Artwork restoration using paired image translation-based generative adversarial networks

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Abstract. Preservation of the artworks has historical and cultural importance. However, with time, environmental factors severely affect artworks, and these damages are often complicated to repair manually and through traditional methods. We propose a method to restore artwork that has been damaged over time. This work proposes a systematic approach using paired image-to-image translation based on a generative adversarial network. The experimental results have been quantitatively evaluated. The experimental results obtained from the presented work visually prove that the presented approach of artwork restoration completely restores the damaged artwork.

Keywords: Image translation, generative adversarial networks, image restoration, deep learning, image inpainting, artwork restoration.

1. Introduction

Artworks are a precious cultural heritage representing humankind's culture and history. However, with time artwork gets damaged because of wear and tear and exposure to various environmental factors like relative humidity, improper light, and abnormal temperature[1]. Therefore, technology is immediately required to protect and restore damaged ancient artworks. The manual restoration of the artwork requires the expertise of a conservationist, and the process is lengthy, tedious, and error-prone. Moreover, restoring the artwork is impossible in some cases due to the lack of information about its damaged portion. Therefore, restoration using artificial intelligence methods can greatly help restore damaged artworks. Further, artworks, once preserved digitally, will not be distorted in the future due to various factors. However, a limited number of methods based on artificial intelligence are available for the virtual restoration of the artworks, and these methods are multistep processes and lack performance.

This paper presents a generative adversarial network-based virtual artwork restoration method. Various applications of generative adversarial networks are image transformation[2], image translation[3], and generative design. However, generative adversarial networks can be explored further for artwork restoration.

This paper proposes an approach to restore damaged artwork using a novel generative adversarial network virtually. The main contributions of this work are

i) We present a systematic, less time-consuming, and labor-intensive method for artwork restoration.

ii) We have appended the realistic damages to the original artwork to be similar to real-world damaged artwork. Then we used paired image translation-based generative adversarial network to restore the damaged artwork digitally.

iii) We have used a patch-based discriminator so that the generator gets feedback for each image patch to generate sharp and colorful restored artwork.

iv) The experimental results of the proposed approach outperform the existing methods of virtual restoration of the artwork.

The rest of the paper contains the following sections. The related work is presented in section 2. Section 3 details the proposed workflow and dataset description. The proposed system architecture is discussed in section 4. Section 5 discusses the training and results. In the end, section 6 provides the conclusion and future scope of the work.

2. Related work

The image restoration area has much-related work, but the digital restoration of artwork is unexplored. We have only a few instances of work related to the digital restoration of the artworks. This section discusses various restoration techniques for images and artworks.

2.1 Artwork Restoration

Image restoration through image inpainting uses the optical information of surrounding pixels for inpainting with mechanisms like distance field [4][5] and through the prior information of the images[6]. Further, some other approaches for inpainting use gradient directions, probabilistic models, and neighboring pixels-based methods to fill in missing holes in the images [7][8][9][10][11]. However, these techniques can not restore the images containing large distorted patches. Over the years, researchers have also proposed using deep convolutional neural networks for image restoration[12] and image inpainting[13]. Further pre-trained network[14] and multistage encoder-decoder architecture[15] has also been used to restore degraded images. L. Gatys et al. [16] use a VGG network [17] to encode input image features. Y. Zeng et al.[18] proposed a multiscale Convolutional Neural Network (CNN) framework for pixel-wise prediction. However, these approaches rely on mask generation for restoration, and these approaches can not restore complex and finer features of the images. The approach proposed in this work does not require mask generation.

Few restoration methods for artworks and murals have been proposed. V. Gupta et al. [19] proposed an approach based on mask generation [20] and inpainting for restoration using U-Net. Z. Zhou et al. [21] proposed an approach to restore beams using deep learning algorithms. J Cao et al.[22] used consistency-enhanced generative networks to restore ancient murals. J. Li et al.[23] proposed digital restoration of ancient murals using U-Net based generative adversarial network. More recently, P. Kumar and V. Gupta[24] proposed the method of restoration of damaged artworks based on generative adversarial networks. Due to the limitations of the proposed methods proposed for image and artwork restoration, there is a requirement for a better architecture of the generative adversarial network for restoring the damaged artworks.

A summary of the related work in tabular form is given in Table-1.

