image quality by processing images such as feature extraction and recognition. Based on the assessment results based on machine vision, corresponding optimization strategies are adopted to adjust the art and design CAD model.

In the training stage of GAN, the generating model $G$ and the discriminating model $D$ compete with each other, and constantly alternate iterative optimization to gradually reach a balance. The objective function of GAN optimization is shown in the following formula:

$$\min_G \max_D V(D,G)=E_{x-P_{data}(x)}\left[\log D(x)\right]+E_{z-P_z(z)}\left[\log(1-D(G(z)))\right] \tag{6}$$

$$\max_D V(D,G)=E_{x-P_{data}(x)}\left[\log D(x)\right]+E_{z-P_z(z)}\left[\log(1-D(G(z)))\right] \tag{7}$$

The second step is to optimize the generation model $G$ :

$$\min_G V(D,G)=E_{z-P_z(z)}\left[\log(1-D(G(z)))\right] \tag{8}$$

If the assessment results show that the clarity of the image is insufficient, the sharpening algorithm of the enhanced model can be used to improve the clarity of the image; If the color saturation is not sufficient, the color mapping function of the model can be adjusted to enhance color performance. Through these optimization strategies, it is possible to iteratively optimize art and design CAD models based on feedback from machine vision, gradually approaching ideal artistic effects.

For $m$ random variables $y_i \;\; i=1,\ldots,m$ , the mutual information $I$ is defined as follows:

$$I \;\; y_1,y_2,\ldots,y_n \;\; = \frac{m}{i=1} \;\; y_i \;\; -H \;\; y \tag{9}$$

$$I \;\; y_1,y_2,\ldots,y_n \;\; = \sum_i H \;\; y_i \;\; -H \;\; x \;\; -\log\left|\det W\right| \tag{10}$$

Assuming that random variables are uncorrelated and have unit variance, then:

$$E \;\; yy^T \;\; = WE \;\; xx^T \;\; W^T \tag{11}$$

$\left|\det W\right|$ is a constant, and because of the unit variance of $y_i$, the difference between entropy and negative entropy is only one sign, so we get:

$$I \;\; y_1,y_2,\ldots,y_n \;\; = c - \sum_i J \;\; y_i \tag{12}$$

Here $c$ is a constant that does not depend on $W$ .

## 4 EXPERIMENTAL ANALYSIS AND DISCUSSION

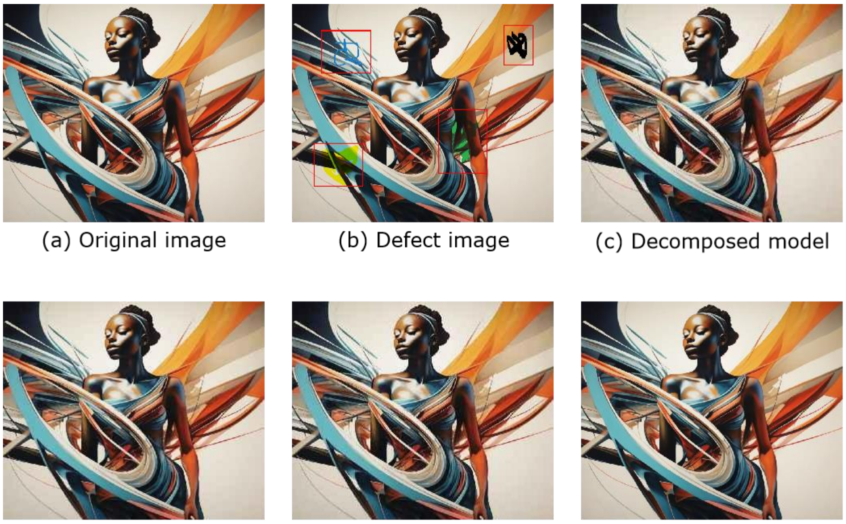
This article proposes an art and design CAD model construction and machine vision feedback optimization method that combines GAN and sparse encoding algorithms. Effective classification of art styles was achieved through learning art styles and sparse encoding algorithms, and machine vision feedback was combined to optimize art design CAD models. The results indicate that this method can improve the quality and visual effects of art and design works, bringing new methods to the field of art and design.

