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Image Revivification System using GAN

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ABSTRACT: Converting a colored picture into black and white is a common process nowadays using various filters, but the reverse is not as easy as it seems. Colorization of black and white images is a difficult task. It does not work well when done manually by using various software like photoshop as it takes a lot of time on the research as well as conversion. Therefore, this system takes grayscale images as input and converts them into colorful images as output using deep learning to solve for possible colors by combining features from multiple colored images with a small dataset and really short training times. The purpose of this method is to reduce the number of handicrafts needed to color the image. Image features can be automatically extracted from training data using deep learning models. This can be accelerated by using the Generative Adversarial Networks (GAN). We use image coloring using Advanced Neural Networks and cGAN models while using pre-trained models to produce better features..

KEYWORDS: Deep Learning, Conditional GAN, Colourizer, U net, Advanced Neural Networks.

I. INTRODUCTION

Image colorization is the process of assigning colors to grayscale images to make the image more aesthetically appealing and perceptively meaningful. This is known to be a sophisticated task that often requires prior knowledge about the image content and manual adjustments to achieve artifact-free quality. Also, because objects can have many different colors, there are many ways to assign colors to pixels in an image, meaning there is no universal solution to this problem. There are two main approaches for image colorization: one that requires the user to assign colors to some regions and extends such information to the whole image, and another the one that tries to learn the color of each pixel from a color image of similar content. In ancient times, when photography began, most of the images were black and white. As a result, efforts began to colorize old black and white images to give images different perspectives and capture beautiful moments. Coloring attempts began with paints and brushes in the early 1900s. This painstaking process took days, and sometimes weeks, to create a rough replica of reality. The trend is shifting towards using computer software such as Adobe Photoshop, and GIMP, but the process is the same. Today's techniques for manually coloring these black and white images are cleaning the image, adjusting the tones and contrasts of the image, converting the image to RGB, and finally spotting color to a specific object in the image. It is an addition. However, even digital coloring using software like Photoshop has helped to color every pixel, improving the handling of gradients and color, and reducing manual labor to some extent. But now it seems like a tedious task. Currently, thanks to the color camera, a huge photo gallery is available. It provides a wealth of information for determining the color scheme of common objects, scenes, lighting conditions, and color intensities.

II. RELATED WORK

Izuka et al. [1] In this paper you have combined two networks, one predicting global features of input image and more to customize the local features of input images. World wide network features are trained in image classification as well is directly connected to the network of local features available he was then trained in color photography using L2 Euclidean job loss. Richard Zhang [2] In this paper he presents optimized solution by taking a large data set and one forward transfer pass on CNN. They used custom multinomial cross entropy loss of re-class balance and use of people as subjects they were able to deceive 32% of them with their results. See using the previous color distribution obtained from the training set on it predict the distribution of each outgoing pixel.

Baldassarre et al. [3] In this paper you create a network model which incorporates deep CNN architecture, trained from scratching, with the previously trained Inception-Resnetv2 model of high quality feature background. They train this network in a small set of 60,000 images from ImageNet. This structures similar to those used by Iizuka et al. [1] also and uses the Euclidean (L2) loss function.

III. METHODOLOGY

In the recent past, many dissimilar solutions have been lodged to colorize images by using deep learning. Colorful Image Colorization paper approached the problem as a categorization task and they also contemplated the unpredictability of this problem. Image-to-Image Translation with Conditional Adversarial Networks paper, advancement in general solution to many image-to-image tasks in deep learning which one of those was colorization. In this perspective two losses are used: L1 loss, which makes it a regression task, and an adversarial (GAN) loss, which helps to resolve the problem in an unsupervised manner. In a GAN we have a generator and a discriminator model which learn to resolve a problem in conjunction. In this setting, the generator model takes a grayscale image (1-channel image) and produces a 2-channel image, a channel for *a and another for *b.

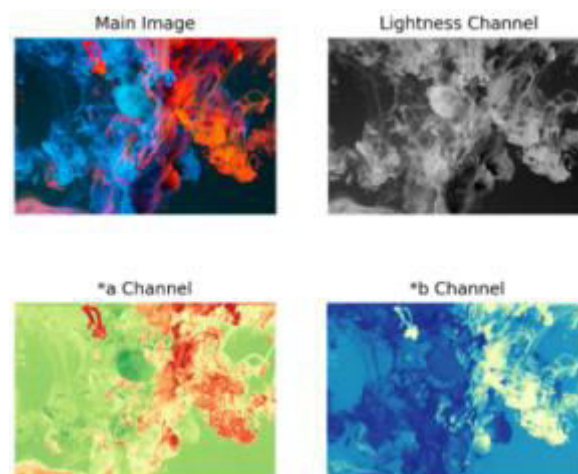


Fig. 1. Channel of L*a*b color space

The discriminator takes these two constructed channels and concatenates them with the input grayscale image and concludes whether this new 3-channel image is fake or real. Certainly, the discriminator also requires to see some real images (3-channel images again in Lab color space) that are not produced by the generator and should grasp that they are real. The grayscale image that both the generator and discriminator see is the ambiance that we furnish to both models in our GAN and expect that they consider this condition

IV. EXPERIMENTAL RESULTS

We used mean absolute error (MAE) and accuracy as performance indicators. The mean absolute error of the generated and source images on a pixel level for each color channel is used to calculate MAE. The ratio of pixels with the same color information as the source to the total number of pixels is used to calculate accuracy. Any two pixels are deemed to be the same color if their underlying color channels are within a certain distance of each other. This is expressed mathematically by a mathematical formula where $x \in \mathbb{R}$ is the indicator function, y is the matching color image, and it is a function mapping from grayscale to color images. The images produced by GAN were noticeably

better in terms of visual quality than those produced by the baseline CNN. The colors in the photographs created by GAN were more bright, but the results from CNN had a light tone. The GAN was able to nearly recreate the ground truth in some circumstances. One disadvantage was that the GAN tended to colorize objects in the colors that were most frequently encountered.



Fig. 2. Gray Scale images to colored images (a) Original grayscale image (b) Colored Images

V. CONCLUSION

In this work, we prospected the quantitative and qualitative results of colorization using image colorization as a deputy task for ocular understanding. Even though GAN is very demanding, the generated images are much better in terms of color, radiance, and severity. Current and relevant research was first inspected and differentiated and to achieve that the previous self-supervised learning methods were instructed and assessed on the same data files. The GAN model was able to spawn images on training on grayscale inputs. Grayscale input surrenders better colorization results than using edge-only input due to the supplementary information it accommodates. Then, conditional generative adversarial networks were dispensed as a way to instruct an image colorizer for the motive of visual feature learning. The experiments were successfully analyzed and demonstrated that the models starting from the pre-trained colorization weights showed better conduct than the models trained from scratch without such initialization. Therefore, we can conclude that self-supervised visual feature learning by using cGANs on the image colorization task is notable for further consideration and has the perspective of being similar to the traditional supervised pre-training.

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