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Applying a Gaussian blur filter to Grayscale Photos and Videos

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ABSTRACT— Colorization refers to the process of turning grayscale photos into visually appealing color pictures. The main goal is to make the audience believe that the result is real. Typically, images of natural settings are captured in grayscale and need coloring. There has been a wide range of colorization systems developed over the last 20 years, from very basic algorithms that still need a lot of energy and effort from humans to extremely complex algorithms that are both more automated and more labor-intensive. Art, machine learning, and deep learning are only a few of the many fields that have contributed to the difficult process of automated conversion. We detail a novel approach to automatically adding color to monochrome images or videos by combining features of the GAN and U-Net models. It is possible to train the model to learn picture colorization from an existing U-Net using this technique. To further combine the local information results based on smaller picture patches with the inclusive priors based on the whole image for each class, the Fusion layer is executed. In addition, the proposed method colors the whole video sequence with little user intervention; color markers need only be applied to a few of reference frames. Because of this, the colorization outcomes are more visually appealing. Finally, we compare our method to the state of the art and conduct an assessment based on user research to verify it. This allows us to make changes.

INTRODUCTION

How it works Adding color to a previously grayscale movie or picture not only gives it new meaning, but it also makes the photo's growth seem more alive and emotional. People can quickly figure out what color something should be by using the knowledge they have about the things in the image and their relative importance. The reason for this is because an image usually has many distinct elements. Contrarily, most items come in more than one hue; for instance, a garment might be red, blue, yellow, or any combination thereof. People may also use their subjective emotions to guess what colors things will be. People are able to make color predictions because of this skill. One of the hardest things for a computer to do is to simulate human emotions and knowledge, which is no easy feat. As a result, users were usually involved in some way with previous colorization systems, whether it was adding color points to provide background information or transferring colors from reference grayscale photos. Users may have been obligated to accomplish one or both of these things, for instance. It is time-consuming to draw color points and much more time-consuming to choose a picture that has all the required object features. A lot of time is needed for each of these procedures.

When a picture is loaded, we get back a rank-3 array with the dimensions (height, width, and color) of the picture. We can see the picture's color data on the last axis of this structure. It is possible that you have prior knowledge of this subject. In a color space called RGB, each pixel is associated with three integers that together form a color. You can see the relative quantities of red, green, and blue in the pixel by looking at these values. The next picture clearly shows that the "primary image" (the left half of the image) has a blue tint.The region now seems darker as a result of the increased values in the blue channel of the picture. This is made clear when you compare the current picture with the one that follows. The picture over there on the left makes this quite obvious.

A single pixel in the color space L*a*b is represented by three integers, but this time each of those numbers is associated with a different property. Because the first number (channel) L, which encodes the brightness of each pixel, is a lowercase letter, the picture we see when we view this channel (the second image in the row below) seems to be monochromatic. Since L is a lowercase letter, this is the result. Encoding the green, red, and yellow-blue ratios contained inside each pixel is the responsibility of the a and b channels. In order to examine each channel separately, the following graphic gives an examination of the L*a*b color space. In every colorization application we looked at and every colorization article I read, the models are trained using the L*a*b color space rather than the RGB color space. The majority of computer displays utilize the

RGB color space, which is different from this. Although several factors contributed to our final decision, I will provide you with an overview of why we have chosen this option. Loading a picture often results in a rank-3 (height, width, color) array, where the color data is stored on the last axis. Each pixel's RGB color representation is defined by three numbers: the pixel's Red, Green, and Blue values. As you can see in the next picture, the blue channel of the image has greater values and has rendered that area of the "main image" (the leftmost image) black because of the blue hue.

Related works:

Scribbled base colorization

Colorization using Optimization (Levin et al). This approach to colorizing black and white images was done using shallow machine learning models. The system divided the matrix into clusters of same intensity and colored it accordingly. The color range was provided as an input to the model. This model produced unexpectedly accurate results. The drawback of these models is intensive manual work and professional skills for providing good scribbles.

Deep Learning Based Colorization

Colorful Image Colorization (Zhang et al) This model owes its architecture to Lizuka et al's Let there be color Given the luminance component of an image, the model estimates its b* components and combines them with the input to obtain the final estimate of the colored image. Instead of training a feature extraction branch from scratch, it makes use of an InceptionResNetv2 network (referred to as Inception hereafter) and retrieves an embedding of the gray-scale image from its last layer. Although only trained to color, the network learns a representation that is surprisingly useful for object classification, detection, and segmentation, performing strongly compared to other self supervised pretraining methods.

METHODOLOGY

Upload image: using this module, uploading the image to convert into colorization.

Upload Video: Using this module, uploading the input video and generating image frames for that video

Run GAN: Using this module, GAN applied on images and videos converting them into colorization.

RESULT AND DISCUSSION

In above screen, left side photo is input image then converting into colorization using GAN.

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CONCLUSION

By merging a pretrained u-net with a generative adversarial network, we have created a novel architecture for the automated coloring of grayscale photos. Using a large dataset of landscape images, we discovered that our model outperformed the competition in terms of colorization while keeping the user study assessment value same. Colorizing images and videos with GANs is a tough but potentially lucrative endeavor. We can produce high-quality color photographs that are almost identical to the originals with the correct dataset, architecture, and training procedure.

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