### 4.1 Experimental Environment and Dataset

The experimental environment is mainly based on a deep learning framework, using Python as the programming language, and utilizing mainstream deep learning libraries such as TensorFlow or PyTorch to construct and train network models. The experimental hardware environment is a computer server with a high-performance GPU. The dataset used in this study is the art image dataset, which includes diverse images of artworks. To the universality of the experiment, the dataset is preprocessed, including normalizing image size, unifying color space, and annotating data. Preprocessing and data augmentation are performed on the training data. The art image dataset used has been carefully screened and processed to ensure the smooth progress of the experiment and the reliability of the results.

### 4.2 Comparative Experiments and Analysis

An in-depth analysis of the results in Figure 3 reveals the performance and characteristics of different models in repairing damaged areas. The method proposed in this article, which combines GAN, sparse encoding algorithm, and machine vision feedback, has shown superior performance in the task of repairing damaged areas in art and design CAD models. This method can not only effectively repair the edges within the defect area but also effectively control the propagation of errors. The painting model performs poorly in repairing the edges of defect areas. The painting model focuses more on the overall structure and texture of the image, and has limited ability to repair edge details.



(a) Original image (b) Defect image (c) Decomposed model

(d) Criminisi algorithm (e) Inpainting model (f) This article model

**Figure 3**: Comparative test.

This repair method obviously cannot meet the performance requirements in art designs that require high edge details. The Criminisi algorithm, Decomposed model, and our model have all shown good results in repairing edges within the defect area. The Criminisi algorithm is a classic image restoration algorithm that can effectively repair edges and textures in damaged areas. However, due to the propagation of errors, this algorithm introduces "new" edges during the repair process. These "new" edges may not fully match the edges of the original image, resulting in the restoration results appearing unnatural in certain areas. The model in this article demonstrates stronger repair ability when repairing the edges within the defect area. This is due to the combination of GAN and sparse encoding algorithms in the model presented in this article, which enables the model to learn and generate edge features of missing areas more accurately. Although the Decomposed model has achieved certain results in repairing damaged areas, its ability to repair the edges within the damaged area is slightly insufficient compared to the model proposed in this article.

The fast convergence of the art image restoration algorithm observed in Figure 4 during the training process. This phenomenon indicates that the algorithm can quickly capture the intrinsic structure and patterns of data during the training phase. In the field of deep learning, the learning ability of a model is usually closely related to its training speed and convergence. The art image restoration algorithm proposed in this article converges rapidly during the training process, indicating that it can quickly capture complex features and patterns in art images. This is mainly attributed to the effective combination of GAN and sparse encoding algorithm, which enables the model to have strong learning ability.

During the training process, the algorithm continuously optimizes model parameters to gradually reduce training losses. When the training loss quickly converges to a lower level, it indicates that the model can fit the training data with small errors. Fast convergence algorithms can make predictions with lower errors when facing new input data. When a new image is input into the model, it can quickly provide accurate repair results. This fast predictive ability enables algorithms to meet real-time requirements while ensuring high-quality repair results.

By applying MATLAB to perform neural network operations and modifying the network accordingly to achieve integration, the image recognition results shown in Table 1 and Figure 5 were obtained. From these results, it can be observed that the improved GAN method has better performance compared to the standard GAN method.

