Image Inpainting Method Based on Generative Adversary Networks

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Abstract

Aiming at the problems of missing and damaged image details, this paper proposes an image inpainting method that is preprocessed and then inpainted. First, through preprocessing that enhances and purifies the image, the clarity, saturation and contrast of the image are improved. Secondly, the image features are dynamically divided through the convolutional neural network, and the image is generated according to the principle of a generative adversarial network, finally, the adversarial strategy is used to promote the expression of the model, to make the repair result more realistic. Compared with other models, the method proposed in this paper has a better quality of repairing effect.

Keywords: Image inpainting, Generative adversary networks, Convolutional neural networks, Feature map, Loss function

1 Introduction

Inpainting technology is a method used to fill in the incomplete image according to the existing characteristics of the incomplete image. It is a revolutionary technology with great competitiveness [1], and has important practical significance. Its application value is reflected in cultural relics restoration, data restoration, virtual reality, image scaling and other aspects. Traditional inpainting technology cannot accurately repair damaged images with large missing areas or complex structures [2].

Inpainting can be divided into four types: inpainting based on structure, inpainting based on texture, inpainting based on sparse representation, and inpainting based on depth learning. Some representative ones are the BSCB repair model proposed by Bertalmio et al. [3], the inpainting model based on curvature diffusion (CDD) proposed by Jianhong Li et al. [4], and the texture synthesis algorithm based on samples proposed by Hanyu Xiang et al. [5]. These two algorithms provide good results in repairing small damaged areas, but for images with larger damaged areas, their repair effect significantly decreases, and there are problems with blurring and visual discontinuity in the repair effect.

The inpainting algorithm based on depth learning can capture more advanced image features than the traditional inpainting algorithm based on structure and texture. Deep learning is a method of machine learning, with the core idea of simulating the structure and function of human neural networks and utilizing multi-level neural networks for feature learning and pattern recognition. The foundation of deep learning is artificial neural networks, especially deep neural networks, which include multiple hidden layers (depths), each containing many neurons. Deep learning utilizes the multi-layer structure of deep neural networks for feature extraction, data representation, and pattern recognition, enabling the processing of large-scale data in various fields and achieving impressive performance in tasks such as image recognition, speech recognition, and natural language processing. The breakthrough of deep learning lies in the ability to automatically learn abstract representations without the need for manual feature design, thus better adapting to various tasks. However, inpainting algorithm based on convolutional neural network (CNN) [6-8] can lead to such phenomena as irrelevance between the repaired area and the image semantics of the surrounding area, boundary artifacts, and structural distortion and blurring.

In 2014, Ian Goodfellow proposed the generation of adversarial networks [9], which generate samples with good quality and fast fitting speed compared to the encoder decoder [10]. The Context Encoder algorithm proposed in [11] utilizes adversarial loss to train a context encoder to predict the damaged area of an image. P. Xiang et al. [12] indicate Conditional Generic Adversary Net-work (IICGAN) which uses a depth convolution neural network (DCNN) to directly learn the mapping relationship between damaged and repaired image detail layers from data. The generative model of facial depth repair proposed [13] combines reconstruction loss, two confrontation loss, and semantic analysis loss for training to ensure the accuracy of generated pixels and the consistency of local-global content. Shuti S. Phutke et al. [14] proposed an inpainting method that transmits effective information around the missing area and penetrates it into the missing area. The repaired image has a better visual effect. In 2009, Barnes [15-16] and others improved the block based on inpainting algorithm by using the principle of fast block matching based on the local correlation of images to repair damaged images.

The inpainting method, based on deep learning, can

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DOI: https://doi.org/10.70003/160792642024112506014

obtain the end-to-end mapping function of the image, obtain the deep Semantic information of the image, and make the repair result more realistic. In 2017, Iizuka et al. [17] introduced two discriminators to ensure the overall consistency and accuracy of the results. This method enhanced the repair effect to a certain extent, but the model requires post-processing. In 2020, Omar Elharrouss et al. [18] introduced the ID-MRF (Implicit Diversified Markov Random Field) regularization scheme [19] in order to enhance local details. This method has better improved the quality of inpainting. In 2020, Shiyan Yang et al. [20] and others proposed a new depth network model algorithm for inpainting to solve problems such as image distortion and texture blur. This method has some deviation in colour and edge texture processing.

