Exemplar Colorization

01.

Introduction

What is the aim of this task and why it is important. Plus, what are the other related works in the same area.

02.

Network Structure

Structure of different parts of the network.

03.

Training Details

Hyperparameters, loss and other assumptions for training.

04.

Results

Representing the results of our implementation.

Introduction

What is the aim of this task and why it is important. Plus, what are the other related works in the same area.

01.

Introduction

- Colorization aims to add color to a gray image.
- This task is popular because it can make images more visually plausible and perceptually meaningful.
- It has colossal applications in practical usages.
- There are no unique answer when dealing with such problems

Related Works

Scribble-based Colorization

Exemplar-based Colorization

Learning-based Colorization

Hybrid Colorization

Scribble-based Colorization

- Are interactive methods that propagate the initial strokes to the whole grayscale image.
- Uses low-level similarity metrics for propagation.
- It is capable of providing plausible colorization results when given good prior colors.
- Faces the challenge of an unprofessional colorization.

Exemplar-based Colorization

Global Transfer Method

By matching global color statics the transformation of color from the reference image to the target one is performed.

Local transfer Method

Considers different level of correspondences,
such as pixel level, superpixel level, and segmented region level.

Exemplar-based Colorization

- Since the spatial pixel information is ignored, the results are unrealistic.

- They are susceptible to generate terrible results when the two images have various appearances but perceptually similar semantic structures.

Learning-based Colorization

- Reconstruct an image by predicting every pixel of the target image with loss functions.

- Learn the parameters of the network from huge image dataset automatically without any user intervention.

- Results are uncontrollable without any user interactions.

Hybrid Colorization

01

Combining scribble-based methods with learning based methods by providing strokes.

02

Utilizing histogram of reference image as a guidance for colorization by pyramid structure network

03

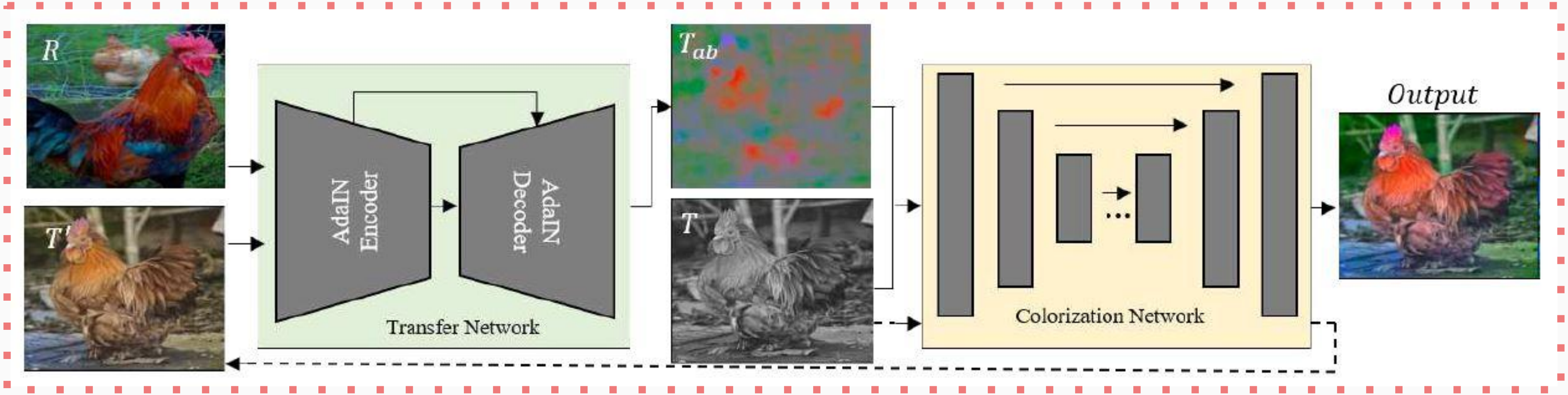
Implementing a similarity network to build bidirectional mapping.

