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Coloring Ancient Egyptian Paintings with Conditional Generative Adversarial Networks

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ABSTRACT

The aim of colorizing gray-scale images is to turn a gray-scale image into a real-looking color image, which is still a difficult task. In this paper, we present a new fully automated colorization technique to assign realistic color images with high levels of textured details, with fewer time and storage requirements than the most recent techniques. Our presented model is designed as a Conditional Generative Adversarial Network with a generator and discriminator to colorize Ancient Egyptian Paintings. Our model is trained using a novel dataset that is aggregated from Ancient Egyptian Paintings and contains more than 1000 images. Our model and traditional deep neural networks are assessed using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM), and Mean Square Error (MSE). The outcomes demonstrate the presented technique's ability to colorize images realistically and naturally while attaining state-of-the-art results.

Keywords:
CGAN; Ancient Egyptian paintings; image colorization

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1. Introduction

The research and application value of image colorization is high. It's the technique of giving each pixel in a target gray-scale image a color. It aids in the detection of information that is overlooked in gray-scale images, and makes them more valuable.

There are two ways to colorize an image: manual image colorization and automatic image colorization. Manual colorization needs a lot of human interaction and is still a time-consuming, costly process. The goal of automatic colorization is to colorize images without the need for human involvement.

Colorizing old images or movies, scientific and educational images, remote sensing images, satellite images, medical images, artistic fields, and ancient Egyptian paintings are just a few of the uses for automatic image colorization.

In this paper, we will investigate a subcategory of colorization: automatic colorization of ancient paintings using generative adversarial networks (GAN) [1], which has shown superior results

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compared to traditional techniques [2,3]. The GAN architecture is made up of a generator model for producing pictures and a discriminator model for identifying whether images are true or false. The generator's training aim is to confound the discriminator model. The Conditional GAN [4], sometimes known as the CGAN, is a GAN architectural modification that provides for image control, such as allowing for the generation of an image of a certain class. Our presented colorization model, which is designed on a Conditional GAN architecture, is intended to colorize the gray-scale input of ancient Egyptian paintings, as illustrated in figure 1.

The following is the layout of this paper. The related works are detailed in section 2. In section 3, we discuss the suggested CGAN method. The study results and evaluation are presented in Section 4. Section 5 provides the conclusions.