The generative adversarial network (GAN) has achieved good results in inpainting and other fields. GAN's excellent feature representation ability can capture highlevel semantic features, effectively maintaining the consistency of image content and semantics, and effectively avoiding distortion problems such as blurring in repaired images.

This paper proposes an inpainting method based on convolutional neural network (CNN) and generative adversary neural network (GAN). The discriminator adopts the discriminant structure mentioned in Liu Yu's article, introduces adversarial training strategies, and evaluates model quality through three evaluation indicators: IoU loss, peak signal-to-noise ratio (PSNR), and structural similarity (SSIM). The complete region information is filled into the damaged area in order to restore the original appearance of the damaged image.

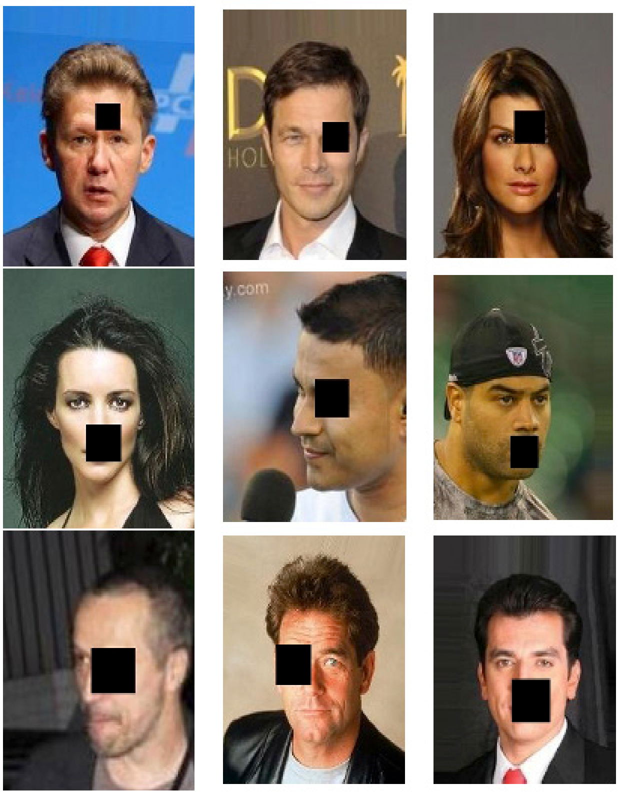

Figure 1. Partial Gaussian mask dataset

2 Related Work

2.1 Establishment of Dataset

This article adopts the open-source dataset FFHQ high-definition facial image dataset for 400 rounds of experiments [21]. For CelebA open-source data set, 6000 images with obvious facial features are selected and processed with random Gaussian mask. The mask position is random to avoid missing the same position, resulting in overfitting of model training [22]. The proportion of the test set and verification set is 8:1: 1. Some data sets are shown in Figure 1.

In order to avoid significant differences in feature vectors due to different features of the dataset, batch normalization is performed before training, and the standard Batch Normalize (BN) method can efficiently utilize the training set [23-26]. BN networks have the advantages of accelerating network convergence speed, preventing 'gradient dispersion', and being able to use a higher learning rate.

2.2 Training Methods

Unlike other deep learning model training, the training of generating adversarial networks requires two steps, namely training the generator and discriminator separately to ensure the same standards. During training, the generator processes the first sample data to obtain the second sample data, and using the first sample data and the second sample data as target input data for the discriminator, it is able to determine the discrimination results of each target input data. Based on the discrimination result, the discriminator and generator are trained by using the objective loss function. The discrimination results include: when the first sample data is determined, a second label corresponding to the specified class is determined, which is the same standard, because during separate training, another parameter needs to be kept unchanged, in order to avoid instability of the model during the training process.

2.3 Principles of Inpainting

Inpainting itself is a pathological problem, and there is no universal model that can handle all the damaged images. By learning and studying the cases and experiences of others on inpainting, this paper adopts the following principles for inpainting:

1. For the missing area to be filled in inpainting, there is a texture block similar to the effective area. The basic conditions of facial expression, skin color, facial structure, organ characteristics, etc. are required for facial inpainting.

