(12) INNOVATION PATENT (11) Application No. **AU 2021107048 A4**
(19) AUSTRALIAN PATENT OFFICE

(54) Title
RESTORATION OF ARTWORK USING GENERATIVE ADVERSARIAL NETWORKS

(51) International Patent Classification(s)
G06N 3/02 (2006.01) *G06N 5/04* (2006.01)
G06K 9/36 (2006.01) *G06T 5/00* (2006.01)
G06K 9/00 (2006.01)

(21) Application No: **2021107048** (22) Date of Filing: **2021.08.24**

(45) Publication Date: **2021.12.02**
(45) Publication Journal Date: **2021.12.02**
(45) Granted Journal Date: **2021.12.02**

(71) Applicant(s)
Varun Gupta;Praveen Kumar

(72) Inventor(s)
Gupta, Varun;Kumar, Praveen

(74) Agent / Attorney
Varun Gupta, 39 Robin Boyd Cres, Taylor, ACT, 2913, AU

2021107048 24 Aug 2021

ABSTRACT

A method for restoration of artworks using generative adversarial networks comprises the following steps: damaged artwork images along with their original versions are loaded; generator as modified U-Net having encoder as ResNet34 architecture and decoder as U-Net layers, is built and pretrained for generating restored versions of the damaged artwork images; the decoder consisting of an initial block of convolutional, dropout and residual layers followed by four blocks of a dropout and two convolutional layers is created and pretrained for assessing the quality of images generated by the generator; the loss function is defined as the Mean Squared Error (MSE) for the generator and Binary Cross-Entropy (BCE) for the discriminator; generative adversarial network having pretrained generator and pretrained discriminator is trained; inference using damaged artwork test images is performed and restored versions of the test images are generated.

2021107048 24 Aug 2021

AUSTRALIA

Patents Act 1990

COMPLETE SPECIFICATION

INNOVATION PATENT

RESTORATION OF ARTWORK USING GENERATIVE ADVERSARIAL NETWORKS

The following statement is a full description of this invention, including the best method of performing it known to me:

2021107048 24 Aug 2021

RESTORATION OF ARTWORK USING GENERATIVE ADVERSARIAL NETWORKS

TECHNICAL FIELD

[0001] The invention belongs to the technical field of computer vision and relates to a method for restoration artwork paintings using generative adversarial networks, a type of deep neural network.

BACKGROUND OF THE INVENTION

[0002] Artworks have huge significance as they represent traditional cultural heritage. When referring to artwork restoration, we mean that we have a damaged artwork containing spots, faded paint, tears, cracks, blisters, mold, blur, noise, holes, smudged areas, and we want to recover the clean non-degraded artwork. There could be many reasons for artwork to degrade, mainly during transmission, formation, and storage. Damages in artwork can also be the result of exposure to light, relative temperature, and humidity. The restoration process is very time-consuming and is a delicate task making it prone to human error. The virtual restoration of digitized artworks can be very helpful in this process.

[0003] The generative adversarial networks are state-of-art deep neural networks. These networks can learn the artistic style of the artworks and thus help predict the damaged parts of artwork images semantically. Based on these digitally restored images, artworks can be physically restored by the artists.

[0004] At present, physical methods for the restoration of artwork are very time-consuming and are delicate tasks making them prone to human errors. The existing virtual restoration methods lack semantic understanding of the artistic style of the

2021107048 24 Aug 2021

artworks. There is also a lack of more accurate scientific and intelligent means to restore artworks.

SUMMARY OF THE INVENTION

[0005] Given the shortcomings of the prior art, the present invention aims to provide an artwork restoration method based on generative adversarial networks, which realize the use of artificial intelligence technology to learn the artistic style of the paintings more scientifically.

[0006] To achieve the above objectives, the present invention adopts the following technical solution:

A method for artwork restoration based on generative adversarial networks, comprising the following steps:

S1. Loading dataset of damaged and original artwork images;

S2. Building and pretraining the generator (G) part of the generative adversarial network as modified U-Net for generating the restored artwork from damaged artwork;

S3. Creating and pretraining the discriminator (D) as a classifier for assessing the quality of generated images by the generator (G);

S4. Defining loss function for generator part of the network as the Mean Squared Error (MSE)and Binary Cross-Entropy (BCE)as the loss function for the discriminator;

S5. Training the Generative Adversarial Network (GAN) having pretrained generator(G) and discriminator(D) defined above as its parts on the artwork dataset loaded in S1. The training and evaluation of the network take place using the loss functions defined in S4;

S6. Perform inference using damaged artwork test images. As a result, restored versions of the artwork images are generated.

2021107048 24 Aug 2021

[0007] The beneficial effect of the present invention is that it realizes the use of artificial intelligence technology to restore artwork images in a semantically rich manner. The invention learns and preserves the style of the artist while restoring the artwork.

DESCRIPTION OF THE FIGURES

Figure 1 is an illustrative diagram of the architecture of the generator part (Modified U-Net) of the Generative Adversarial Network used in the invention;

Figure 2 shows samples of damaged test input artwork images;

Figure 3 shows samples of restored artwork images as test results of an embodiment of the present invention.

DETAILED DESCRIPTION

[0008] The present invention will be further described below in conjunction with the accompanying figures. It should be noted that these embodiments are based on the present technical solution to provide detailed implementation and specific operating procedures. Still, the scope of protection of the present invention is not limited to these embodiments.

