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Molecular & Cellular Biomechanics 2024, 21(2), 563.
https://doi.org/10.62617/mcb563

Article

Utilization of generative adversarial networks (GANs) in the replication and restoration of calligraphy art

Xiaojun Zhu

Institute of Art, Communication University of China, Beijing 100024, China; 987334910@qq.com

CITATION

Zhu X. Utilization of generative adversarial networks (GANs) in the replication and restoration of calligraphy art. Molecular & Cellular Biomechanics. 2024; 21(2): 563. https://doi.org/10.62617/mcb563

ARTICLE INFO

Received: 18 October 2024
Accepted: 25 October 2024
Available online: 22 November 2024

Abstract: With the continuous integration of culture and technology, the replication and restoration of calligraphy art has become a new direction in the restoration of traditional calligraphy and painting. The research on the replication and restoration of calligraphy art is of great significance in contemporary art. However, the accuracy and authenticity of the replicas in the process of replication and restoration calligraphy art are not high, and there are significant differences in material selection. This paper started with GAN (Generative Adversarial Network), collected a large amount of image data from calligraphy art works, trained a generative adversarial network, and used the trained model to process calligraphy art works. Compared with traditional replication techniques, the cost, restoration efficiency, and cultural inheritance and recognition of the two in calligraphy art replication were analyzed. Research has found that the highest score for the restoration of calligraphy art quality using traditional methods can only reach 89.9 points (out of a total of 100 points), while the highest score for GAN can reach 96.4 points. Moreover, the application of GAN can save the cost of calligraphy art for restoration, improve restoration efficiency, and enable flexible application in different scenarios.

Keywords: calligraphy art; replication and restoration; generative adversarial networks; restoration efficiency

1. Introduction

With the continuous progress of technology, traditional art is constantly being inherited and developed through innovation, and the replication and restoration of traditional art are also constantly being explored and researched. Art is a culture with high humanistic value, and it is also a technology that has been widely applied in the development of modern technology. With the advent of the digital age, computer technology has penetrated into various fields, including the art field. With the continuous promotion of cultural heritage protection work, more and more people are paying attention to the protection and inheritance of traditional arts, including calligraphy, traditional Chinese painting, etc. Therefore, the replication and restoration of calligraphy art has become an important research direction for contemporary artists and scholars. However, due to the inability of calligraphy and painting replicas to achieve 100% accuracy and authenticity, and the different selection of calligraphy and painting materials, there are differences in the clarity and material selection of replicas. At the same time, due to the relatively single method of traditional calligraphy and painting restoration techniques, different restoration methods are adopted for different calligraphy and painting works, which has caused a certain degree of damage to the works. By applying GAN technology, not only can the efficiency of replication and restoration be improved, but also restoration can be carried out while preserving the original style and features, providing a new solution for the protection and inheritance of traditional calligraphy art.

This paper applied GAN technology to the process of replicating and restoring calligraphy art, mainly studying the GAN model constructed based on deep learning algorithms for calligraphy art replication and restoration. Through experiments, its feasibility is verified in traditional calligraphy and painting replication and restoration, achieving the replication and restoration of other calligraphy and painting works, and evaluating the effects presented by the replicas.

2. Related works

At present, research on the replication and restoration of calligraphy art in China mainly focuses on digital image processing, computer vision, and computer graphics. Mostovshchykova conducted research on calligraphy in enamel art in his paper, focusing on exploring traditional techniques used in calligraphy restoration and proposing traditional techniques for understanding [1]. Dang studied the color damage of Ming cotton cloth under various preservation conditions, and his results provided valuable information for the preservation and restoration of cultural relics [2]. Liu conducted archaeological research on the clothing in “Han Xi Yu Di” and conducted virtual simulation restoration, proposing an innovative path for cultural relic restoration work [3]. Zhu discussed its important role in cultural relic protection from two aspects: the restoration of ancient literature and the mounting of calligraphy and painting [4]. Guo adopted a composite curve expansion stroke model to model the geometric shape and drawing trajectory of strokes, achieving high-quality drawing of calligraphy works [5]. Liu gave a brief introduction to the construction of the university’s ancient building renovation project [6]. Xi introduced a text oriented hyper parsing algorithm to achieve automatic recognition of text. His study provided reference for the restoration and restoration of cultural relics images [7]. Su studied a Chinese character restoration algorithm based on a dual production adversarial network, targeting the characteristics of ancient Chinese characters. His study employed methods based on deep neural networks, particularly GAN, to improve the ability to restore ancient Chinese characters [8]. Cao introduced a new cyclic consistency adversarial network to achieve automatic generation of Tangut character images, attempting to use a new method for restoring Dangbu Chinese characters [9]. Zhang proposed a GAN method equipped with a triple discriminator for denoising Chinese calligraphy inscription images. His study aimed to improve the quality of image restoration [10].