2. For images with large missing areas, low clarity, and/or complex structures, it is necessary to determine the smoothness, low saturation, and unnatural texture of the missing area boundaries.

3. Establish a reference model for error analysis based on the algorithm model of the repaired image, which has multiple parameters, poor stability, gradient explosion, etc.

2.4 New Progress in Repair Training Methods

In recent years, machine learning technology represented by deep learning technology has made a qualitative leap and achieved a series of outstanding results in numerous research fields. Convolutional Neural Networks (CNN), as a feedforward deep network, have strong abilities in learning and expressing image features, and also have excellent performance in large-scale image processing. The Generative Adversarial Networks (GANs) proposed by Goodfellow et al. have been widely applied in the field of computer vision due to their clever game adversarial learning mechanisms and enormous potential for fitting data distributions. These research achievements greatly compensate for the shortcomings of traditional methods in image semantic understanding in image vision tasks, and to some extent solve the semantic gap between low-level features and high-level semantics of images, making deep learning technology gradually occupy the forefront of the field of computer vision.

Image restoration method based on deep learning. According to the different model structures, deep learning based image restoration methods can be divided into three categories: self-coding based image restoration methods, generative model based image restoration methods, and network structure based image restoration methods.

3 Research Method

The inpainting method proposed in this paper consists of two parts: preprocessing block and inpainting countermeasure network. Firstly, before inputting damaged images, preprocess the images to improve their clarity and contrast. Secondly, generative adversarial networks (GAN) are used to generate images. The specific operation is as follows: randomly occluded images are input into generator G, and convolutional neural networks (CNN) are first introduced to extract image features in the generator. Effective and occluded regions are dynamically divided, and then the image is generated using the principle of multiscale feature fusion [27]. In order to make the details and texture of the repaired portrait to be perfectly balanced, this paper introduces GEFGAN network to improve the effect of the repaired image again. This network processes the portrait and background separately through the degradation removal module and the pre-trained face generator, and performs spatial modulation through the multiple channel separation spatial feature transform layer (CS-SFT), so that more features can be saved, so that the image has a high fidelity. Moreover, incorporating facial component loss into the local discriminator further enhances the authenticity and resolution of the repaired portrait. The structure of discriminator adopts the discriminative model mentioned in Yu Liu [28] and introduces the confrontation training strategy. Finally, the generated image is compared with the real image and the model quality is evaluated using three evaluation indicators: IoU loss, peak signal-to-noise ratio (PSNR), and structural similarity (SSIM).

3.1 Image Preprocessing

Image preprocessing can improve the quality of the image to a certain extent, making the repair effect more realistic. At the same time, preprocessing the image can also reduce the computational pressure of the model. In deep learning, convolutional neural networks are more prominent in image preprocessing and have good processing results [29].

Convolutional neural network is composed of weights and neurons. Each neuron can receive and transmit data. It can carry out effective supervised and non supervised learning. It has certain representation learning ability and convolution computing ability. Convolution neural network is divided into the convolution layer, pooling layer and full connection layer. Generally, there is a activation function before pooling layer to enhance the expression ability of the model, and the network performs convolution on three colors: red, green, and blue simultaneously. Its network structure is shown in Figure 2.

In order to enable the repair model to quickly locate the area to be repaired and enable the GAN network to accurately repair missing parts of the image, in the image preprocessing stage, this article uses an improved object detection network model SSD (Single Shot MultiBox Detector). By replacing the VGG-16 network in the traditional SSD network model with a lightweight Mobile-Net network, the network model reduces the number of parameters by three times compared to the VGG-16 network, but improves accuracy by 0.5%, which can improve detection speed and accuracy. The schematic diagram of the MobileNet model and the improved SSD model are as Figure 3.

The image as a whole is a residual block network structure, and the X on the side is the connection from the input end to the output end, so that the output of the entire model structure is X+self. Conv (X). Using LeakyReLU activation function instead of RELU activation function can better speed up training and improve image clarity, such as Formula 5 and function image as shown in Figure 4.

