

Introduction

Colorization of grayscale images is an essential problem in computer vision that has seen considerable interest recently. The goal is to produce a colored version of a monochromatic image that is perceptually plausible and appealing. This problem is inherently under-constrained as multiple colorizations can be equally valid for a single grayscale image. Significant advancements have been made in recent years by the use of deep learning models. These can learn complex mappings from data, enabling more accurate and realistic colorizations when being trained on large datasets of colored images.

Dataset

- ▶ We used the MIT Places dataset [3], which consists of over 40.000 RGB images of size 256 x 256.
- ▶ The images are converted to the CIELAB color space, where the L* channel serves as the grayscale input of the network, and the a* and b* channels are used as the ground truth chrominance channels.
- ▶ The dataset was splitted in a 90% of data for training and a 10% for validation.

Models

Figure 1 shows the architecture of our model. It consists of two main components: a feature extraction module and a colorization module. The feature extraction module is based on the ResNet-18 architecture pretrained on grayscale inputs. The colorization module comprises several blocks of upsampling layers that gradually increase the spatial resolution of the feature maps. The final output of the network is a two-channel image representing the a* and b* channels of the Lab color space, which is then combined with the original grayscale image to produce the final colorized image.

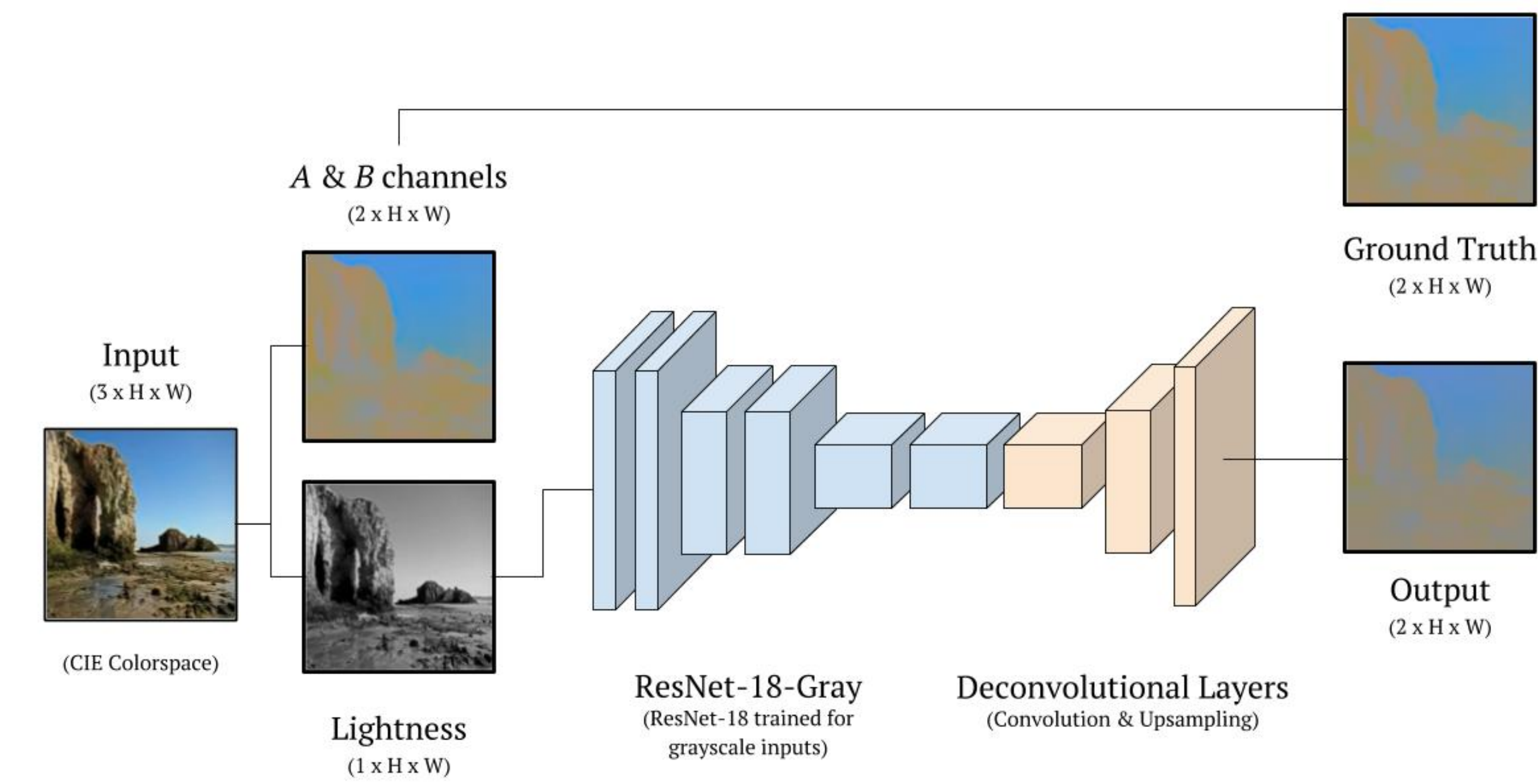


Figure 1: Our model architecture.