Although these scholars have achieved certain results in their research, they cannot fully restore calligraphy and painting works. Existing technologies mainly rely on manual operations and digital image processing technology in calligraphy reproduction and restoration. Although manual reproduction and restoration can retain certain artistic and humanistic values, there are limitations in efficiency and the accuracy of the reproduction. Digital image processing technology improves the clarity of the reproduction and the accuracy of the material, but there are still challenges in the reproduction of artistry and realism. In contrast, generative adversarial networks (GANs) train generators and discriminators through adversarial training. The generator is responsible for generating data samples that are as realistic as possible, while the discriminator is responsible for judging the authenticity of the input samples. This adversarial training mechanism enables GANs to generate high-quality, high-resolution images, which are suitable for the reproduction and restoration of calligraphy works of art. This paper combined the advantages of GAN technology and utilized GAN technology to replicate and restore calligraphy works. Firstly, representative works of calligraphers and painters were selected, copied and made into replicas. Then, these replicas were subjected to image processing to achieve better clarity and accuracy. Different restoration methods were used for different types of calligraphy and painting works, and GAN technology was utilized to generate high-definition images, achieving replication and restoration of calligraphy and painting works.

3. Methods

3.1. Generating adversarial networks

GAN is a neural network that includes a generator and discriminator. The generator generates new output data from a series of raw input data, and the discriminator compares these output data with the input data and determines whether they are true. When the output of the generator is consistent with the output of real data, the discriminator determines that it is true; when the output of the generator is inconsistent with the output of real data, the discriminator determines it as false. The discriminant model consists of two parts: a generator and a discriminator. The generator generates new data through the generator network, while the discriminator determines whether it is true through the discriminator. If both are true, it indicates that the data generated by the generator has high authenticity, and the discriminator determines that the generated data is true; if both are false, it indicates that there is a problem with the data generated by the generator, and the discriminator determines that it is false.

The generator is the most important component of GAN, which is the intermediate layer that connects the network in the generator with the network in the discriminator. Generators typically consist of multiple residual connection layers, each consisting of several feedforward neural networks connected to residual structures, enabling learning of a series of different features of input data. The input of the generator is a random noise sample, which can be of any size or type, but cannot contain any structural information. The generator first learns the distribution of input data through an unsupervised learning process, extracts feature from it, and then inputs the features into a discriminative model for training. The training process of the generator is shown in **Figure 1**:

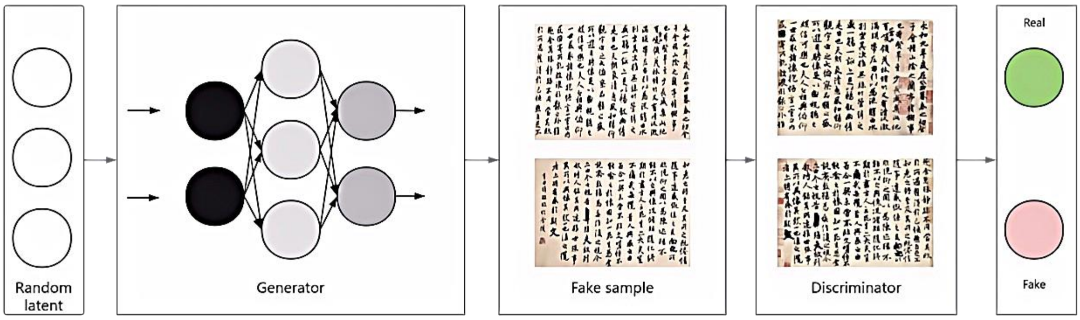

Figure 1. Generator training process.

The generator randomly extracts a certain number of samples from the raw data. Then, these samples are input into their respective residual connection layers, and each residual is sequentially connected by the connection layers. Each residual structure is composed of a feedforward neural network as the forward transfer layer, which extracts a feature information from each input sample, and then uses this feature information to learn different features contained in the output sample. By training the network, the generator can to some extent extract information from the original data and use this information to generate new data. During the training process, the generator first starts training from a random noise sample. Among them, noise samples are randomly sized data samples that do not contain any structural information. Then, the generator sequentially inputs these randomly sized data samples without any structural information into each residual connection layer for training according to certain rules. After all residual connection layers are trained, the generator can generate new output data. When the output data generated by the generator matches the input data trained by the discriminator, the discriminator determines that the output data is true; on the contrary, it is judged that the output data is false. By continuously training and adjusting the generator network, data with high authenticity is output and robustness is generated. The generator uses a multi-layer convolutional network structure, including multiple residual blocks to enhance the learning ability of the network and reduce the gradient vanishing problem during training. The discriminator uses the PatchGAN structure, which allows the model to better capture local features and improve the discrimination ability. During the training process, an alternating training strategy was adopted, that is, the generator was fixed first and the discriminator was trained; then the discriminator was fixed and the generator was trained. The learning rates of the generator and discriminator were set to 0.0001 and 0.0004 respectively, and the batch size was set to 64. As for the optimizer, the Adam optimizer was selected. Due to the inability of the discriminator to accurately determine whether the generated data contains information or structural information, the discriminator continuously corrects the parameters of the generator network to improve the generation effect. The discriminator trains the generator through a simple loss function, namely:

$$L_D = -\frac{1}{m}\sum_{i=1}^{m}(log\, D\,(x^i) + log\ (G((1-D)z^i))) \quad (1)$$

Among them, m is the number of training samples; x^i is a sample from the real data distribution; z^i is the noise vector randomly sampled from the noise distribution; G is the input of the generator; L represents sample output; D is the output of the discriminator. The loss function is the distance between the discriminator vector and the true value, and by calculating the loss function, it can be determined whether the discriminator has correctly classified the data. During the training process, the discriminator continuously adjusts the loss function to adapt to the output of the generator. After multiple trainings, when the gap between the data generated by the generator and the real data continues to shrink, the discriminator would assume that the generated data is the same or similar to the real data, and at this point, it can determine whether there is a problem with the data generated by the generator. In order to better learn about changes in data distribution, it is necessary to train a gradient descent algorithm. This algorithm learns the optimal solution by training the generator and discriminator separately into an optimal solution. When the two can influence each other, the algorithm can train a new discriminant function to determine whether the generated data is consistent with the input data.

3.2. Application steps of generative adversarial networks in art replication and restoration

With the continuous development of technology, artificial intelligence technology is also constantly improving and developing, and it has been widely applied in various fields. GAN is an artificial intelligence algorithm based on supervised learning that can train network models by manually inputting data (that is, input images) to generate new images or videos with authenticity and complexity. The steps for replicating and restoring calligraphy art using GAN in this paper are shown in **Figure 2**:

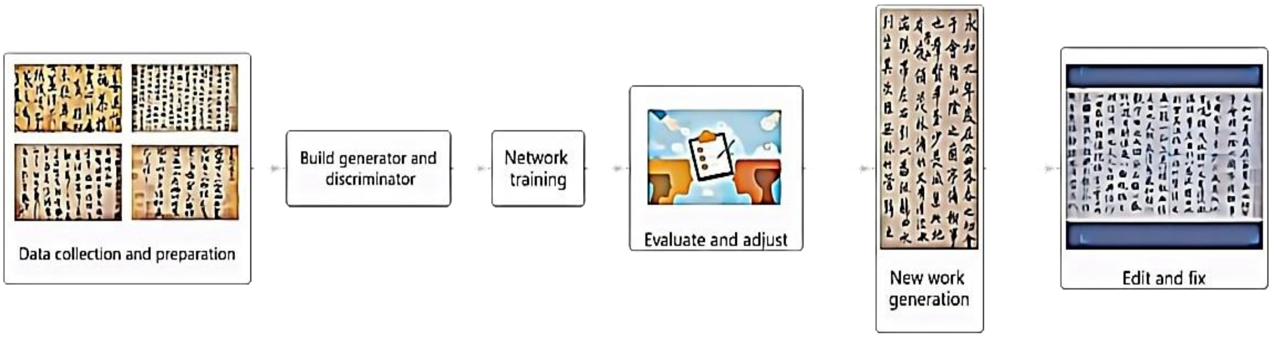

Figure 2. Application steps of generative adversarial networks in calligraphy art replication and restoration.

In the field of image generation, GAN models can generate different images or videos based on different features in the input image, including pixel level, pixel-color level, and pixel-texture level. GAN can automatically extract useful information from a large amount of data through continuous training, and can generate complex, diverse, and realistic images or videos while preserving the original data. GAN technology has been widely applied in many fields, such as film and television production, natural language processing, virtual reality, etc.

GAN technology is also applied in the replication and restoration of calligraphy art. The use of GAN technology can achieve the replication and restoration of calligraphy works. The principle is to use GAN models to generate new works with certain complexity and richness, and then edit and process them to form new works. Compared with traditional replication, GAN technology has significant advantages, such as reducing manual intervention, making the generation process more realistic and interpretable, and generating richer content. However, there are also some issues, such as overfitting during the training process, as the GAN model is built on a large amount of data training. Therefore, how to solve these problems is an urgent issue for the development of GAN technology.