Network Structure

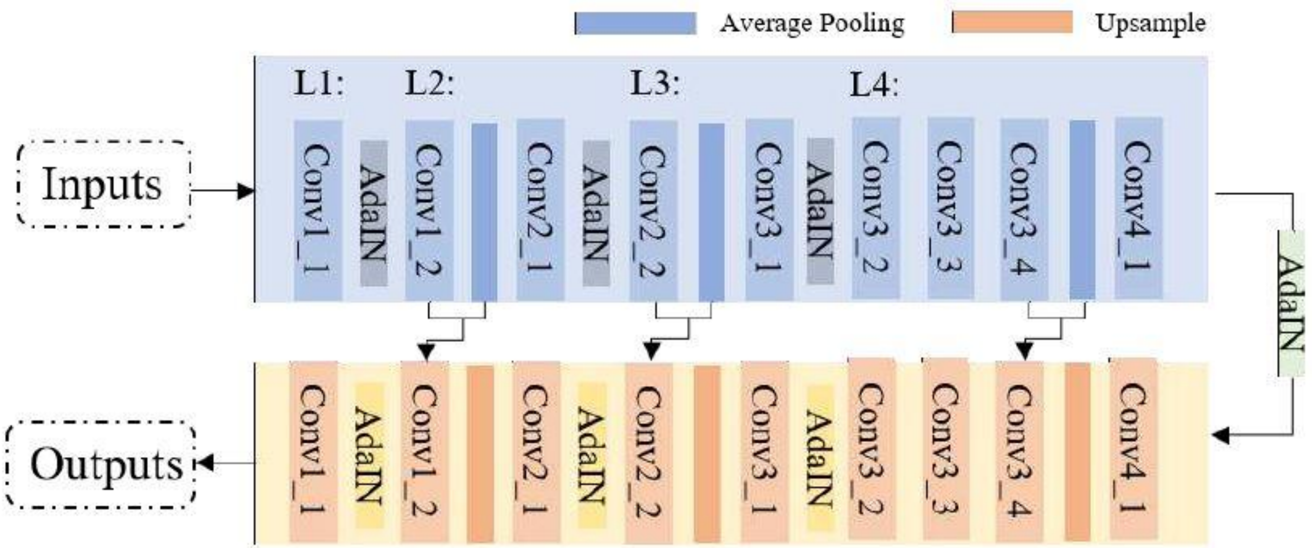
Structure of different parts of the network.

02.

Stylazation-Based Colorization

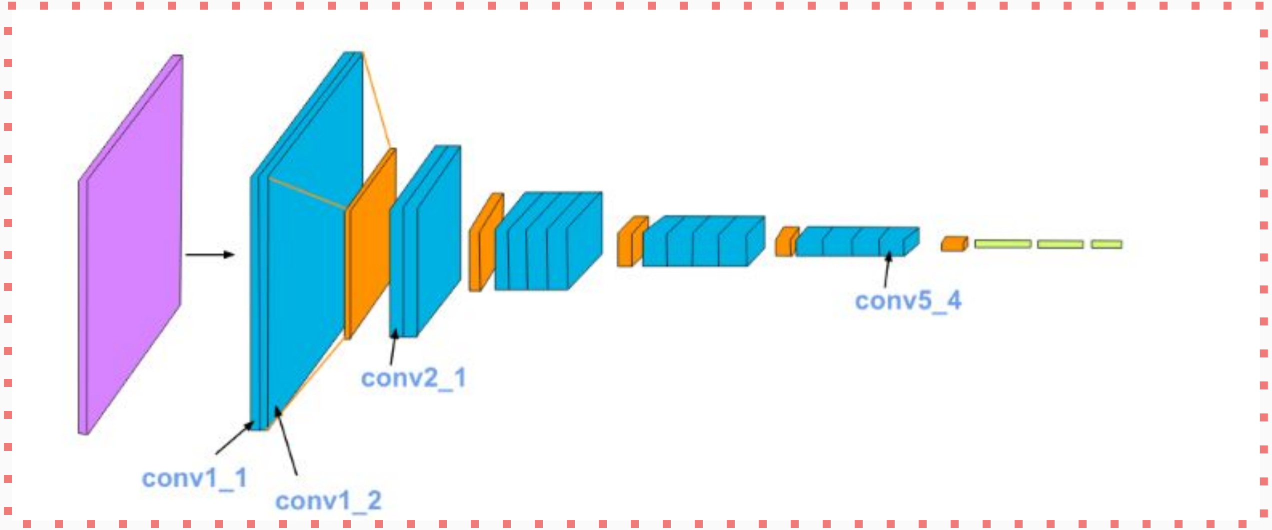


Transfer Sub-Net



Transfer Sub-Net: Encoder

A VGG19 is employed with some alternations.