Loss Functions

- We tested different loss functions that are usually used in the colorization task [1]:
- ▶ **Mean Squared Error (MSE) Loss:** Penalizes the squared color deviation.
 - ▶ **Smooth-L1 Loss:** Blend of L1 and L2 characteristics to improve gradient stability.
 - ▶ **Total Variation (TV) Loss:** Encourages spatial smoothness. Less noisy color transitions. Regularization factor.
 - ▶ **Color Weighted Loss:** Focus on infrequent colors (Figure 2), helping diversify the color spectrum of the generated images.

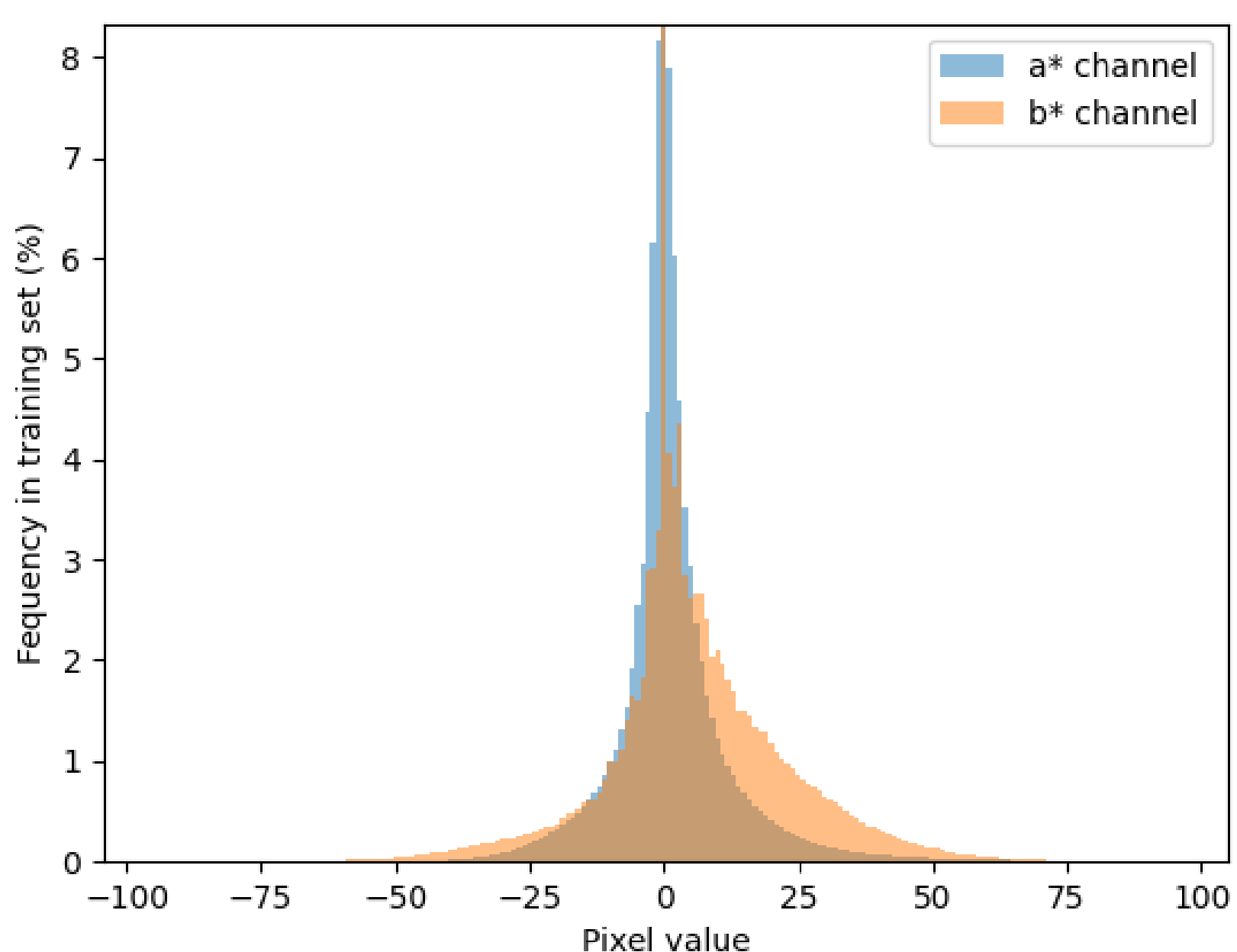


Figure 2: Pixel value frequency in a* and b* channels in the training set.

Results

We visually compared the results we obtained when training with MSE loss and the color weighted loss with the results using the model from Zhang, et al. [2].