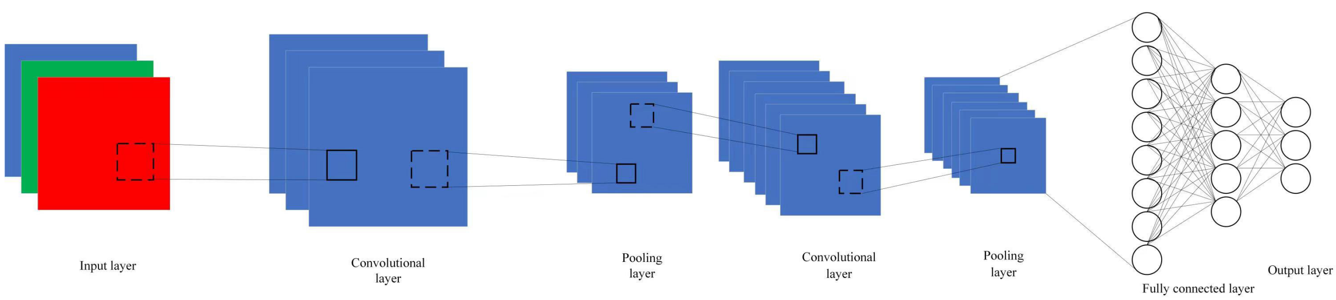

Figure 2. Convolutional Neural Network structure

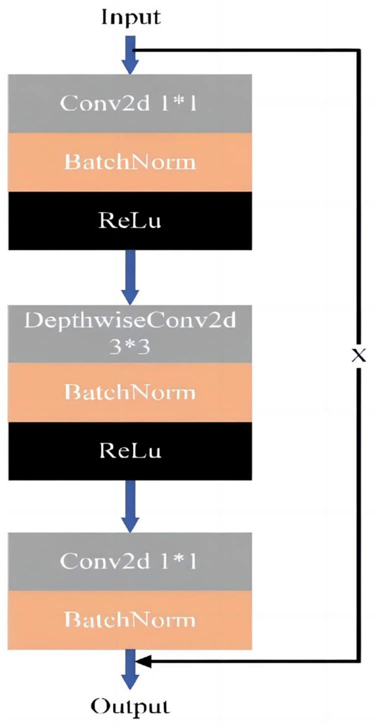

Figure 3. Framework diagram of the MobileNet V2 network model

$$Leaky\ ReLu(x) = \begin{cases} x & x \geq 0 \\ ax & x < 0 \end{cases} \quad (1)$$

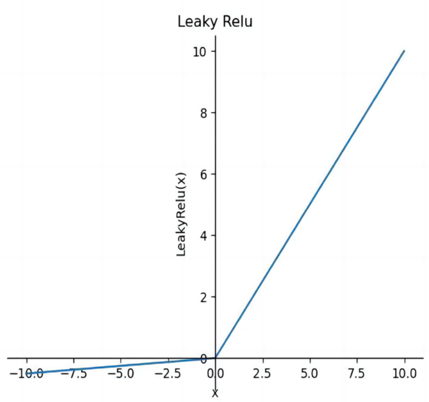

Figure 4. Leaky ReLu function image

3.2 Image Restoration Adversarial Network

In 2022, Yongchun Guo et al. [30] proposed a generative adversarial network, whose network structure is shown in Figure 5. This network model consists of a generator and a discriminator, which promote each other through confrontation, resulting in a more realistic repair image. The working principle is: First, the generator generates synthetic data g (i) based on the input missing image. Then, g (i) and real data x are inputted into discriminator D, and the discriminator compares the similarity between the two to determine the authenticity of this sample. Finally, the results are fedback to the generator. During the training process, the two confront and promote each other to improve the repair effect and accuracy.

Experiments show that GAN can achieve good repair effect in inpainting. Therefore, GAN is selected as the main network architecture in this paper. The specific inpainting countermeasure network model is shown in Figure 5.

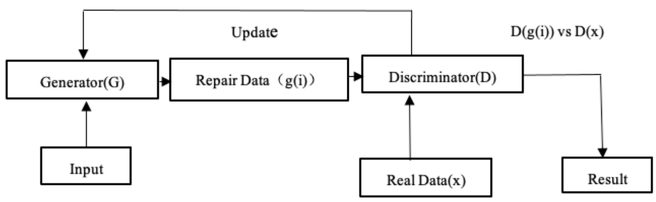

Figure 5. Generative confrontation network structure

The inpainting generator proposed in this paper first inputs the occluded image into generator G, introduces a convolutional neural network to extract image features, and adds a residual network to avoid gradient dispersion. Secondly, the effective area and occlusion area are dynamically divided through parameters. Finally, the image is generated using the principle of multiscale feature fusion, and the model structure is shown in Figure 6. In the inpainting discriminator, a discriminative model is introduced. At the same time, the output of the generative model is optimized by confrontation. The experiment shows that this method effectively improves the details of the generated image.