Style Transfer

Content: Objects and their arrangement

Style: colour and texture

vgg19.features: Convolutional and pooling layer

Transfer Sub-Net: VGG Alternations

01

Replacing Max-Pooling with Average Pooling

02

Adding Skip Connections

03

Adding Adaptive Instance Normalization

Adaptive Instance Normalization

- AdaIN is a normalization method that aligns the mean and variance of the content features with those of the style features.

$$AdaIn(x, y) = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y)$$

- Unlike BN or IN, AdaIN has no learnable affine parameters. Instead, it adaptively computes the affine parameters from the style input.

Transfer Sub-Net: Decoder

- This module needs to be implemented and trained thoroughly.
- The decoder, consists of four slices.
- This input consists of the output of convolution layer from encoder and the output of the up-sampling layer.

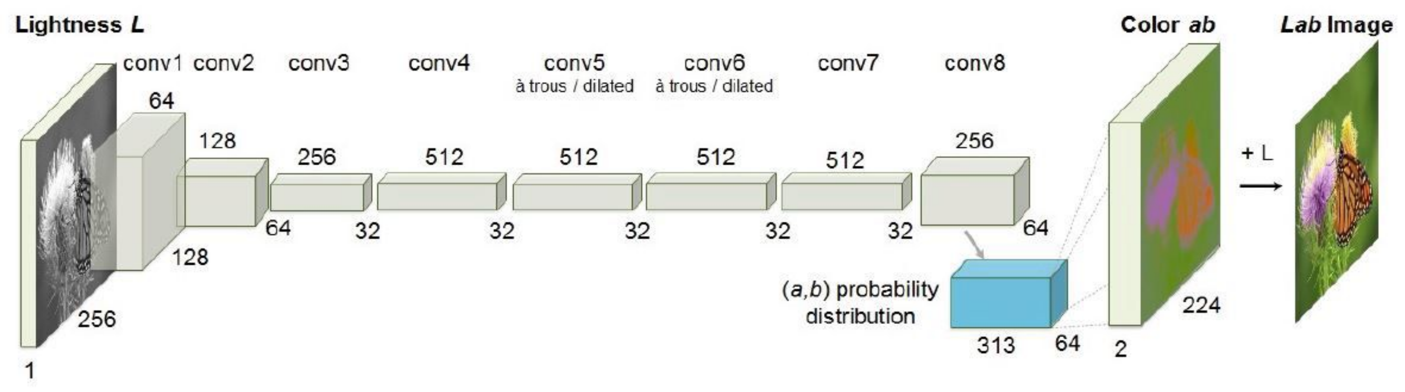
Colorization Network

- Hallucinating colors of a gray image seems daunting, since much of the information has been lost.
- The semantics of the scene and its surface texture provide ample cues for many regions in each image.
- All kinds of semantic priors do not work for everything.

produce a plausible colorization that could potentially fool a human observer.

Colorization Network: Method 1

- An encoder-decoder structure is implemented.
- Multinomial cross-entropy loss is used instead of L_2