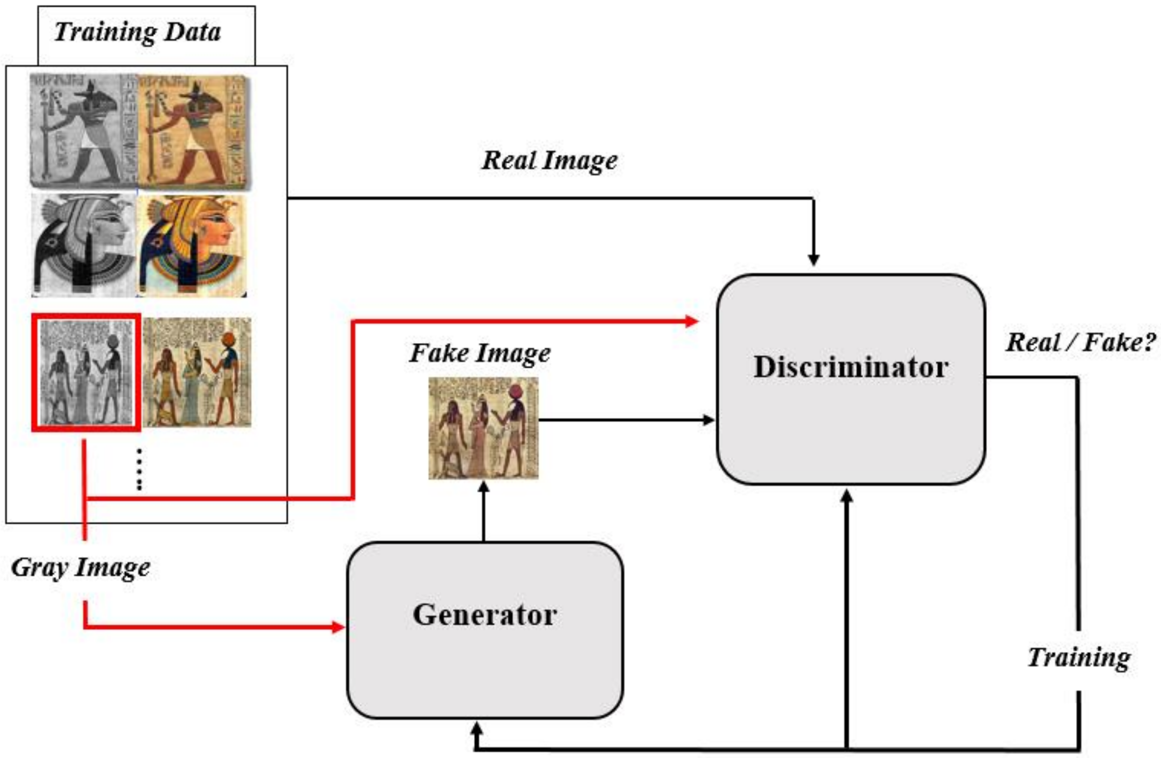

Fig. 1. Conditional Generative Adversarial Network Architecture Diagram

2. Related Works

Levin *et. al.*, [5] suggested a colorization method in which the user must manually allocate color scribbles to the specified (Certain) area (image regions). They think that pixels with equal intensities should have colors that are similar. As a result, a least-squares optimization method propagates allocated colors over the remaining pixels automatically. An adaptive edge detection approach was utilized by Huang *et. al.*, [6] to decrease color blending at image edges. Another colorization approach proposed by Welsh *et. al.*, [7] is the example-based approach. The colored image for reference and the gray-scale image are the inputs for this approach. The reference colourful image's color cues can be transmitted to the target gray-scale image. By comparing the images' brightness values and texture information. From a segmented source image, Ironi *et. al.*, [8] used texture feature matching to transfer specific color values.

Fully automated colorization models have been proposed that require gray-scale images only. Cheng *et. al.*, [9] suggest a fully automated colorization approach that uses image descriptors as inputs to the deep neural network. Iizuka, Serra *et. al*., [10] propose a network that detects color information for each pixel by combining global and local image features. An automatic colorization approach is proposed with user interactions by Zhang *et. al*., [11], which allows users to alter the color at any position.

Recently, some methods using conditional GANs to colorize gray-scale images have been proposed. Isola *et. al*., [12] recommends using conditional GANs with a U-Net [13] based generator for matching an input picture to an output picture. They use a combination of the L1-loss and a modified GAN loss to train their network. Nazeri *et. al*., [2] offer a modification that includes high-resolution pictures while also speeding up and stabilizing the training process. To produce a variety of colorizations, Cao *et. al*., [14] use conditional generative adversarial networks that sample the input noise multiple times. Kiani *et. al*., [15] colorize gray-scale images using CGAN and a transfer learning method.

In this study, a CGAN model for fully automated gray-scale picture colorization is suggested. It is tested on a new benchmark for ancient Egyptian paintings.

3. Proposed Approach

3.1 Architecture

Our model, which is implemented as a conditional generative adversarial network (CGAN), is depicted in figure 1. Traditional GAN is inapplicable to the automated colorization problem since the inputs to our problem are grayscale images rather than noise. In conditional GAN, generating an output is based on a condition and the generator input is treated as zero noise with a gray-scale input as shown in figure 2.

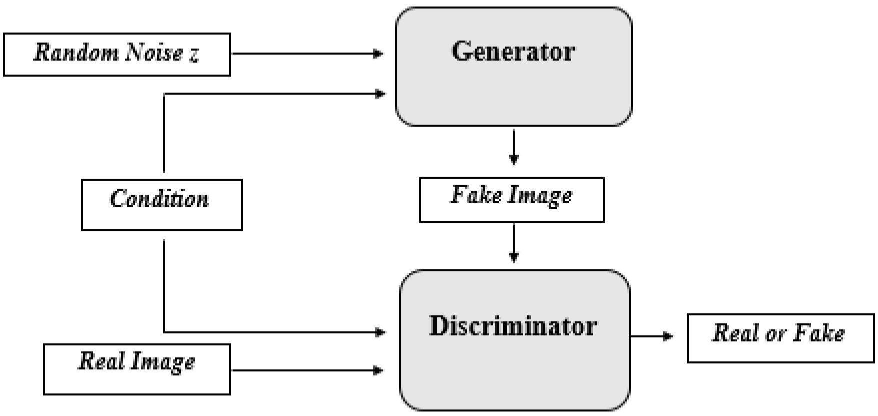

Fig. 2. CGAN Architecture

Two distinct neural network models make up the architecture: a generator (G) and a discriminator (D). In both the generator model and discriminator model, Convolution-Batch Normalization-ReLU layers are used, as is usual in deep CNNs.