3.3 Loss Function

In the process of image acquisition, generation, storage, and transmission, due to different technical methods or operational errors, the image may be damaged and even affect its application. This process is called image degradation, as shown in (2).

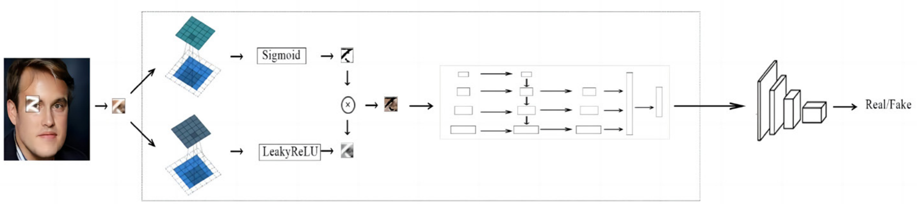

Figure 6. Image restoration confrontation network

$$P_K = P_0 \odot K, P_K \in (\Omega \cup \Phi) \quad (2)$$

Among them, P_k represents the image to be repaired, P_0 represents the input image, and K is the mask of the image, which is a two-dimensional matrix composed of 0 or 1. The missing area k to be repaired has a value of 0, and the other areas a have a value of 1. Image restoration is based on the establishment of inpainting model, and the restoration process is shown in (3).

$$\overline{P} = P_0 \odot K + P_r(1-K) \quad (3)$$

Among them, $\overline{P}$ represents the output image after repair, P_r represents the image repaired through the inpainting model, and the input image P_0 and the repaired defect area to complete inpainting.

In depth learning, whether inpainting meets the requirements is judged by the error between the real value and the predicted value. This error is called the objective function of the deep learning model. Generally, the smaller the error, the smaller the gap between the two, and the closer the model prediction results are to the real value. Such objective function is called loss function, so the effect of inpainting becomes a problem of loss value calculation. The working mechanism of generative model is to generate high-dimensional spatial samples from randomly distributed data mapping by learning data distribution. The discriminator model learns how to identify real samples and false samples (generate samples), so as to establish the loss function of the model. The loss function is shown in the generated countermeasure network (4).

$$\begin{aligned}\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] \\ + E_{i\sim p_{i(i)}}[\log(1-D(G(z))] \end{aligned} \quad (4)$$

In the formula: $E(*)$ is the expected value of the distribution function, $P_{data}(x)$ represents the true sample distribution, $P_i(i)$ is defined as a low dimensional noise distribution, $D(x)$ is the generated sample, and $D(G(z))$ is the discriminant of the generated sample.

When the generator is invariant, the generated sample data is always 0, while the real sample data is 1, the discriminator can accurately distinguish whether the generated sample is false at this time. Its training discriminator is shown in Equation (5).

$$\max_D \begin{pmatrix} E_{x\sim p_{data}(x)}\left[logD(x)\right] + \\ E_{i\sim p_i(i)}\left[log\left(1-D(G(z))\right)\right] \end{pmatrix} \quad (5)$$

The composition of the loss function of the model is similar to that of the loss function of the traditional anti neural network, but the residual network is added to the model in training to extract features from the image, which will result in a certain feature loss. Therefore, the feature matching loss is added to the composition of the loss function of the traditional model. This feature matching loss uses L1 loss to extract features from different scales of the active layer for “matching” to enhance training stability, The formula is shown in (6).

$$\begin{aligned} L = {} & E_{x\sim p_{data}(x)}\left[logD(x)\right] \\ & + E_{i\sim p_i(i)}\left[log\left(1-D(g(i))\right)\right] \\ & + \sum_{i=1}^{T} \frac{1}{N_i} \left\| D^{(i)}(x) - D^{(i)}(g(i)) \right\|_1 \end{aligned} \quad (6)$$

In the formula (6): T represents the total number of convolutional layers, N_i represents the number of elements of the i-th active layer, and $D^{(i)}$ represents the activation function of the thirteenth layer.