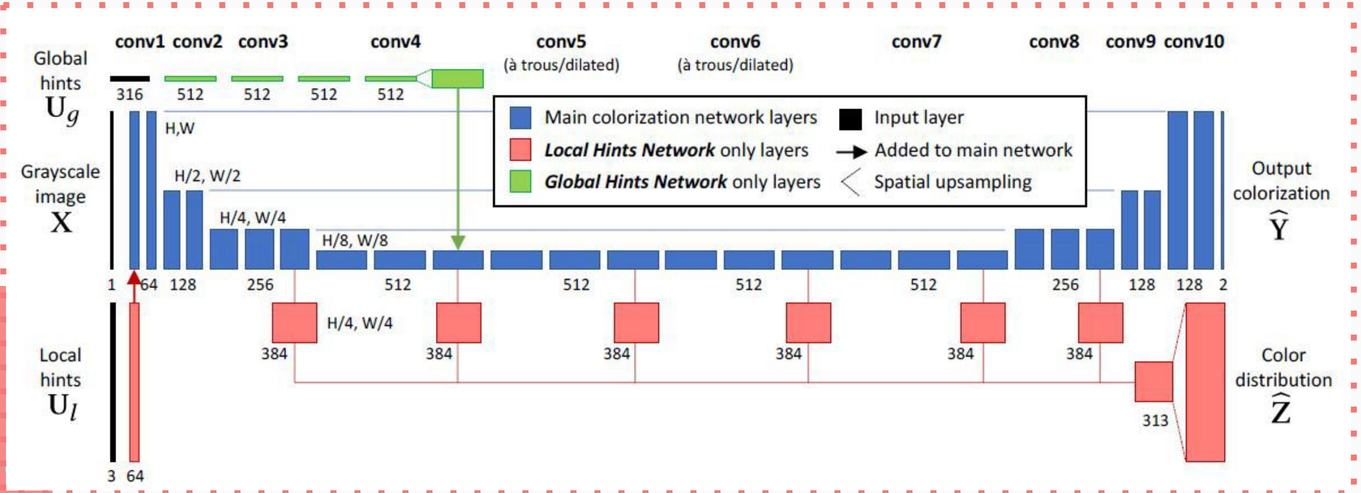


Colorization Network: Method 2

- Human intervention is added.

Random Mask

- *Smooth* L_1 loss is used to train the network.

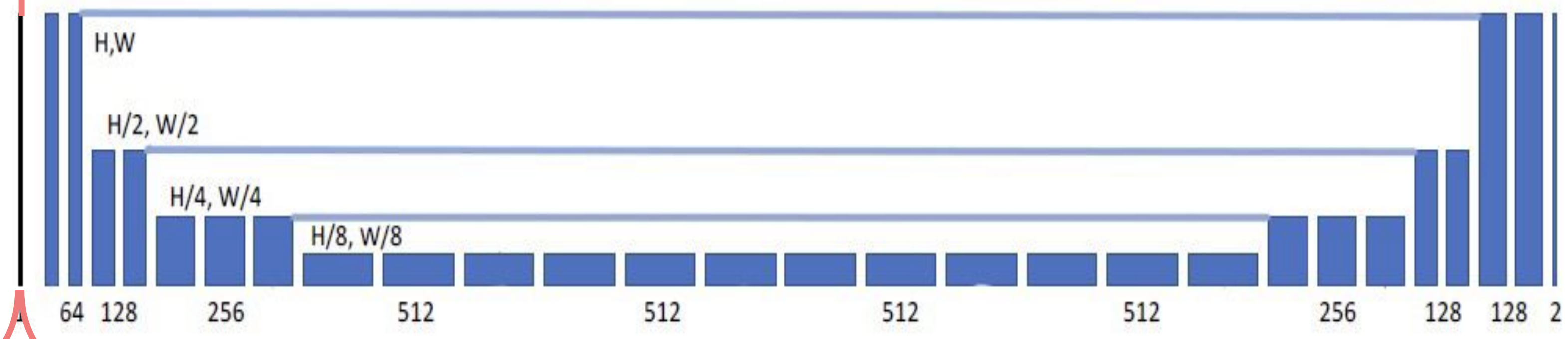


Colorization Network: Given Paper

- Masking T_{ab} instead of ground-truth.
- *Weighted Smooth L_1 loss* is used to train the network.

