

# TensorFlow Implementation and analysis of Image Colorization

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## 1 Introduction

I have implemented the CNN based image colorization technique as suggested by Satoshi, Edgar and Hiroshi in their 2016 Paper named as “*Let there be Color! : Joint End-to-end Learning of Global and Local Image Priors for Automatic Image Colorization with Simultaneous Classification* (Satoshi Iizuka, 2016)”. I have tried to analyze its result on various datasets.

## 2 Model architecture

I have used the same model architecture as suggested in the original paper with a Low-Level features extraction layer whose output is send to Mid-Level feature extraction and Global feature extraction outputs from both are than fused together in a fusion layer and then sent for deconvolution<sup>1</sup>.

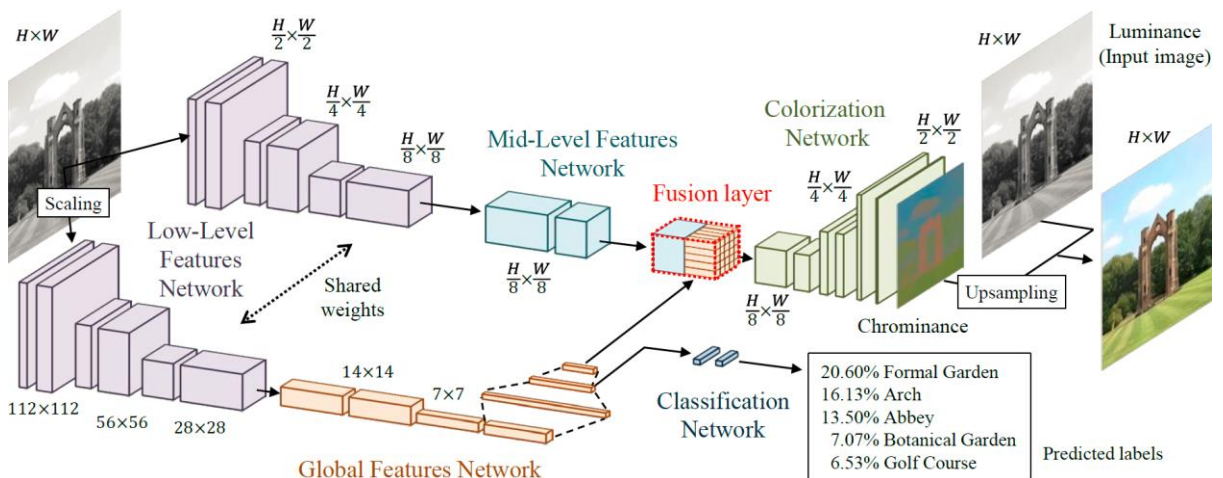


Figure 1 Model Architecture (Satoshi , Edgar, SIGGRAPH 2016)

<sup>1</sup> In original paper it Up Sampling layer was used but I have used 2D deconvolution.

## 2.1 Layer specification

| Low-Level Features Network |              |              |         |
|----------------------------|--------------|--------------|---------|
| Type                       | Kernel       | Stride       | Outputs |
| Conv2D                     | $3 \times 3$ | $2 \times 2$ | 64      |
| Conv2D                     | $3 \times 3$ | $1 \times 1$ | 128     |
| Conv2D                     | $3 \times 3$ | $2 \times 2$ | 128     |
| Conv2D                     | $3 \times 3$ | $1 \times 1$ | 256     |
| Conv2D                     | $3 \times 3$ | $2 \times 2$ | 256     |
| Conv2D                     | $3 \times 3$ | $1 \times 1$ | 512     |

| Colorization Network <sup>2</sup> |              |              |         |
|-----------------------------------|--------------|--------------|---------|
| Type                              | Kernel       | Stride       | Outputs |
| Fusion                            | -            | -            | 256     |
| Conv2DTranspose                   | $3 \times 3$ | $1 \times 1$ | 128     |
| Conv2DTranspose                   | $3 \times 3$ | $2 \times 2$ | 64      |
| Conv2DTranspose                   | $3 \times 3$ | $1 \times 1$ | 64      |
| Conv2DTranspose                   | $3 \times 3$ | $2 \times 2$ | 32      |
| Conv2DTranspose                   | $3 \times 3$ | $2 \times 2$ | 2       |

| Global-Level Features Level |              |              |         |
|-----------------------------|--------------|--------------|---------|
| Type                        | Kernel       | Stride       | Outputs |
| Conv2D                      | $3 \times 3$ | $2 \times 2$ | 512     |
| Conv2D                      | $3 \times 3$ | $1 \times 1$ | 512     |
| Conv2D                      | $3 \times 3$ | $2 \times 2$ | 512     |
| Conv2D                      | $3 \times 3$ | $1 \times 1$ | 512     |
| Flatten                     | -            | -            | -       |
| Dense                       | -            | -            | 1024    |
| Dense                       | -            | -            | 256     |
| Dense                       | -            | -            | 512     |

| Mid-Level Features Network |              |              |        |
|----------------------------|--------------|--------------|--------|
| Type                       | kernel       | stride       | output |
| Conv2D                     | $3 \times 3$ | $1 \times 1$ | 512    |
| Conv2D                     | $3 \times 3$ | $1 \times 1$ | 256    |

## 2.2 Batch Normalization

In order to improve the Learning Time after every convolutional layer I added Batch normalization layer. I found a significant decrease in the learning time.