The generator model creates a translated version of an image when given an image as an input. A specified input picture and a true or created paired picture are fed into the discriminator model. The discriminator model has to find out if the paired picture is true or not. It's also important to note that the generator's training aim is to confuse a discriminator model in order to minimize the difference between generated and anticipated target pictures. This is seen in figure 1. Ultimately, after training, only the generator network is kept after training to generate future colorizations.

3.1.1 Generator Model.

The U-Net [13] is utilized to design the generator model. We used U-Net instead of the standard Encoder-Decoder structure as it allows low-level information to be streamlined across the model. Skip connections are used to connect layers in identically sized encoded and decoded feature maps. Convolutional layers downsample the input source image to a bottleneck layer using a 2 × 2 stride in the encoder section of the model. The model's decoder reads the bottleneck output and upsamples it to the necessary output image size using transposed convolutional layers. The Generator takes a gray-scale ancient painting image (source image) and generates a colored image (target image) as shown in figure 3.

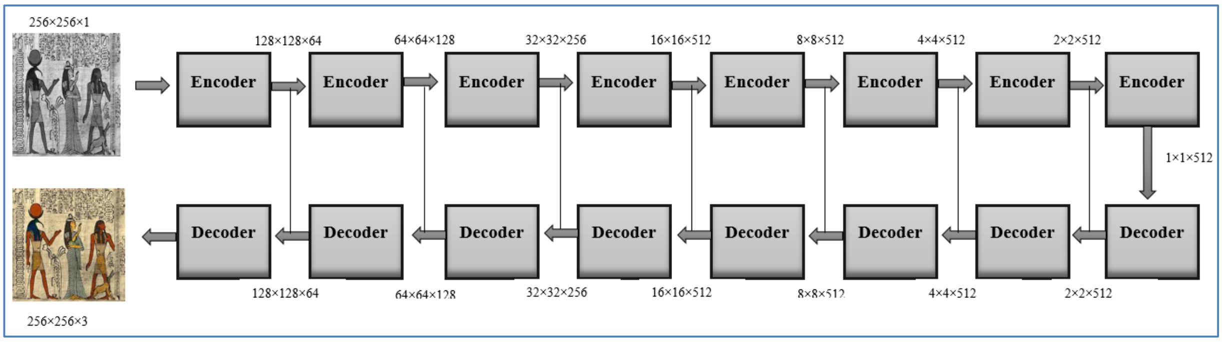

Fig.3. U-Net Generator Architecture

1.1.2. Discriminator Model.

The discriminator network is based on the Markovian discriminator architecture (PatchGAN [12]) and performs conditional-image classification. Using a picture from the source domain (grayscale ancient painting image) and a color picture from the target domain, the discriminator model predicts whether the color image is true or not. The discriminator's design is identical to the generator's first five levels.

4. Experiments and Discussion

4.1 Dataset and Training

The dataset used in this model is ancient Egyptian paintings images. The data is presented in the form of paired pictures, with gray-scale photos of ancient Egyptian artwork on one side and color images on the other. Each image has a resolution of 512×256 (width × height).

We aggregated a large number of Ancient Egyptian paintings on tomb walls images. In training, we use 1,000 images; validation uses 250 images; and testing uses 250 images. The images are in JPEG format.

The model is designed to take and create color images with a size of 256 × 256 pixels and may also be used to input images of other sizes. The implementation will utilize the Keras [16] deep learning framework based directly on the model.

4.2 Evaluation Metrics

There are three types of assessment metrics that have been used on the generated image; SSIM, MSE, and PSNR. The average difference between pixels across the image is the MSE. The disparity between the actual image and the generated image is significant when the MSE is large. Peak Signal to Noise Ratio (PSNR) is computed by comparing the PSNR values of the generated and actual pictures. The image appearance is better when the PSNR value is higher. Structural Similarity Index (SSIM) is evaluated by taking the pixel density values of both images. A score of 1 indicates that the images are similar and a score of -1 indicates that they are different.