$$L_c = L_h((1 + \lambda M) \odot F_c(x), (1 + \lambda M) \odot y)$$

Masks



T_{ab}

Channel L

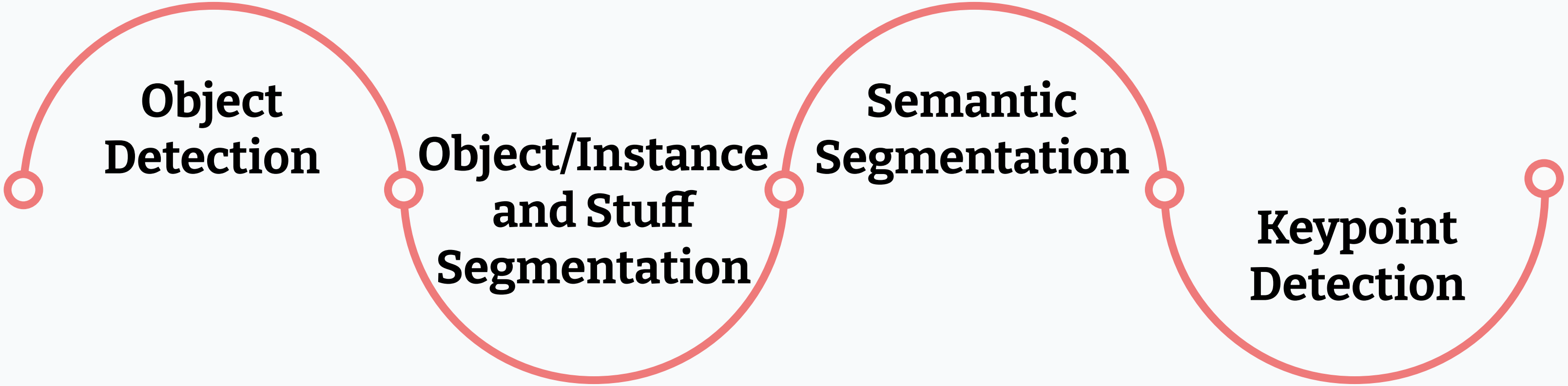
The network is pre-trained

Training Details

03.

Hyperparameters, loss and other assumptions for training.