## 3 Dataset

1. **CelebA dataset**(Large-Scale Celeb Faces Attributes Dataset (Liu, 2015))  
Dataset Contains more than 200k images of celebrity faces from different countries. I used 1000 images from them as training data 200 as validation data and 200 as test data.
2. **Linnaeus 5 dataset** (Chaladze, 2017) .Dataset contains two parts Test and Train, Train contains 6000 classes divide equally between 5 classes and Test contains 2000 images divided equally among 5 classes. I used images of '*flower*' class from the dataset because they were more colorful and thus giving model more colors to learn

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<sup>2</sup> Structure of colorization network is different from original network

## 4 Training

### 4.1 CIE L\*a\*b\* Color Space

Before giving the image as a model to the input I converted the image into CIELAB color space and then used the Lightness value(L) as input which is effectively gray scaled image than output channels were selected 2 as given in model architecture.

This restricts us to predict only two channels. Predicting three channels would have been difficult for our model

### 4.2 Accuracies

1. For CelebA dataset : Total 200 epochs with 100 steps per epoch and batch size 50.

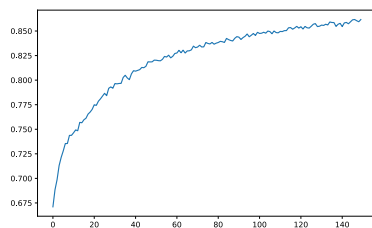


Figure 2 Accuracy vs number of epochs 0 to 150 epoch (CelebA)

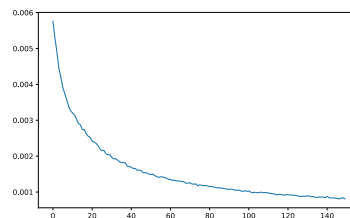
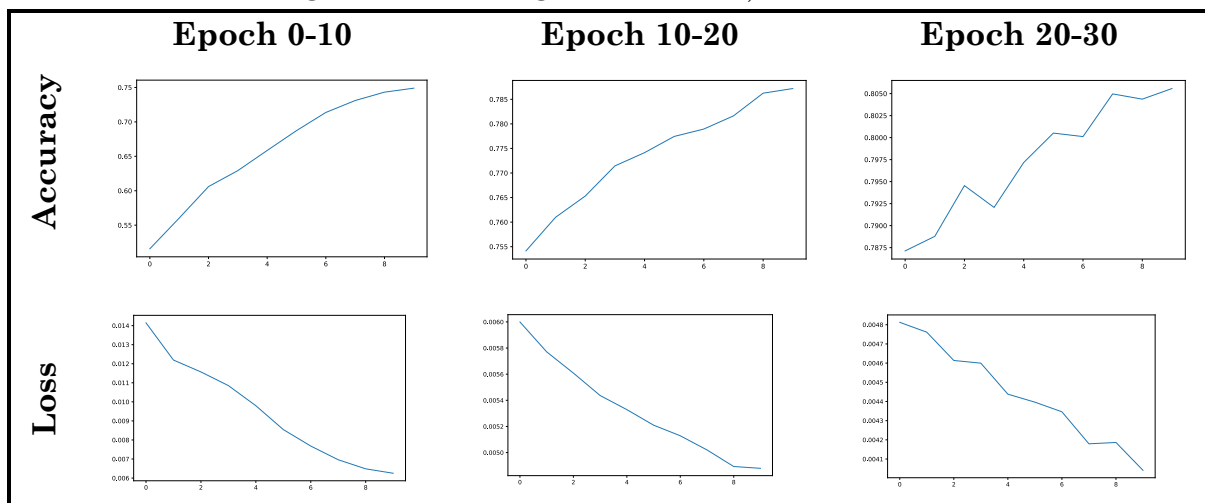