3.3. Loss function

In the replication of calligraphy works, this paper divides identification algorithms into two categories: one is discrimination algorithms, and the other is optimization algorithms. The discrimination algorithm is based on real data and fake data to determine the corresponding labels; the optimization algorithm determines the corresponding labels based on the sample distribution of the training and testing sets. This paper combines GAN and discriminative networks to better solve the problem of replicating and restoring calligraphy art works. According to the distribution of training samples in the neural network, discrimination models can be divided into three categories: uniform distribution discrimination models, non-uniform distribution discrimination models, and mixed distribution discrimination models. Among them, the uniform distribution discrimination model is trained based on real data and fake data; the non-uniform distribution discrimination model is trained based on generated data and forged data; the mixed distribution discriminant model uses three different types of training sets for training.

In GAN, the input of the discriminator is the original image data, while the output of the generator is to add a new noise data to the image data, so that the discriminator can distinguish between the original image data and the newly generated noise data. Therefore, GAN can be seen as a neural network with both generator and discriminator structures. The main task of a discriminator is to determine whether the image generated by the generator is really based on the difference between the image generated by the generator and the real image, which is also known as the discriminant problem in this paper. Since the discrimination problem can be well solved, there is no need to model the discrimination problem in GAN. In GAN, both the generator and discriminator have a common goal of identifying the differences between input data and newly generated data. Therefore, a discriminative network can be set up to determine which parts of the GAN are feasible and which parts are infeasible. However, in practical applications, this paper requires the discriminant network to obtain the optimal solution with the smallest possible loss function, so a discriminant function needs to be set. When the discriminant function exceeds the threshold, there is a difference between the generated data and the actual data. The larger the discriminant function, the more similar the generated data is to the real data; on the contrary, it indicates that the generated data is less similar to the real data. Therefore, in practical applications, a discriminant function is set to determine whether there is a difference between the data generated by the generator and the actual data.

GAN differs from other neural networks in terms of loss function. In terms of loss function, GAN no longer uses mean square error or maximum gradient to measure the learning ability of the network, but instead uses mean square error or maximum gradient to measure the generalization ability of the network. This paper uses mean square error to represent the learning ability of the GAN network, and maximum gradient to represent the generalization ability of the GAN network. The formula for calculating mean square error (MSE) is shown in Equation (2):

$$MSE = \frac{1}{C}\sum_{i=1}^{L}(y_{ri} - y_i)^2 \tag{2}$$

The formula for calculating the maximum gradient (J) is as follows:

$$J = MSE = \frac{1}{C}\sum_{i=1}^{L}(y_{ri} - y_i)^2 \tag{3}$$

$$\frac{2J}{\partial y_i} = \frac{\partial \frac{1}{C}\sum_{i=1}^{L}(y_{ri} - y_i)^2}{\partial y_i} = \frac{2}{C}(y_i - y_{ri}) \tag{4}$$

Among them, *C* is a hyperparameter; y_{ri} is the *i*-th attribute value of the actual label value; y_i represents the *i*-th attribute value of the predicted value. In GAN, as the training sample set increases, the generalization ability of the GAN network gradually enhances. During the training process, if the learning ability of the generator network becomes stronger, the output of the generator network obtained on new data becomes more similar to the output of real data.

3.4. Establishment of datasets

The establishment of a dataset is a prerequisite for using GAN technology for the replication and restoration of calligraphy art. Without a standard, detailed, reliable, and authentic dataset, the application of GAN technology in calligraphy art replication and restoration cannot be achieved. To address the problem that previous datasets were focused on a specific period and lacked diversity, this study expanded the scope of the dataset to include more calligraphy works from different historical periods and styles. Such an approach ensures that the GAN model can better generalize to different calligraphy styles and historical contexts. To this end, this paper collected a series of traditional calligraphy works covering different dynasties and styles. The dataset now includes works from the pre-Qin period to the modern era, covering a variety of calligraphy styles such as regular script, running script, cursive script, and official script. Each work has been carefully selected to represent the unique characteristics of its corresponding period and style. **Table 1** shows the relevant information of calligraphy art replication and restoration works as a dataset in this paper:

Table 1. Calligraphy art replication and restoration works.