COCO Dataset Tasks



COCO Dataset Selected Classes

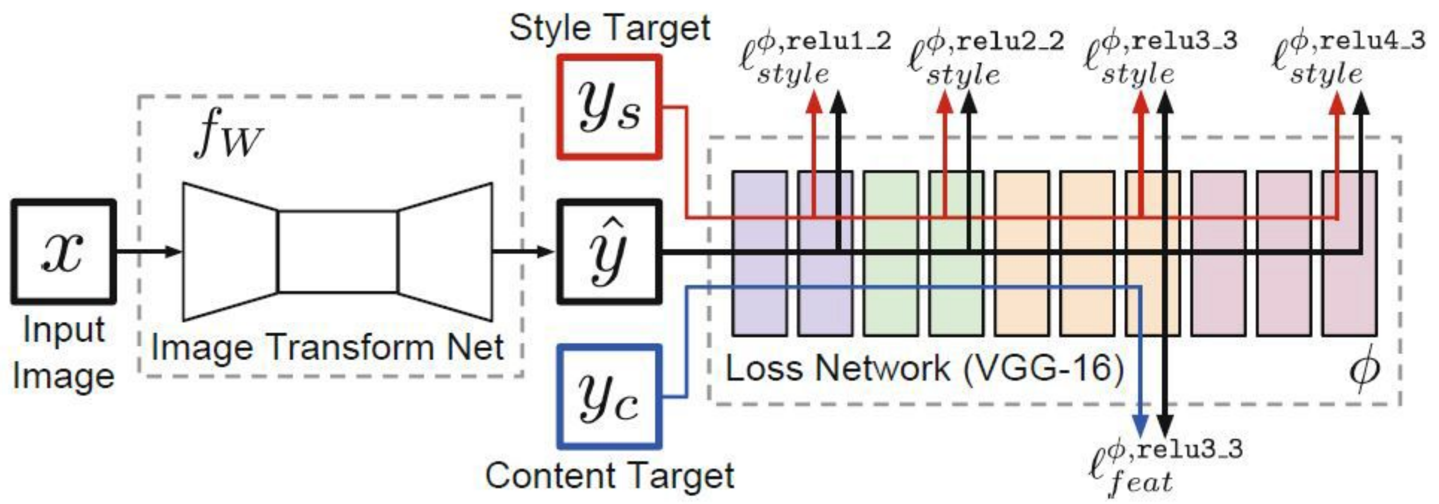
Giraffe

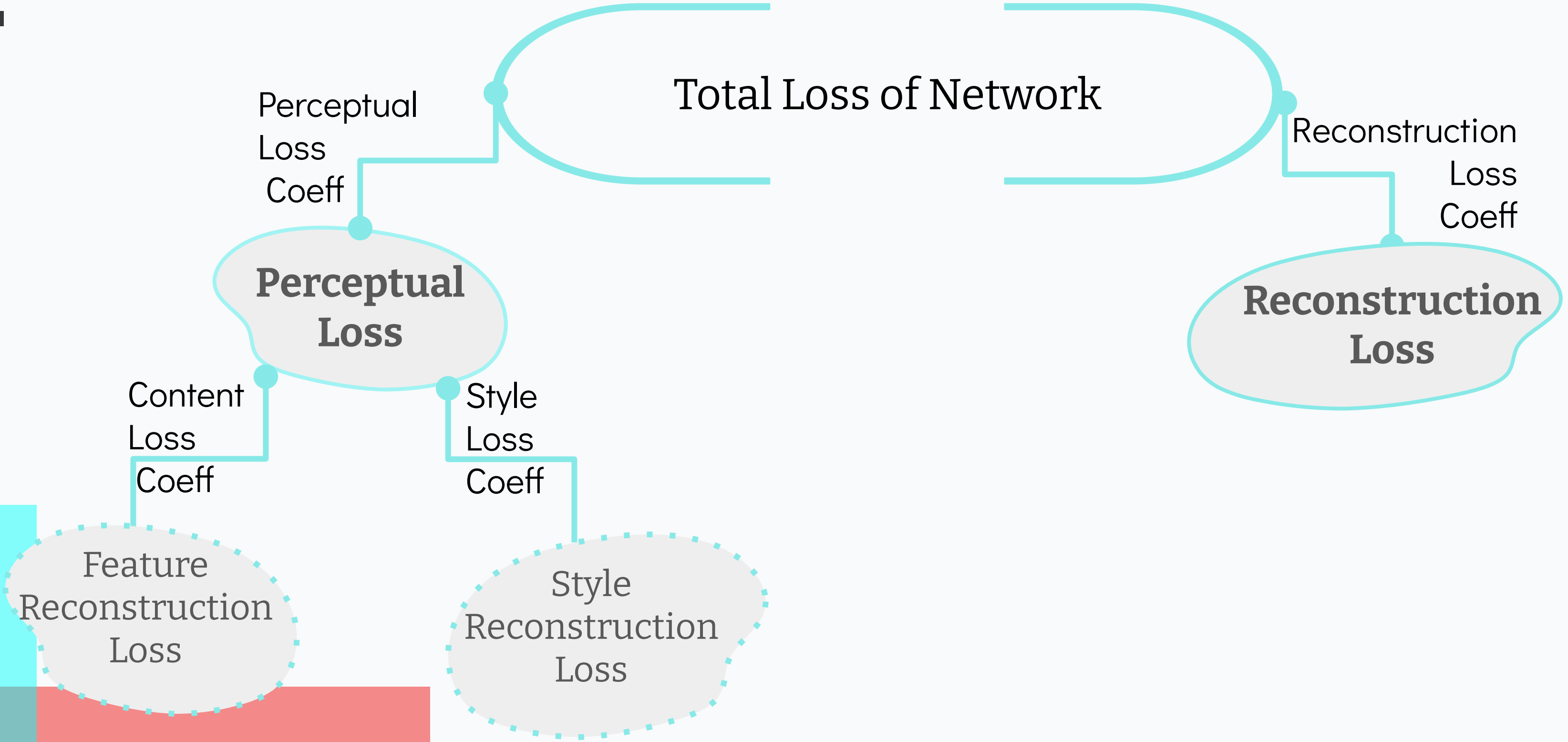
Zebra

Snowboard

Surfboard

Transfer Sub-Net Training: Loss





Total Loss of Network
Perceptual Loss Coeff
Perceptual Loss
Reconstruction Loss Coeff
Reconstruction Loss
Content Loss Coeff
Style Loss Coeff
Feature Reconstruction Loss
Style Reconstruction Loss