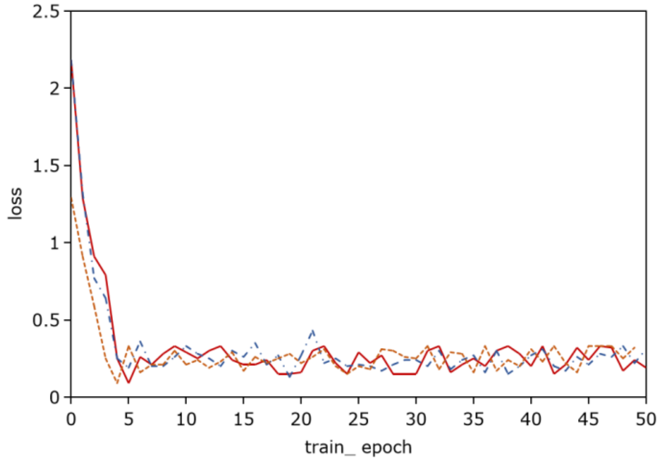



**Figure 4**: Training situation of the algorithm.

| *Number of experiments* | *Improved GAN* | *GAN* |
|---|---|---|
| 10 | 0.673 | 0.659 |
| 20 | 0.677 | 0.664 |
| 30 | 0.699 | 0.662 |
| 40 | 0.778 | 0.648 |
| 50 | 0.726 | 0.694 |
| 60 | 0.812 | 0.735 |
| 70 | 0.817 | 0.718 |
| 80 | 0.837 | 0.726 |
| 90 | 0.959 | 0.739 |
| 100 | 0.929 | 0.738 |

**Table 1**: Image recognition accuracy of neural network integration.

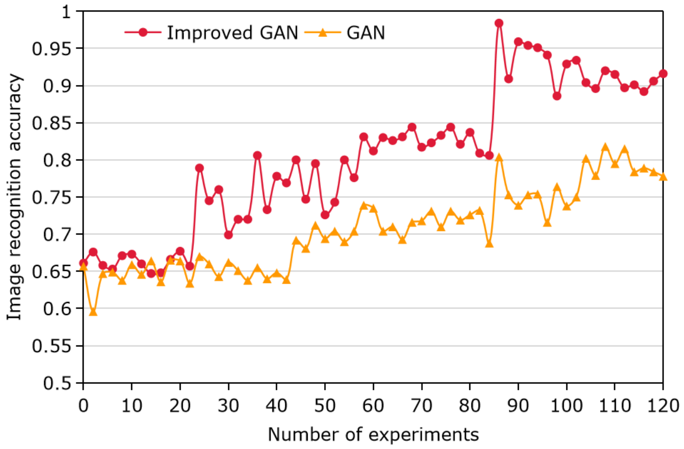



**Figure 5**: Accuracy of image recognition.

The improved GAN method has significantly improved its performance in image recognition tasks. The improved GAN method has significantly higher accuracy than the standard GAN method. By introducing integration technology, the improved GAN method can better learn and extract image features. Improving the GAN method can more accurately restore the details and textures of complex and diverse images. In contrast, the standard GAN method appears relatively rough and has some distortion and blur when processing these images. In improving the GAN method, corresponding adjustments and optimizations were made to the structure of the neural network. These optimizations include introducing deeper network layers, using more effective activation functions, etc., thereby improving the network's representation and learning capabilities.

The comparison results in Figure 6 further validate the advantages and performance of the art image restoration algorithm in this article. By comparing the quantity of incorrect pixels on each frame, it is clear that this algorithm outperforms other methods in most video frames.