Name	Serial number	Calligraphy style	Additional notes
The orchid pavilion collection	A	Regular script	The pinnacle of running script
Seventeen model calligraphy scrolls of the jade terrace	B	Running script	Includes a variety of styles
Three-body script	C	Cursive	Strong expressiveness, free form
Sun Guoting's script	D	Clerical script	Calligraphy theory work
Self-explanatory scroll	E	Running script	A fine piece of running script
Inscriptions on stone drums	F	Large Seal script	Ancient inscriptions, model of seal script
The Han Dan Yao Nian inscription	G	Clerical script	Clerical script style, simple and vigorous
Natural text	H	Regular script	Medical work, neat regular script
Huai Su's calligraphy	I	Cursive	Smooth cursive script
Great calligraphy	J	Running script	A collection of fine running scripts
Monument to Yan Qinli	K	Regular script	A model of regular script
Tahoto monument	L	Regular script	Far-reaching influence
Sacrificial essay for my nephew	M	Running script	Sincere emotions
Huangzhou cold food post	N	Running script	Natural running script
Autobiography	O	Cursive	Free cursive script
Diamond sutra of mount tai	P	Clerical script	Clerical script style, solemn
"Quick snow and sunny day post"	Q	Running script	A classic of running script
Mid-autumn festival postcard	R	Cursive	Exuberant cursive script
Bo Yuan Tie	S	Running script	Waelegant running script
Thousand-character classic	T	Regular script	Beautiful regular script
"The memorial to the emperor on leaving the capital"	U	Regular script	Neat regular script
The goddess of Luo River	V	Running script	Smooth running script

This paper compares and analyzes calligraphy works from different sources and periods, and selects 20 representative calligraphy works as samples. These samples undergo cleaning, replicating, printing, and production processes to finally form 20 sample datasets.

3.5. Model training and application

GAN technology is built on a large amount of data, and its training requires a lot of data and time. The replication and restoration of calligraphy art involves traditional artistic creation processes, which mainly rely on manual operations. Therefore, a key issue needs to be addressed during the training process, which is how to process a large amount of data and avoid overfitting. There are two main methods to solve this problem: one is to use statistical methods, using regression models to process the data; another method is to utilize machine learning methods. Regression models require a large amount of data and time to train, but in calligraphy art replication and restoration, due to limited data, they may not meet the requirements. Therefore, machine learning methods can be used to train calligraphy art replication and restoration processes as a regression problem. During the training process, regression models can be used to address key issues in calligraphy art replication and restoration based on the content and requirements involved. Using machine learning algorithms to classify data requires a large amount of data and time, but can yield more accurate classification results. Both of these methods can effectively solve the problem of overfitting during the training process. At present, the application of GAN technology in the replication and restoration of calligraphy art mainly involves processing the images of calligraphy works. The use of GAN technology can achieve the replication and restoration of calligraphy works. Specifically, the images of calligraphy works can be processed, including enhancing and converting the original images. Due to GAN being a deep learning method, it can achieve better training results through a large amount of training data. In the application process, generative adversarial network technology can effectively improve the training efficiency of the algorithm. Applying GAN technology to the replication and restoration of calligraphy art can solve the problems existing in traditional calligraphy art replication and restoration, which is beneficial for improving the efficiency and quality of replication and restoration.

4. Results and discussion

4.1. Experimental design

This paper compares with traditional methods in terms of cost and resource consumption, calligraphy art restoration efficiency, replication and restoration quality, as well as cultural inheritance and recognition, in order to comprehensively evaluate the application of GAN in calligraphy art replication and restoration. Among them, the parameter settings of traditional methods are shown in **Table 2**:

Table 2. Traditional method parameter settings.

Parameter combination	Brush strokes	Paper material	Ink	Evaluation
1	Hard brush pen	Cooked rice paper	Black ink	94
2	Soft brush	Premium rice paper	Light ink	89
3	Bristle pen	Raw rice paper	Thick ink	83
4	Fine brush	Parchment	Mixed ink	78

The combination of the above parameters takes into account the smoothness of strokes, the texture of paper, and the expressive power of ink, thus comprehensively evaluating the effect of each parameter combination. From the overall evaluation of usage, it can be seen that the best combination of brush strokes, paper materials, and ink usage is used in the process of replication and restoration. The difference in the material of the brush has led to changes in the thickness, smoothness, and brushwork of the lines. In the evaluation, the hard brush is the best because it can write clean and precise lines, and also has strong stroke control ability, which is helpful for reflecting the rhythm of calligraphy. In terms of material selection, the differences in materials used also have a certain impact on their texture, ink absorption capacity, and durability. Among these materials, the texture of cooked rice paper is relatively delicate; the surface is relatively flat; there are few fibers. Its ability to absorb ink is also poor, making it suitable for fine calligraphy and can express clear and smooth lines. Mature rice paper is more suitable for writing neat and meticulous fonts, or for works that require meticulous depiction. The color, concentration, and density of ink have a significant impact on the appearance and texture of fonts. Black ink is more artistic due to its strong dot effect.