Transfer Sub-Net Training

- Perceptual Coefficient: 0.2
- Reconstruction Coefficient: 0.8
- Content Coefficient: 1
- Style Coefficient: 10^6

Transfer Sub-Net Training

- **Optimizer:** ADAM optimizer → learning rate = 0.001
- **Batch Size:** 4
- **Number of Epochs:** 1
- **Style Weights:** conv1_1 → 1.0
  conv2_1 → 0.75
  conv3_1, conv4_1, conv5_1 → 0.2

Total Network Training

- Optimizer: ADAM optimizer → learning rate = 0.00001
- Batch Size: 4
- Number of Epochs: 1
- Mask Probability: 0.99
- Lambda: 10

Results

Representing the results of our implementation.

04.

Transfer Sub-Net Results

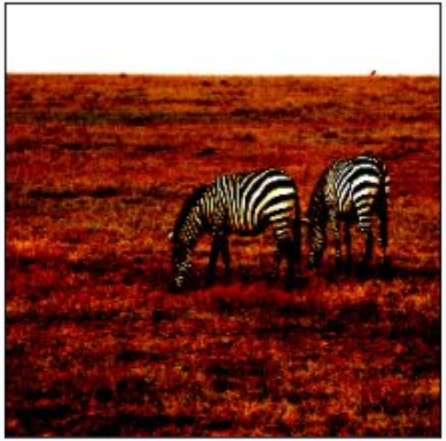
Input Image

Refrence Image

output Image

Transfer Sub-Net Results

Input Image



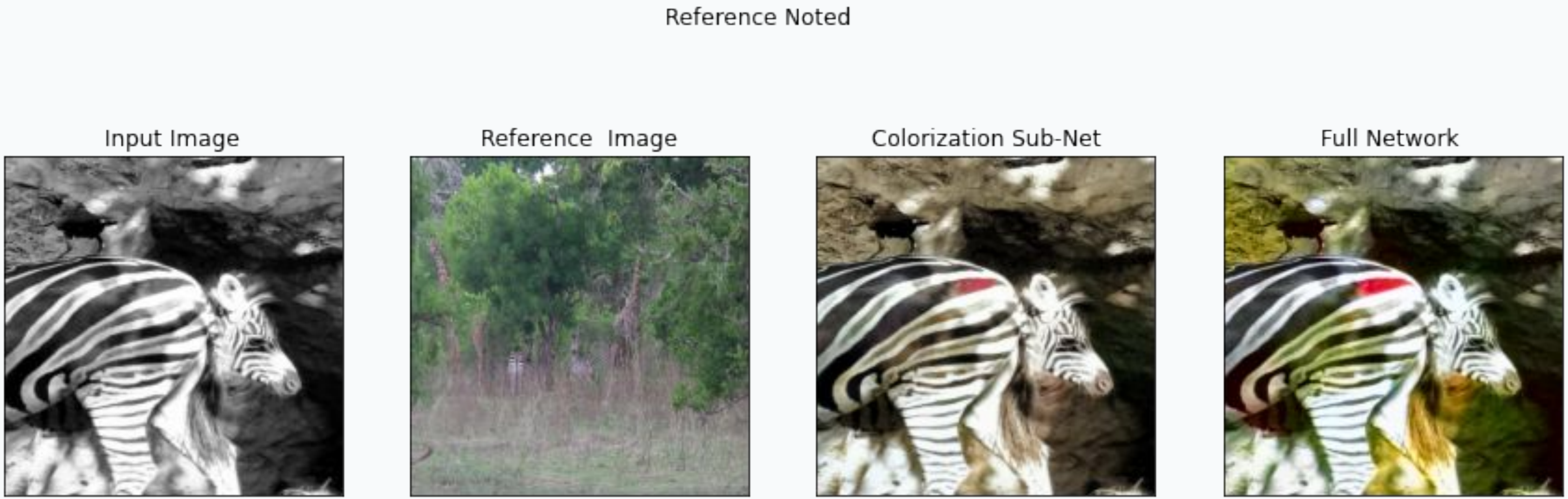
Refrence Image

output Image

Total Network Results

Reference Noted

Total Network Results



THANKS!

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