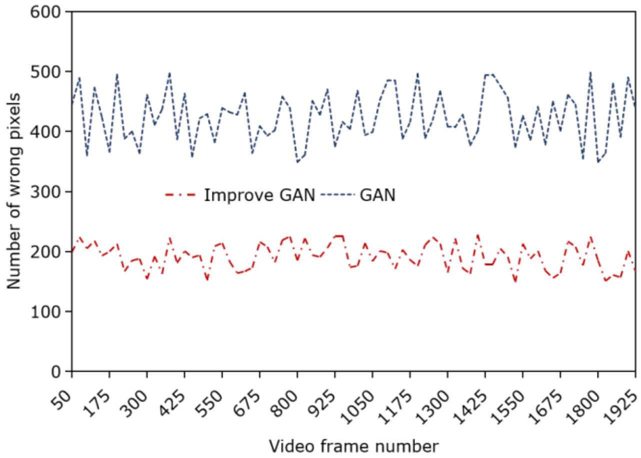



**Figure 6**: Comparison of the quantity of wrong pixels per frame.

Artistic images often have rich details and complex textures, thus requiring restoration algorithms to have high pixel level accuracy. For art designers and image processors, restoration algorithms can generate images that are closer to real artworks, greatly improving their work efficiency and restoration quality. The algorithm in this article can generate more natural and realistic repair results by accurately restoring the pixel information of the missing area.

The data shown in Figure 7 provides a comparison of subjective assessments by observers between the improved art and design CAD modeling method and the traditional design method. From the graph, it can be seen that the improved method achieved higher ratings.

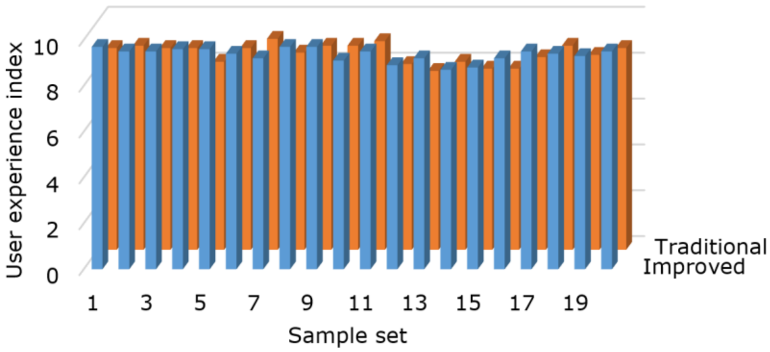



**Figure 7**: Subjective assessment of modeling images given by observers.

The ratings of observers directly reflect their subjective feelings and preferences towards design methods. By introducing technologies such as GAN, sparse encoding algorithm, and machine vision feedback, the improved method may provide more diverse and higher quality artistic design results. Art and design not only generate beautiful images, but also require good interaction and communication with users. The improved method may provide a more user-friendly interface, more flexible parameter adjustment options, etc., making observers feel more comfortable and satisfied during use.

By introducing advanced GAN, sparse encoding algorithms, and machine vision feedback technology, the art and design significant advantages. Whether from the objective perspective of image restoration accuracy, quantity of incorrect pixels, or subjective assessment, the improved method has achieved high assessment. By combining the advantages of multiple technologies, this method can significantly improve the accuracy of image restoration, reduce the quantity of erroneous pixels, and generate higher quality artworks. By analyzing the performance, accuracy, and user satisfaction of these methods in depth, valuable feedback and experience can be obtained, providing direction for future innovation in art and design methods.

## 5 CONCLUSION

The quality and processing effect of images are directly related to the visual effect and expressive power of works. The traditional method of processing art and design CAD models is difficult to achieve ideal results when facing complex and diverse art and design works. In this context, how to process artistic images more accurately and efficiently is a focus of attention in the academic and artistic circles. This article applies GAN, sparse encoding algorithm, and machine vision technology to the modeling methods of art and design CAD. Compared with other traditional design methods, the results show that the improved method has significant restoration accuracy, quantity of erroneous pixels, and subjective assessment by observers. The research results reflect important value in promoting the deep integration of art and design with technology. It showcases the potential of technology and art in innovative design, encouraging designers and researchers to explore more possibilities. Through the research and verification of this article, an improved art and design CAD modeling method has been developed, which has higher accuracy, user satisfaction, and creative potential. This study provides important basis and driving force for the innovative development of art and design, helping to promote the integration of art and technology, and bringing new insights and ideas to the field of art image processing.

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