4.2. Cost and resource consumption

In the process of replicating and restoring calligraphy artworks, traditional methods usually first collect the original calligraphy and painting images, convert them into digital images, and then process them. For damaged or aged calligraphy artworks, image restoration is usually used. At present, the restoration mainly adopts manual restoration methods, using conventional restoration methods such as restoring fonts to restore its original appearance. Replicating calligraphy art is usually done manually or mechanically to create multiple copies. After the replication and restoration work is completed, an aesthetic evaluation is conducted on the work, and appropriate corrections are made based on the evaluation results to ensure that the work is consistent with its artistic characteristics. This paper compares and analyzes the cost and resource consumption of various resources in the process of replicating and restoring brush art works using traditional methods and GAN. For the sake of convenience, they are converted into the same unit. The cost and resource consumption data obtained are shown in **Figures 3** and **4**:

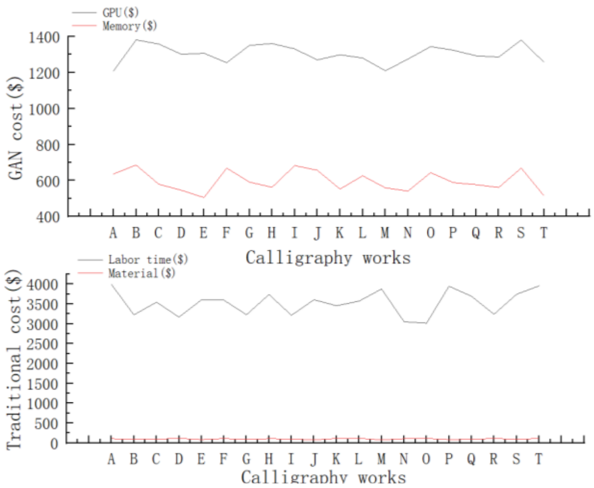

Figure 3. Replication cost and resource consumption.

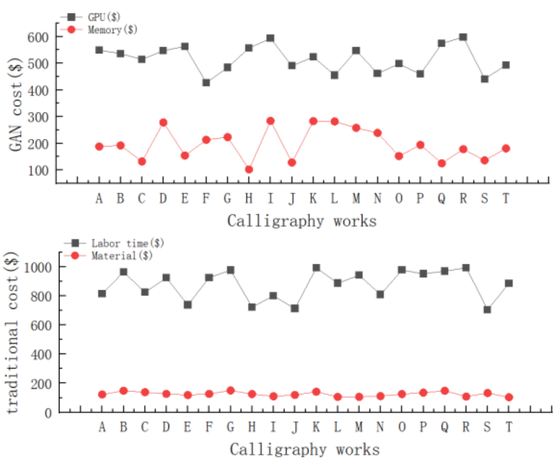

Figure 4. Restoration costs and resource consumption.

From the data in **Figure 3**, it can be seen that in the process of replicating calligraphy art works, the GAN method mainly consumes a large proportion of GPU and memory, while traditional methods mainly focus on labor, time, and materials. In different calligraphy works, the overall cost consumption of GAN is lower than that of traditional methods, with the cost of replicating 20 works only reaching \$38021, while the total cost of traditional methods is \$72436. It can be found that the cost consumption of GAN is mainly concentrated on the GPU, with the highest GPU cost consumption accounting for 72.13% of GAN cost consumption, while the cost consumption of traditional methods in the replication process of calligraphy art works is mainly concentrated on manual time. Traditional methods require a large amount of manual operation, and manual replication of calligraphy artworks requires professional operation and processing. The cost of labor time is the main cost of traditional methods.

From the data in **Figure 4**, it can be seen that the cost of GAN in the restoration process of calligraphy art works is also lower than that of traditional methods, with a total restoration cost of US \$14233 and a total cost of US \$20008 under traditional methods. It can be seen that GAN can significantly save costs and resource consumption during the restoration process. In order to evaluate the application of different methods in different scenarios, this paper performs mean processing on the cost and resource consumption data in Figure 3, and collects data on style transformation and data augmentation between GAN and traditional methods for comparison. The obtained data is shown in **Table 3**:

Table 3. Cost data for different usage scenarios.

Scenes to be used	**Gan**		**Tradition**		**Difference (\$)**
	GPU (\$)	**Memory (\$)**	**Labor time (\$)**	**Material (\$)**	
Calligraphy art replication	1303.75	597.3	3521.4	100.4	1720.75
Calligraphy art work restoration	515.55	196.1	875.55	124.85	288.75
Style transfer	132.32		267.29		134.97
Data augmentation	142.78		168.34		25.56

The data in **Table 3** shows that the average GPU and memory costs of GAN in replicating calligraphy art works are \$1303.75 and \$597.3, respectively, while the average labor cost under traditional methods reaches \$3521.4, and the average material cost is \$100.4. From this, it can be seen that GAN significantly saves costs compared to traditional methods. In the process of restoring calligraphy art works, the average total cost of GAN is \$288.75 lower than traditional methods, which also indicates that GAN has a cost advantage in the process of restoring calligraphy art works. In terms of style conversion and data augmentation, the cost of GAN is \$132.32 and \$142.78, respectively, while the cost of traditional methods is \$267.29 and \$168.34. The cost of GAN method is also lower compared to traditional methods. This indicates that GAN has advantages over traditional methods in different usage scenarios of calligraphy art works.