Table-1: Summary of related work

Type of restoration methods	Proposed Approach	Limitations
Traditional image restoration methods[4][5][6][7][8][9][10][11]	Methods used for restoration are distance field, prior information of the image, gradient direction, probabilistic models, and inpainting.	These methods use the neighboring pixels' information to inpaint the image's damaged part. However, these methods can not inpaint the damaged image having large patch sizes having hugely distorted colors.
Image restoration using deep Learning-based method [12][13][14][15][16][17][18]	Image inpainting, multistage encoder-decoder deep neural networks, pre-trained networks, and VGG network, Automatic mask generation and image inpainting using U-Net, multiple deep learning-based algorithms,	These techniques can not restore the complex, finer features of the images, and these techniques also require an additional step of mask generation for restoration.
Artwork and mural restoration methods[19][20][21][22] [23][25][24]	U-Net, generative adversarial network	These methods make the restoration a multistep process. Moreover, the results are not color-consistent, and there is a visible difference between the original and restored parts of the image.

3. The proposed workflow and dataset description

The dataset used for experimentation is the best artwork of all time dataset[1]. The dataset has 2073 artwork images. Of these, 1192 artwork images are used for the training, and 881 are used for testing.

Table 2. Dataset details

Dataset	Total images	Total images used for experimentation	Training data set	Test data set
Best artworks of all time dataset	2073	2073	1192	881

The steps required for executing the presented work are (i) the Creation of artificially distorted artwork, (ii) Creating the generator based on dynamic U-Net, (iii) Creating the patch-based discriminator, (iv) Deciding the loss function, (v) Training of the network and (v) Resoration of the artwork.

A detailed explanation of the presented work is given as under
i) Creation of artificially distorted artwork: During this step, we will generate the synthetically damaged artwork images for training the proposed network.
ii) Creating the generator based on dynamic U-Net: The presented generative adversarial network has a generator based on a dynamic U-Net consisting of encoding, bottleneck, and decoding blocks[26][27][28]. The generator's structure is a deep network consisting of encoding, bottleneck, and decoding blocks. Artwork restoration is a complex problem requiring dense connectivity and strong gradient flow during backpropagation

iii) Creation of the patch-based discriminator: The discriminator of the proposed network will output a classification matrix quantifying each image patch as real or fake. The patch-based discriminator will slide through its field of view across all 16x16 size patches in the image.

iv) Deciding the loss function:
We define the adversarial loss and reconstruction are the loss function for the generator of the presented network, as given in equation (1).

Generator Loss: = $min_g\ (Adversarial\ Loss + \lambda * Reconstruction\ los)$ (1)

Reconstruction loss term= $\sum_{i=1}^{n} |restored\ artwork - original\ artwork|$ (2)

Generator Loss= $BCE\ Loss + \lambda \sum_{i=1}^{n} |restored\ artwork - original\ artwork\ |$ (3)

$$BCE\ Loss = -\frac{1}{m}\sum_{i=1}^{m}[y^{(i)}\ h\left(x^{(i)},\theta\right) + \left(1-y^{(i)}\right)\ log\left(1-h\left(x^{(i)},\theta\right)\right)] \quad (4)$$

v) Training of the network: In this step, the network is trained using the damaged and original artwork images.

[1] https://www.kaggle.com/datasets/ikarus777/best-artworks-of-all-time?resource=download

vi) Restoration of the artwork: The proposed method generates high-quality restored artwork images.

4. The proposed system architecture

Fig. 1 presents the system architecture for restoring the damaged artwork. The proposed network consists of the dynamic U-Net and patch-based discriminator. The generator generated the restored artwork from the damaged artwork. The discriminator will classify the generator output as real or fake. The patch-based discriminator gets the damaged artwork as input concatenated with either the restored or real artwork.