3.4 Robustness of the Algorithm

The GAN image restoration method is not very robust for images with extreme damage. Because the GAN image repair method repairs images by learning their distribution, and for extremely damaged images, their distribution has undergone significant changes, the GAN image repair method may not be able to accurately learn the distribution of the image, resulting in poor repair results.

GANs are able to learn complex data distributions, which makes them more robust in repairing images containing extreme damage; Although the GAN image restoration method performs well in terms of robustness, there are still some challenges that may need to be adjusted and optimized according to specific tasks. The evaluation of robustness usually needs to be conducted in diverse datasets and various damage scenarios to ensure the performance of the model in different scenarios.

Some GAN image restoration methods also use noise robustness techniques to cope with noise or extreme damage in the input image. This includes introducing noise models, using noise layers, or increasing the model’s robustness to input changes through other means.

4 Experiment and Verification

4.1 Evaluation Setup

In order to verify the effect of the inpainting method proposed in this paper, experiments and training were conducted on CelebA face recognition dataset, and 10000 images were randomly selected from the dataset to train the model. The specific experimental configuration and training parameter settings are shown in Table 1:

Table 1. Experimental configuration and training parameter settings

Software configuration	Computer operating system	Windows 10
	Programming language	Python3.6
	Language editor	PyCharm
	Deep learning framework	TensorFlow
	CUDA	10.1

Hardware configuration	CPU	i7-10750H
	GPU	NVDIA RTX2060
	Running memory	16G
	Graphics card memory	6G
Model parameter settings	Activation function LeakReLu	α =0.2
	Enter image size	256 × 256
	Learning rate	0.001

4.2 Evaluation Indicators

This article evaluates the quality of the proposed model through three evaluation indicators: IoU loss, peak signal-to-noise ratio (PSNR), and structural similarity (SSIM). IoU is the ratio of the intersection and union of the true and test values, $IoU\ Loss = 1 - IoU$, and the smaller the IoU loss value, the smaller the loss, and the better the effect. The formula is shown in (7), where d represents the test value and t represents the true value:

$$IoU\ loss = -In\frac{Intersection\left(d,\mathrm{t}\right)}{Union\left(\mathrm{d},\mathrm{t}\right)} \tag{7}$$

The peak signal to noise ratio [20] (PSNR) is an index to judge the repair effect, which is defined by the mean square error MSE. MSE reflects the quality of the repair effect by calculating the difference between the real image pixel points and the repair image pixel points. The larger the PSNR value, the better the inpainting effect. The MSE formula is shown in (8), and the PSNR formula is shown in (9).

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{i=0}^{n-1}\left\|I(i,j)-K(i,j)\right\|^2 \tag{8}$$

$$PSNR = 10\cdot\log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20\cdot\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \tag{9}$$

Where m and n are the dimensions of images I and K, $I(i, j)$ is the pixel representation of the real image, $K(i, j)$ is the pixel representation of the repaired image, and MAX_I represents the maximum value of the color at a certain point in the image.

Structural Similarity [22] (SSIM) judges the restoration effect of an image from three aspects: brightness, contrast, and structure, roughly reflecting the model's ability to reconstruct the original content. The larger the SSIM value, the better the restoration effect. The SSIM formula is shown in (10-12).

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_y^x + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{10}$$

$$b_1 = \left(q_1 R\right)^2 \tag{11}$$

$$b_2 = \left(q_2 R\right)^2 \tag{12}$$

Where x represents the true value of a point in the image, and y represents the repair value corresponding to the position of x; μ_x and μ_y are the averages of x and y; σ_x and σ_y are the variances of x and y; σ_{xy} is the covariance of x and y; b_1 and b_2 are constants used to maintain stability; R is the dynamic range of pixel values, $q_1 = 0.01$, $q_2 = 0.03$.

4.3 Experimental Result

Compare this research method with popular schemes in recent years and prove through qualitative and quantitative analysis that the proposed method has good repair effects. The comparison scheme we choose here is Patch Match (PM) and CA, Patch Match (PM) is a block based on inpainting method proposed by J. Yu et al. in 2018 [31], and CA is a model of inpainting using contextual attention features proposed by H. Yang et al. in 2022 [32].