4.3. Restoration efficiency

In addition to evaluating cost and resource consumption, this paper also collects time data from GAN and traditional methods in the process of art restoration to evaluate restoration efficiency. The specific restoration time data is shown in **Figure 5**:

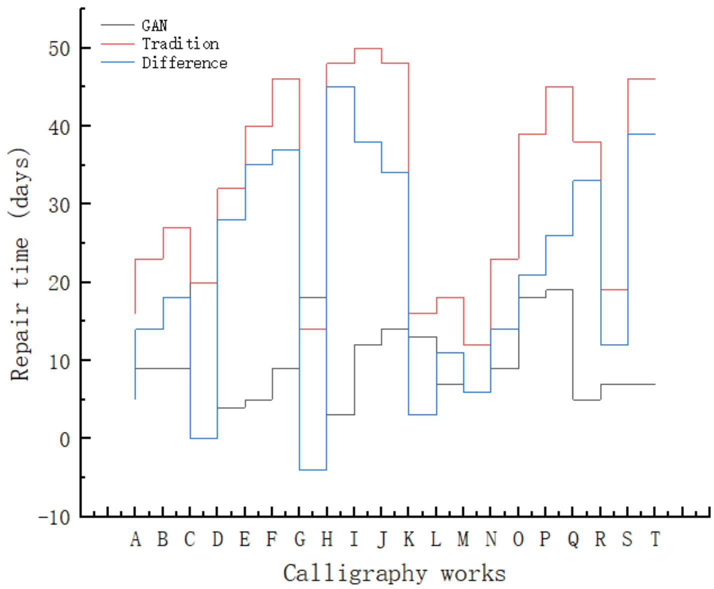

Figure 5. Restoration time.

From the data in **Figure 5**, it can be seen that although GAN takes more time to restore some works than traditional methods, overall, it takes less time. Among them, GAN can restore the same calligraphy artwork as quickly as 45 days faster than traditional methods, indicating that GAN has a higher overall restoration efficiency in the restoration process than traditional methods. Moreover, it can complete the work restoration within 3 days at the fastest, while traditional methods can only complete the work restoration within 12 days at the fastest. GAN can significantly reduce restoration time and improve restoration efficiency in the restoration of calligraphy art works.

The amount of repair time can be used as an indirect indicator to evaluate the stability of the generative adversarial network (GAN). From the data in Figure 5, it can be seen that among different methods, the time of GAN is more stable overall, which can explain to a certain extent that GAN is more stable than traditional methods.

4.4. Replication and restoration quality

While ensuring the efficiency of restoration, it is also extremely important to evaluate the quality of replication and restoration of calligraphy works. The quality, realism, and accuracy data of calligraphy art replication and restoration collected in this paper are shown in **Figure 6**:

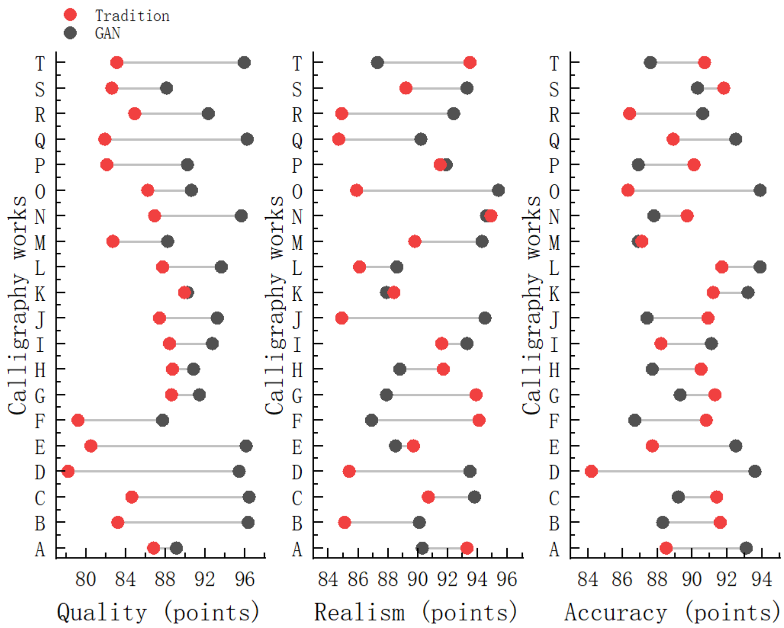

Figure 6. Quality of calligraphy art replication and restoration.