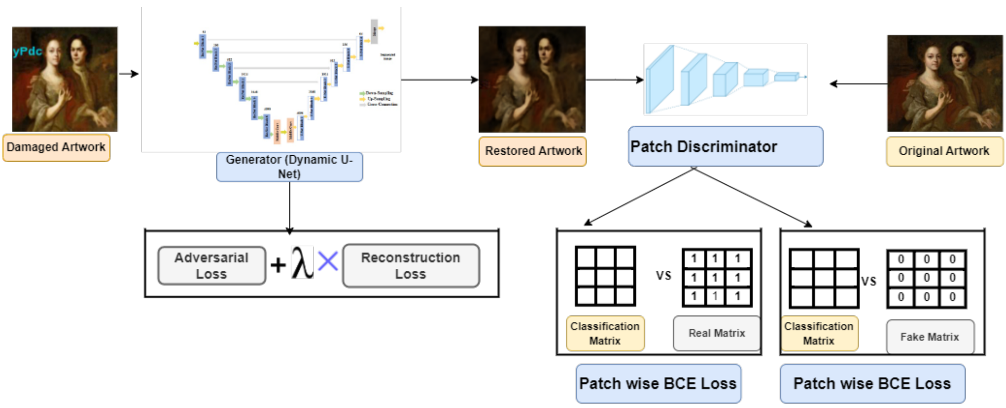

Figure 1: Proposed System Architecture

5. Training and Results

This section provides the details regarding the training of the presented system along with quantitative and visual results obtained from the experimentation.

5.1 Experimental Setup

The experimentation has been done using the Pytoch library, and network training has been done using Quadro RTX 6000-A GPU. Table 3 provides hyperparameters values used while training the network.

Table 3. Hyperparameters

Hyperparameter	Value
Learning rates	2x10-4 (during the first 100 epochs), 5x10-5 (during the next 100 epochs)
Image size	256x256

Batch size	2
Generator loss function	BCE Loss (Adversarial loss) + λ *L1 loss (Reconstruction/ Pixel distance loss) λ =500
Discriminator loss function	BCE Loss
Adam optimization algorithm values	$\beta 1 = 0.9$, $\beta 2 = 0.999$ Weight decay=10^{-3}
Image patch size	16x16

5.2 Performance evaluation using metrics

The performance of results obtained from the presented approach has been measured using PSNR, MSE, and SSIM metrics. Further, the quantitative results of the presented network for artwork restoration on the experimented dataset of 'Best artwork of all times' using metrics of PSNR, MSE, and SSIM are presented in Table 4.

Table 4. Quantitative results of the presented network

Metric	**Values**
Mean Squared Error (MSE)	86.37
Peak Signal-to-Noise Ratio (PSNR)	28.90
Structural Similarity Index (SSIM)	0.53

The effectiveness of the presented network is proved by all three metrics, as shown in Table 3.

5.3 Quantitative comparison with the other method

A comparative analysis of the results of the proposed approach with that of the other method with a U-Net generator and a non-patch-based discriminator on the ''Best artwork of all time dataset' dataset is given in Table 5.

Table 5. Comparative analysis of the results with other methods on the experimented dataset

	Average SSIM	Average PSNR	Average MSE
GAN with U-Net generator and without Patch-based Discriminator	0.11	22.34	84.15
Proposed work (GAN with pre-trained U-Net generator and with Patch-based Discriminator)	0.53	28.90	86.37

5.4 Visual analysis

This section presents the qualitative assessment of the restored artwork obtained after the proposed experimentation. The sample outputs from the experimented dataset are presented in Fig. 2.

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Fig. 2 Optical comparison of the results of the proposed experimentation

5.5 Real-life Applications and Limitations of the proposed approach

The proposed methods present the systematic method for digitally restoring distorted artwork. The digitally restored version of the damaged artwork can help conservationists and art professionals physically restore the artwork. Also, art galleries and art museums can use the proposed method to restore damaged artworks. Moreover, the proposed method can also be used to restore the paintings on the historical buildings. Though the proposed work performs well on the complex problem of artwork restoration, it is difficult to find convergence during the training of deep learning-based generative adversarial networks. Further, these networks require heavy computational resources for training.

6. Conclusions and future work

Restoration and preservation of the artworks can do the preservation of humankind's culture and heritage. There is a need to explore the use of technology in artwork restoration. This paper provides an approach for restoring damaged artwork using a novel generative adversarial network. The reconstruction of damaged artwork takes place using the network consisting of a generator based on dynamic U-Net and an image patch classifier as the discriminator. While the generator in the proposed network effectively restores the artwork using a combination of adversarial and reconstruction loss. The patch discriminator provides feedback on each patch of the image to the generator. The unique design of the generator and discriminator of the proposed network has produced promising results, and the network has effectively restored the damaged part of the artwork. The experimental results are evaluated using the evaluation metrics of SSIM, PSNR, and SSIM, and the results obtained from the proposed approach qualitatively prove the effectiveness of the proposed network in respect of other similar works of artwork restoration.

Further, to continue our work, we will explore the possibility of using unpaired image translation-based generative adversarial networks for artwork restoration.

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