International Journal of Scientific Research & Engineering Trends
Volume 5, Issue 6, Nov-Dec-2019, ISSN (Online): 2395-566X

Image Colorization Using Deep Learning

Abhishek Thakur abhishekthakur237@gmail.com
Sumit Pandey sumitp2398@gmail.com
Priyanka Dusane pkdusane@gmail.com
Nidhi Sharma nidhipranjan@gmail.com
Dept. of Computer Engineering
Bharati Vidyapeeth College of Engg
BelpadaNavi Mumbai, India

Abstract **-The idea of colorizing black and white films and pictures is a very old notion dating back to 1902. Today it is accepted as enrichment to the art form. Today, colorization is usually done by hand in Photoshop and other software. This takes a lot of time and proficiency. In short, an image can take up to one month to colorize. It requires considerable research. A face alone requires up to 20 layers of pink, green and blue shades to get it just right. In this project we are attempting to recolor B/W or Grayscale images using Convolution Neural Networks. This survey paper covers a few techniques that automate the task of recoloring desaturated images. These techniques employ the use of image processing and machine learning to achieve the desired outputs.**

Keywords-**Colorization, Vision for Graphics, CNNs, Selfsupervisedlearning.**

I. INTRODUCTION

Let's first define the colorization problem in terms of the CIE Lab color space. Like the RGB color space, it is a 3channel color space, but unlike the RGB color space, color information is encoded only in the (green-red component) and b (blue-yellow component) channels. The L (lightness) channel encodes intensity data only. The grayscale image we want to color can be thought as the L-channel of the image in the Lab color space and our objective to find the and b components. The Lab image so obtained can be transformed to the RGB color space using standard color space transforms. For example, in OpenCV, this can be achieved using cvtColor with COLOR_BGR2Lab option.

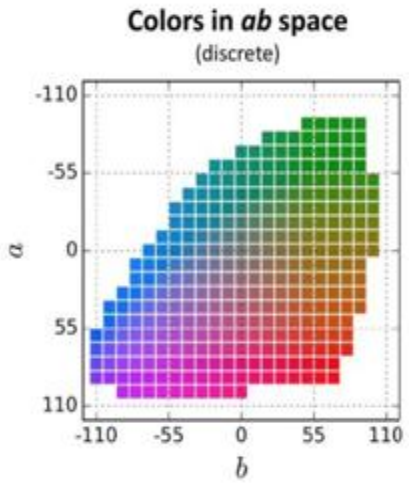

Fig. 1 ab Color Space

To simplify calculations, the ab space of the Lab color space is quantized into 313 bins as shown in Figure 2. Instead of finding the a and b values for every pixel, because of this quantization, we simply need to find a bin number between 0 and 312.Yet another way of thinking about the problem is that we already have the L channel that takes values from 0 to 255, and we need to find the ab channel that takes values between 0 to 312. So the color prediction task is now turned into a multinomial classification problem where for every gray pixel there are 313 classes to choose from for classification.

II. LITERATURE SURVEY

1. Scribbled Based 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.

Fig. 2 Scribbled Based Colorization .

2. Deep Learning Based Colorization - I

© 2019 IJSRET

Deep Koalarization Image Colorization using CNNs and Inception-Resnet-v2(Baldassarre et al)
This approach was intended to remove the effort giving the inputs to the model. In this system, the coloring model was based on neural networks which were trained on a training set of images. This automated the coloring process and 30% of the outputs gave satisfactory results. Also the neural networks based model required as less as 20 images to be able to colour images.

Fig. 3 Deep Learning based Colorization I

3. Deep Learning Based Colorization - II

Colorful Image Colorization (Zhang et al)
This model owes its architecture to Lizuka et al'sLet 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 Inception-ResNetv2 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 pre-training methods.

Fig. 4 Deep Learning Based Colorization - II

III.ANALYSISOFSTUDIEDSYSTEMS

1. Colorized pictures aren't environment aware
In systems where unguided algorithms are used the model tends to color parts that have same lighting to the same color. This is because the model is not able to locate borders and patterns in the image due to consideration of one pixel during prediction of color. This resulted in mixing of colors in and along the borders of objects.

2. Classification problem becomes very complex
Guided systems are accurate with borders but fail to color around tiny spaces as the user has not given any input for the section. At this point the classifier has 256 classes (colors) to classify the pixel into. This increases the load on classifier and decreases the quality of output along with causing long running time.

3. Difference from the state-of-the-art colorization methods and those using CNNs
The previous algorithms typically use one similar reference image or a set of similar reference images from which transfer color values to the target gray image. Deep Learning based method is the state-of-art example-based method as it outperforms others in performance and application scope. However, its performance highly depends on given reference image as demonstrated in their works. DNN based method can obtain a very good colorization result using a reference image containing identical object(s) as the target grayscale image. However, when the reference image is different from the target, its performance is quite low. To minimize the high dependence on a suitable reference image, CNN utilizes a large reference image database. It "finds" the most similar pixel from the database and "transfers" its color to the target pixel. This is why this approach is robust to different grayscale target images.

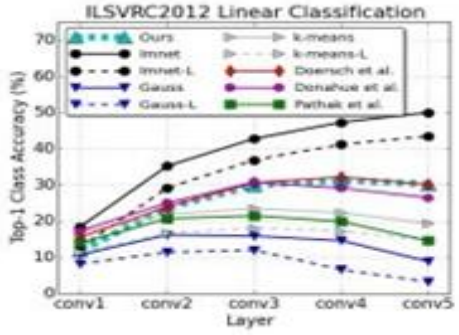

Fig.5. Accuracy graph.

IV. CONCLUSIONS

This paper reviews a few of the novel, full-automatic colorization methods using deep neural networks to minimize user effort and the dependence on the example color images. Informative yet discriminative features including patch feature and a new semantic feature are extracted and serve as the input to the neural network. The output chrominance values are further refined using

© 2019 IJSRET

joint bilateral filtering to ensure artifact-free colorization quality. Numerous experiments demonstrate that our method outperforms the state-of-art algorithms both in terms of quality and speed.

REFERENCES

[1]. G. Charpiat, M. Hofmann, and B. Scholkopf. Auto- ¨ matic image colorization via multimodal predictions. In ECCV, pages 126–139. Springer, 2008. 1, 2, 6, 7.
[2]. D. Comaniciu and P. Meer. Mean shift: A robust approach toward feature space analysis. PAMI, 24(5):603– 619, 2002. 7.
[3]. C. Dong, C. C. Loy, K. He, and X. Tang. Learning a deep convolutional network for image superresolution. In ECCV, pages 184–199. Springer, 2014. 1.
[4]. E. S. Gastal and M. M. Oliveira. Domain transform for edge-aware image and video processing. In TOG, volume 30, page 69. ACM, 2011. 5.
[5]. R. K. Gupta, A. Y.-S. Chia, D. Rajan, E. S. Ng, and H. Zhiyong. Image colorization using similar images. In ACM international conference on Multimedia, pages 369–378. ACM, 2012.
[6]. Federico Baldassarre, Diego González Morín, Lucas Rodés-GuiraoDeep Koalarization: Image Colorization using CNNs and Inception-ResNet-v2arXiv:1712.03400v1 [cs.CV].
[7]. Levin, Anat&Lischinski, Dani & Weiss, Yair. (2004). Colorization using Optimization. ACM Transactions on Graphics. 23. 10.1145/1015706.1015780.
[8]. Richard Zhang, Phillip Isola, Alexei A. Efros (2016) Colorful Image ColorizationarXiv: 1603.08511v5 [cs.CV].

© 2019 IJSRET