From the data in **Figure 6**, it can be seen that GAN has a general advantage over traditional methods in terms of quality in the replication and restoration of calligraphy art. This is reflected in the distribution of GAN's quality scores ranging from 87.7 to 96.4 points, while traditional methods have quality scores ranging from 78.2 to 89.9 points. This indicates that GAN has better quality in the replication and restoration of calligraphy art. However, there is not much difference between the two methods in terms of realism and accuracy. The traditional method uses experienced restoration personnel, so its restoration realism and accuracy are relatively high. The realism and accuracy of the GAN method are not significantly different from traditional methods, indicating that the application of GAN in calligraphy art replication and restoration can achieve a higher level of realism and accuracy.

4.5. Cultural inheritance and recognition

This paper evaluates cultural inheritance and recognition from the aspects of personalized customization, artistic creation, large-scale production, automated processing, and recognition, which is rated by professional personnel. The collected rating data (total of 100 points) is shown in **Table 4**:

Table 4. Cultural inheritance and recognition.

	GAN	Tradition	Difference
Personalized customization	83.17	93.64	−10.47
Artistic creation	73.89	92.58	−18.69
Mass production	94.23	88.62	5.61
Automated processing	96,75	81.37	15.38
Recognition	87.58	86.34	1.24

From the data in **Table 4**, it can be seen that GAN scores lower than traditional methods in personalized customization and artistic creation, indicating that GAN still lacks in personalized customization and artistic creation of calligraphy art works, and has advantages over traditional methods in large-scale production and automated processing. In terms of recognition evaluation, GAN scores 1.24 higher than traditional methods, indicating that GAN is also more recognized than traditional methods.

The development of GAN technology has also brought about complex ethical and legal issues, especially in the cultural dimension. GAN technology plays an important role in preserving and reproducing the original artistic value. By learning the distribution of a large amount of real data, GAN is able to create new and realistic data instances, which is particularly important in the field of art reproduction and restoration. When using GAN technology, it is necessary to assume certain social responsibilities and ethical standards to ensure that the use of GAN technology is in line with ethical standards and is not used for illegal or unethical purposes. With the development and application of GAN technology, its ethical challenges have become increasingly complex, which requires the social, legal, technical and ethical circles to work together to ensure that this powerful technology is used responsibly while minimizing its negative impact.

5. Conclusions

This paper combined GAN with calligraphy art replication technology, using GAN for digital image generation and restoration, which is of great significance for calligraphy art replication and restoration work. Research has found that GAN can effectively address the issues of accuracy and material selection in calligraphy and painting works. Applying GAN technology to the replication and restoration of calligraphy art can improve the efficiency of replication and restoration while preserving the original style and features, and save costs. However, there are still issues with the restoration efficiency of GAN in the application process. Future research can improve the generalization ability of the model through advanced regularization techniques and network architecture to solve the overfitting problem in the GAN training process, improve the personalization and artistry of generated works, and develop conditional GAN to allow more refined control over the generated style.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

References

1. Mostovshchykova D. Calligraphy in enamel art: World and Ukrainian experience[J]. International Journal of Conservation Science, 2022, 13(2): 619-628.
2. Dang R, Kang Y, Tan H. Color Damage of Visible Light on Plain-Woven Silk in Different Conservation States of Paintings and Calligraphy in Collections[J]. Fibers and Polymers, 2024, 25(1): 235-242.
3. Liu K, Wu H, Gao Y. Archaeology and virtual simulation restoration of costumes in the Han Xizai banquet painting[J]. AUTEX Research Journal, 2023, 23(2): 238-252.
4. Zhu Wenjun. Ancient book restoration and painting and calligraphy mounting technology from the perspective of cultural inheritance [J]. Beautify Life, 2022 (05): 180-183.

5. Guo D, Ye L, Yan G. CCD-BSM: composite-curve-dilation brush stroke model for robotic chinese calligraphy[J]. Applied Intelligence, 2023, 53(11): 14269-14283.
6. Guoqing Liu. A brief analysis of the experimental teaching construction of cultural relic restoration in colleges and universities [J]. Educational Science Development, 2022, 4(4): 44-46.
7. Xi Chenchen, He Xin, Meng Yalei. Super-resolution method of natural scene text images based on text semantic guidance [J]. Journal of Air Force Engineering University, 2023, 24(6): 96-103.
8. Su B, Liu X, Gao W. A restoration method using dual generate adversarial networks for Chinese ancient characters[J]. Visual Informatics, 2022, 6(1): 26-34.
9. Cao Y, Ma J, Hao C. Tangut character image generation based on cycle-consistent adversarial networks[J]. Journal of Intelligent & Fuzzy Systems, 2023, 44(4): 6341-6358.
10. Zhang J, Shi J, Li M. Triple discriminators-equipped GAN for Denoising of Chinese calligraphic tablet images[J]. Multimedia Tools and Applications, 2022, 81(29): 42691-42711.