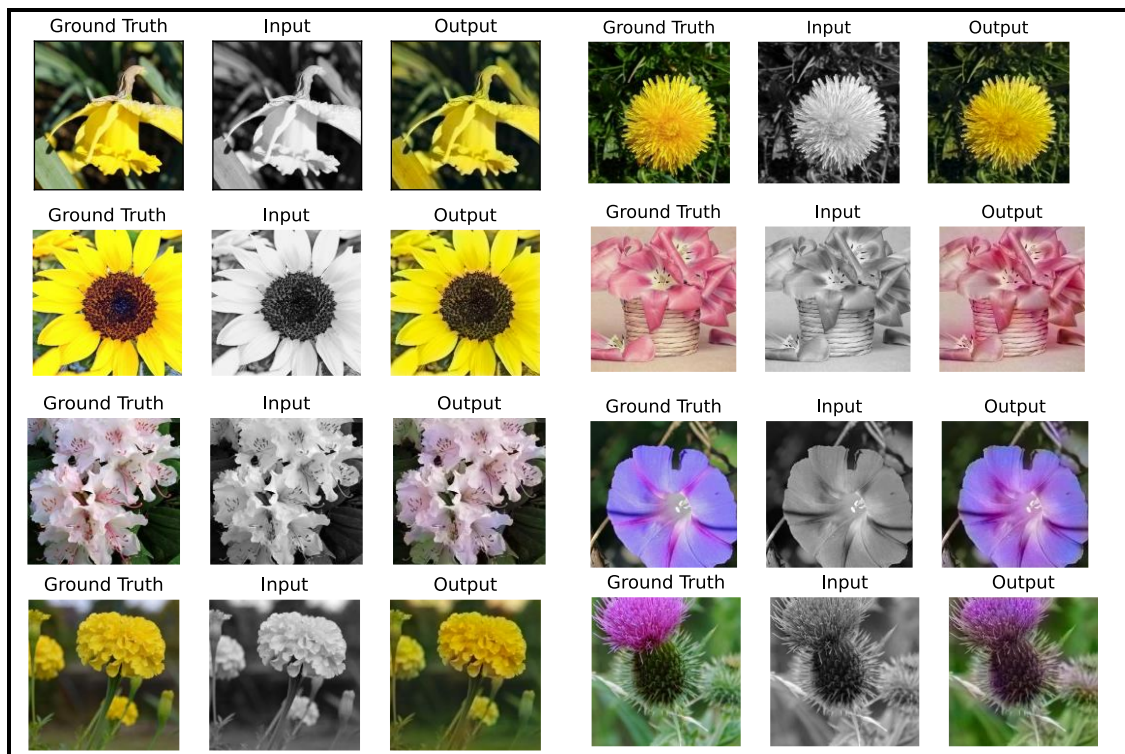
Figure 3 Loss vs Number of Epochs 0 to 150 epoch (CelebA)

2. For Linnaeus 5 dataset: 30 epochs 100 steps per epoch with batch size 50 (1hr 20 min training time with Google Colab GPU)

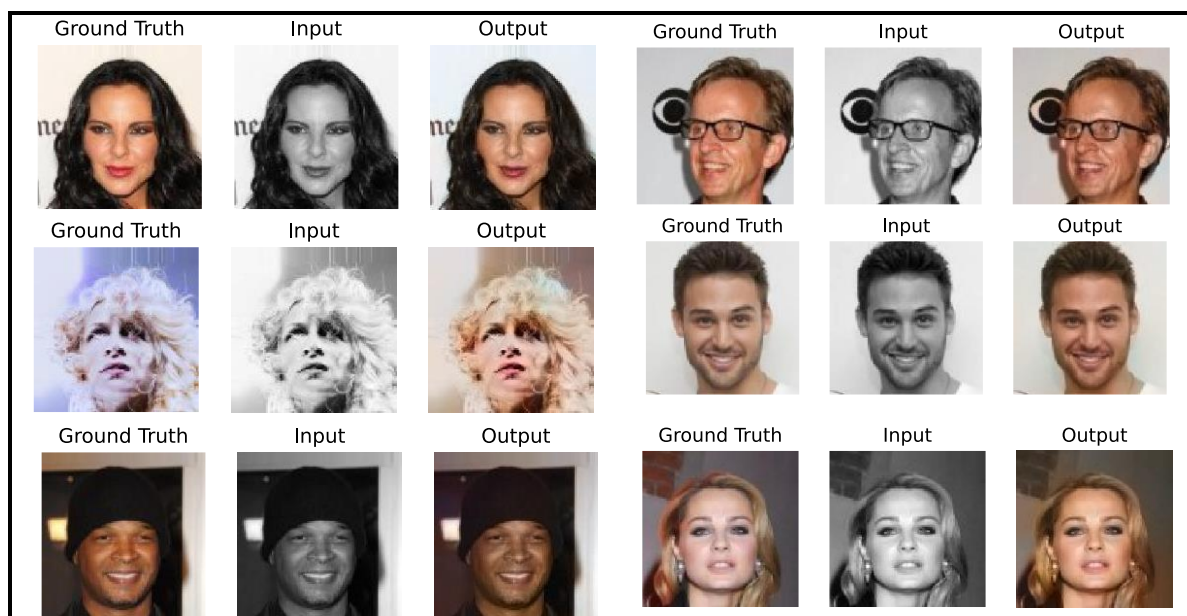


## 5 Results

### From Linnaeus 5



### From CelebA



## 6 Works Cited

1. Chaladze, G. K. (2017). *Linnaeus 5 Dataset for Machine Learning*. Retrieved from <http://chaladze.com/l5/>

2. Liu, Z. a. (2015). *Deep Learning Face Attributes in the Wild*.
3. Satoshi Iizuka, E. S.-S. (2016). *Let there be Color!: Joint End-to-end Learning of Global and Local Image Priors for Automatic Image Colorization with Simultaneous Classification*. *ACM Transactions on Graphics (Proc. of SIGGRAPH 2016)*, 35(4), 110:1--100:11. Retrieved from <http://iizuka.cs.tsukuba.ac.jp/projects/colorization/en/>