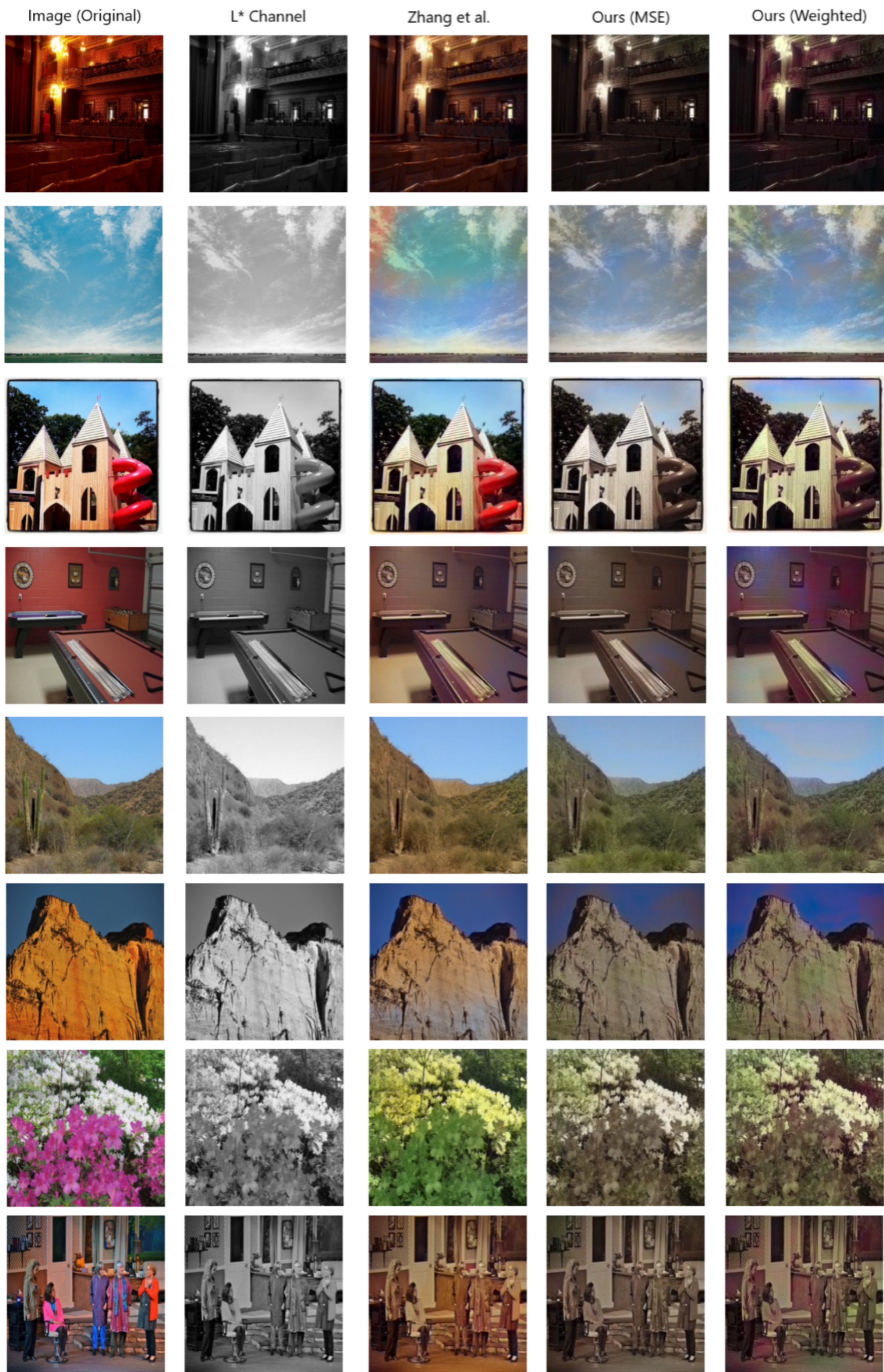


Figure 3: Results comparison. From left to right: original image, greyscale image, results from [2], our results with MSE loss, and our results with Color weighted loss.

Performance

Table 1: Quantitative results comparing our method with the original color using different metrics.

Network	Loss Function	Epochs	Learning Rate	SSIM	PSNR	MSE
Zhang, et al.	-	-	-	0.0241	6.79	15296.60
Ours	MSE	100	1e-4	0.1264	9.22	8799.35
Ours	MSE	98	1e-3	0.8197	17.79	1214.07
Ours	MSE	101	1e-4	0.8244	18.39	1076.04
Ours	MSE	93	1e-4	0.1267	9.25	8720.09
Ours	MSE	100	1e-4	0.8235	18.71	1024.60
Ours	L1	100	1e-3	0.8148	18.30	1137.31
Ours	L1	100	1e-3	0.8148	18.30	1137.31
Ours	L1Smooth	100	1e-3	0.8185	18.33	1092.50
Ours	L1Smooth	100	1e-4	0.8220	18.80	1027.55
Ours	WeightedColorLoss	100	1e-3	0.8163	18.77	994.90
Ours	WeightedColorLoss	100	1e-4	0.8188	18.90	978.10

References

[1] S. Huang, X. Jin, Q. Jiang, and L. Liu. Deep learning for image colorization: Current and future prospects. *Engineering Applications of Artificial Intelligence*, 114:105006, 2022.

[2] R. Zhang, P. Isola, and A. A. Efros. Colorful image colorization. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part III 14*, pages 649–666. Springer, 2016.

[3] B. Zhou, A. Lapedriza, J. Xiao, A. Torralba, and A. Oliva. Learning deep features for scene recognition using places database. *Advances in neural information processing systems*, 27, 2014.