4.3 Results

We input several images into the generator model once it was trained. figure 4 shows colorization results from our suggested technique with 100 and 130 epochs, as well as results from the existing most recent methods: Federico *et. al.*, [17], Zhang *et. al.*, [18], and Lizuka *et. al.*, [10]. To make a comparison between them, below each image we compute the MSE, SSIM and PSNR values of the generated images with respect to the actual.

Table 1 shows the outcomes of the experiments. We can see that our MSE, SSIM, and PSNR values are often greater in practice than those produced by [17, 18, and 10]. Furthermore, comparing them of our two variants epochs, the greatest one is obtained by 130 epochs. Our model produces high-quality colorization results, as demonstrated by numerical and visual comparisons.

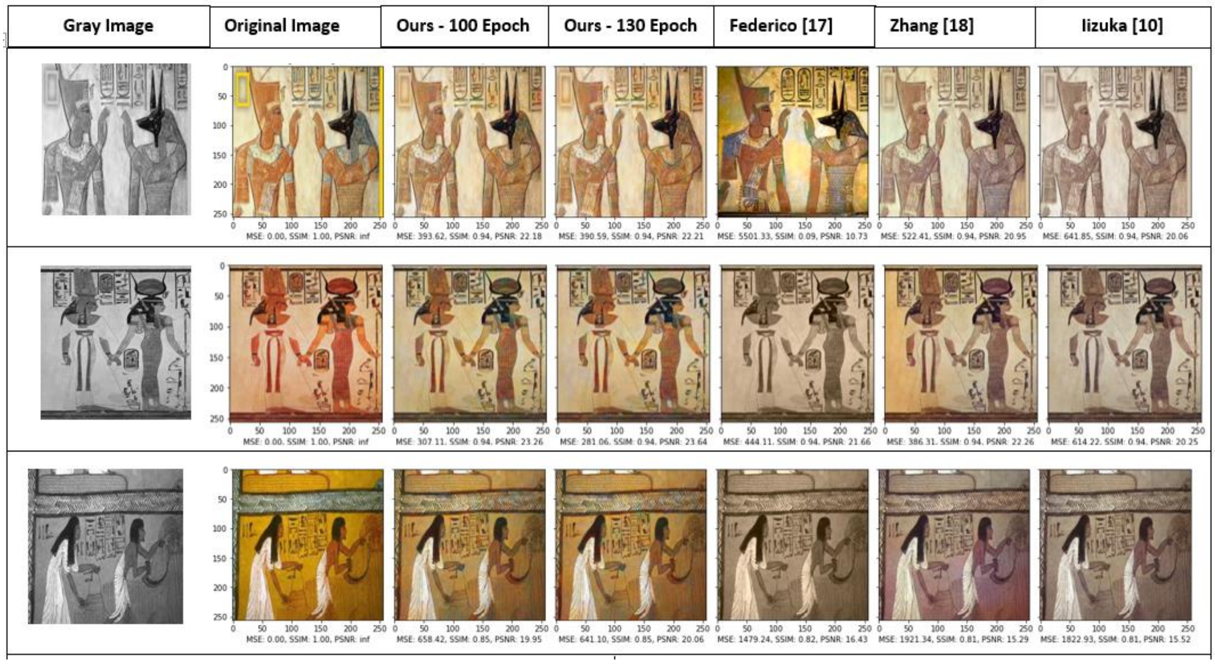

Fig. 4. Comparison of our colorization network's performance with those of other techniques, from right to left: Gray image, Ground truth, our model with 100 Epoch, our model with 130 Epoch, Federico [17], Zhang [18] and Iizuka [10].

Table 1
A numerical comparison of several colorization techniques is performed

	MSE	SSIM	PSNR
Ours – 100 Epoch	**658.42**	**0.85**	**19.95**
Ours – 130 Epoch	**641.10**	**0.85**	**20.06**
Federico [17]	1479.24	0.82	16.43
Zhang [18]	1921.34	0.81	15.29
Iizuka [10]	1822.93	0.81	15.52

5. Conclusion

The paper proposes a conditional GAN-based automated image colorization technique. It takes gray-scale ancient painting images as input and generated color images as output. The network model is trained in the GPU environment using aggregated ancient Egyptian painting images as a training dataset. Through experimental comparison, our model can achieve a better image colorization result, with lower MSE, greater PSNR, and SSIM than the original colorization when compared to different colorization methods.

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