4.3.1 Qualitative Analysis

Figure 7 shows the comparison of the proposed method and the repair effects of PM and CA on the CelebA dataset. In most cases, the method proposed in this article performs better than the comparative methods in terms of structural reconstruction and detail texture reconstruction.

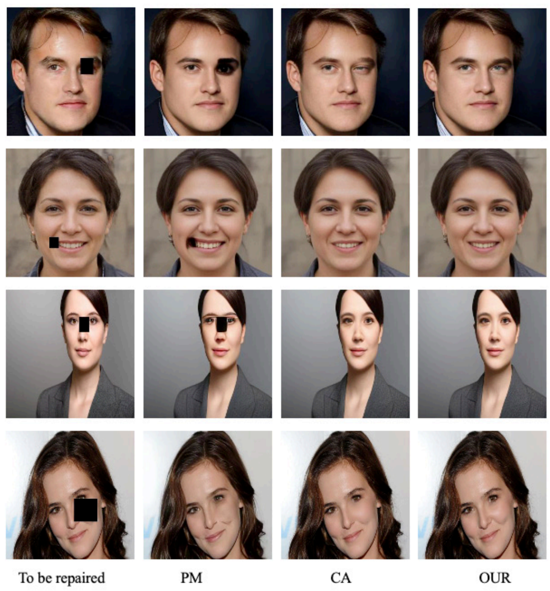

Figure 7. Comparison results

From Figure 8 [33], it can be seen that the image details repaired by the PM method are relatively blurry, and the contour is also unclear, making it difficult to distinguish the five facial regions. The CA method can restore the overall outline of the original image, but the details are not well filled, the edges are blurry, and the repair effect is average. According to the repair method proposed in this article, the effect is good, restoring the details and contours of the original image to a certain extent, but there are still some deviations in texture repair. In order to improve the quality of the repaired images, this article uses the open-source dataset FFHQ high-definition facial image dataset to train the model. Due to the large number of high-definition images in this dataset, it can further improve the repair image effect. From the comparison of Figure 8 [33], it can be seen that the blurring, fading, low color saturation, and other phenomena in the original image have basically disappeared. The portrait restoration effect is good, and details such as the eyes and hair can be clearly restored. However, there is still some room for improvement in the complex background and clothing details processing, as well as in the photos with some excessive sharpening.

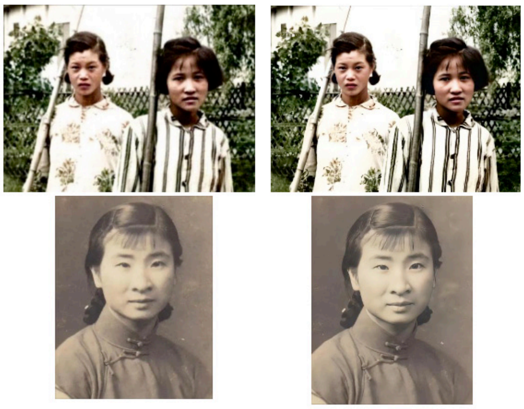

Figure 8. Comparison of results

The change curves of model loss rate and accuracy obtained after a thousand training sessions are shown in Figure 9, Figure 10, and Figure 11.