[0009] This embodiment provides a method for restoration of artwork images based on a generative adversarial network, comprising the following steps:

S1. Loading dataset of damaged and original artwork images;

S2. Building generator (G) part of the generative adversarial network as modified U-NET for generating the restored artwork from damaged artwork. The generator has mainly two

2021107048 24 Aug 2021

components: encoder and decoder. The encoder of the modified U-Net model is a ResNet34 architecture that has been pretrained on ImageNet and performs feature encoding. The decoder consists of several U-Net blocks followed by a merge layer. Each U-Net block receives the output of the last block to be upsampled and activation features from an intermediate layer of the encoder. The final restored image result is obtained by taking the result of the passed-on convolutions and cross-connection of the input image. Then, pretraining the generator on damaged artwork for eight epochs using a learning rate of 10^{-3};

S3. Creating the discriminator (D) as a classifier for assessing the quality of images generated by the generator (G). Discriminator has an initial block of convolutional, dropout and residual layers followed by four blocks of a dropout and two convolutional layers. Afterward, pretraining the discriminator on damaged and restored artwork for six epochs with a learning rate of 10^{-3};

S4. Defining loss function for generator part of the network as the Mean Squared Error (MSE) and Binary Cross-Entropy (BCE) as the loss function for the discriminator as defined below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

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

S5. Training the Generative Adversarial Network (GAN) having pretrained generator(G) and discriminator(D) defined above as its parts on the artwork dataset loaded in S1. The training and evaluation of the network take place using the loss functions defined in S4;

The network is trained on the artwork dataset by switching from discriminator to generator and vice-versa. Many iterations of the discriminator are done to get its loss < 0.5. Then one iteration of the generator takes place. The GAN is trained for 40 epochs with a learning rate of 10^{-4}. Afterward, the network is saved and then trained further for ten epochs with half learning rate ($0.5 * 10^{-4}$);

S6. Perform inference using damaged artwork test images. As a result, restored versions of the artwork images are generated.

[0010] The above are only the preferred embodiments of the present invention and are not used to limit the protection scope of the present invention. The present invention is not limited to the implementation schemes described here, and the purpose of these implementation schemes is to help the present invention.

EDITORIAL NOTE

2021107048

There are two pages of claims only

2021107048 24 Aug 2021

CLAIMS

The claims defining the invention are as follows:

1. A method for restoration of artwork based on generative adversarial networks, characterized in that, comprising the following steps:

S1. Loading dataset of damaged and original artwork images;

S2. Building and pretraining the generator (G) part of the generative adversarial network as modified U-Net for generating the restored artwork from damaged artwork;

S3. Creating and pretraining the discriminator (D) as a classifier for assessing the quality of generated restored images by the generator;

S4. Defining loss function for generator part of the network as the Mean Squared Error Loss (MSE)and Binary Cross-Entropy Loss (BCE) as the loss function for the discriminator;

S5. Training the Generative Adversarial Network (GAN) having pretrained generator(G) and discriminator(D) defined above as its parts on the artwork dataset loaded in S1. The training and evaluation of the network take place using the loss functions defined in S4;

S6. Perform inference using damaged artwork test images. As a result, restored versions of the artwork images are generated.

2. The method according to claim 1, characterized in that, in step S2, the encoder of the modified U-Net model being used as the generator of the GAN is a ResNet34 architecture which has been pre-trained on ImageNet and effectively encodes and

2021107048 24 Aug 2021

classifies images. The decoder of the modified U-Net consists of several U-Net blocks followed by a merge layer.

3. The method according to claim 1, characterized in that, in step S3, the discriminator has an initial block of convolutional, dropout, and residual layers followed by four blocks of a dropout and two convolutional layers.

4. The method according to claim 1, characterized in that, in step S4, GAN is trained using the Mean Squared Error (MSE)and Binary Cross-Entropy (BCE) as the loss function.

5. The method according to claim 1, characterized in that, in step S5, GAN is trained on the artwork dataset by switching from discriminator to generator and vice-versa. Many iterations of the discriminator are done to get its loss < 0.5. Then one iteration of the generator takes place. The GAN is trained for 40 epochs with a learning rate of 10^{-4}. Afterward, the network is saved and trained for ten epochs with half of the initial learning rate ($0.5 * 10^{-4}$).

2021107048 24 Aug 2021

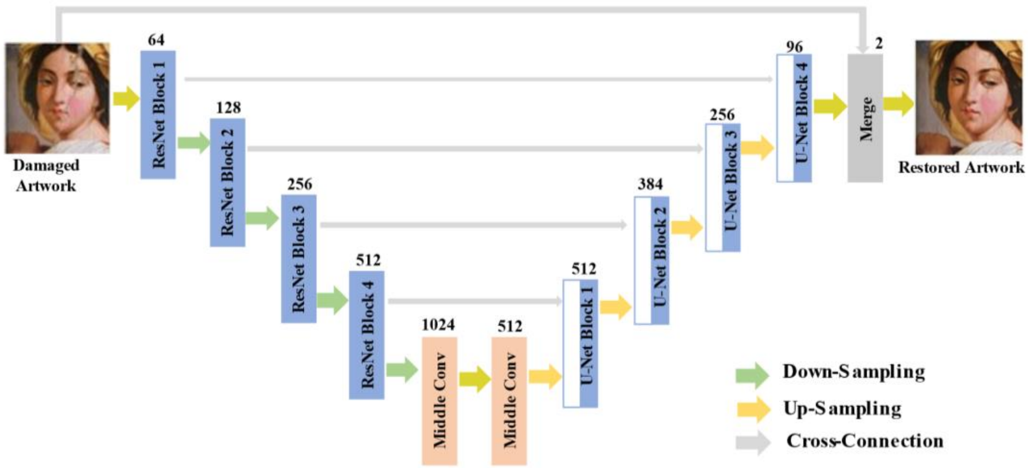

Figure 1

Figure 2

2021107048 24 Aug 2021

Figure 3