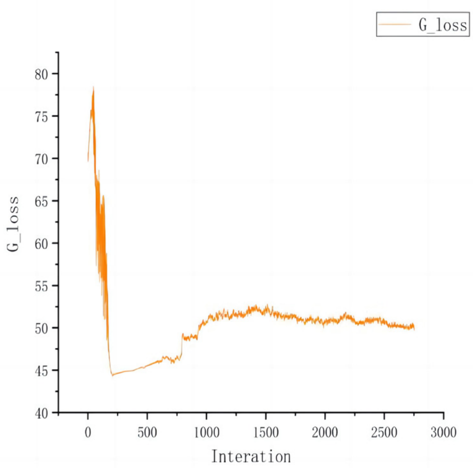

Figure 9. Model loss value

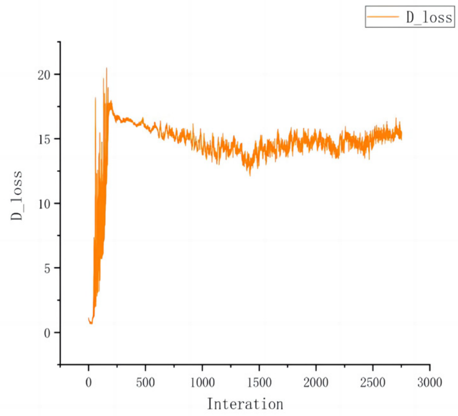

Figure 10. Model loss value

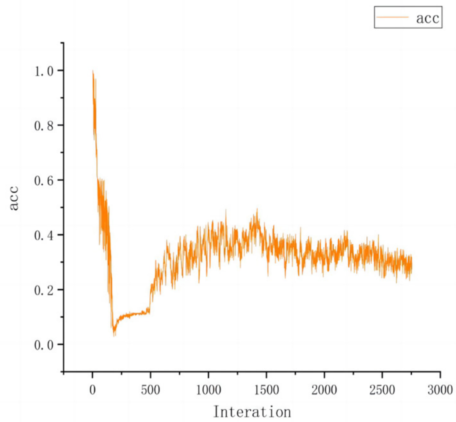

Figure 11. Model accuracy

From the model accuracy image, it can be seen that during the first training, the state of the discriminator is the optimal state, which can accurately distinguish the authenticity of the input image. However, when trained 200 times, the accuracy of the discriminator can only reach about 10%, indicating that there is a significant difference between the discriminator's discrimination quality and the generator's generation quality, making it difficult to effectively distinguish. As the number of training sessions of the model increases, the generator and discriminator play games and promote each other. After 800 training sessions, the overall equilibrium state is reached, indicating that the model training results have reached an ideal state.

4.3.2 Quantitative Analysis

This article uses three evaluation indicators, IoU Loss, PSNR, and SSIM, to evaluate the quality of the proposed model. The results are shown in Table 2. From the table, it can be seen that the repair model proposed in this article has increased the PSNR value by 22.78% and 44.57% compared to the CA and PM models, and has in-creased the SSIM value by 1.92% and 4.04%, respectively. However, IoU Loss decreased by 35.85% and 44.26%. Furthermore, it shows that the inpainting method based on generative adversary network (GAN) proposed by us has certain advantages.

Table 2. Quantitative comparison

	PSNR			SSIM			IoU Loss		
Data	CA	PM	OUR	CA	PM	OUR	CA	PM	OUR
CelebA	26.34	22.37	32.34	0.885	0.867	0.902	0.053	0.061	0.034

5 Conclusion

In order to solve the problems of missing details and small area damage in inpainting, we propose a new inpainting method. This method consists of two parts: the preprocessing block and the inpainting countermeasure network. The preprocessing block enhances the purified image, while the inpainting countermeasure network has two parts: the image generator and the image discriminator. The image generator uses the convolution neural network and multiscale feature fusion method to repair the image. The image discriminator judges the authenticity of the image according to the counter-measure strategy, and ultimately makes the image generated by the image generator more realistic. Finally, we introduce the GFPGAN to improve the overall effect of image restoration, with a focus on image resolution, portrait texture, and color saturation. Compared with the classical mainstream inpainting methods, the method proposed by us has certain advantages. However, due to the computing ability of the equipment, it is not possible to train and detect a large number of data sets at present, and the robustness of the model needs further research. Therefore, compared with current advanced methods, although there is a certain gap, this algorithm is easy to apply in teaching and simulation experiments. Therefore, how to present a good repair effect in the training of small sample data sets, how to train and repair when the computational power is low, and how to reduce the parameters of the model and build a loss function are the future work directions.

The research of this method is based on the restoration of facial images, while for non-facial restoration, it is currently only attempted in the restoration of ancient architectural images and calligraphy works, which can be used for reference.

In the future, we will explore the restoration research in the field of building and geological cracks, and secondly, study the repairability of images with large and non-standard loss areas.

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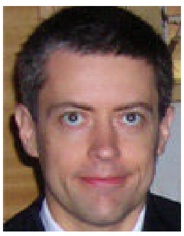

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