

Problem statement



Generative Adversarial Networks (GANs)



Proposed approaches



Results



Image Colorization and Upscaling using DC-GANs

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Image colorization

Image upscaling

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Possible approaches

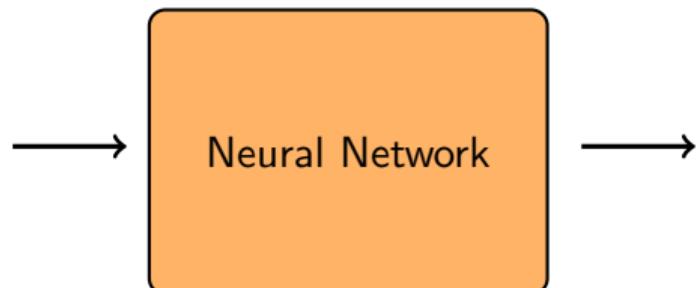
Models

Results

Separate training results

Joint training results

The image colorization problem

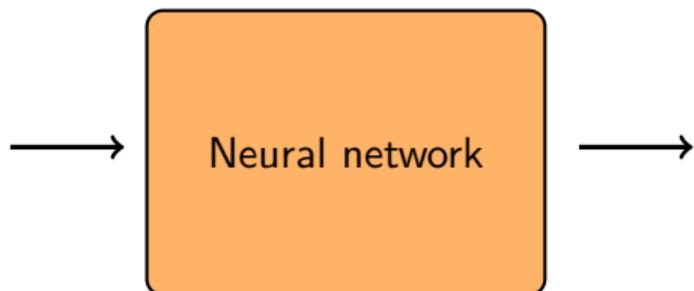


Grayscale image



Colorized image

The image upscaling problem



Low-resolution image



High-resolution image

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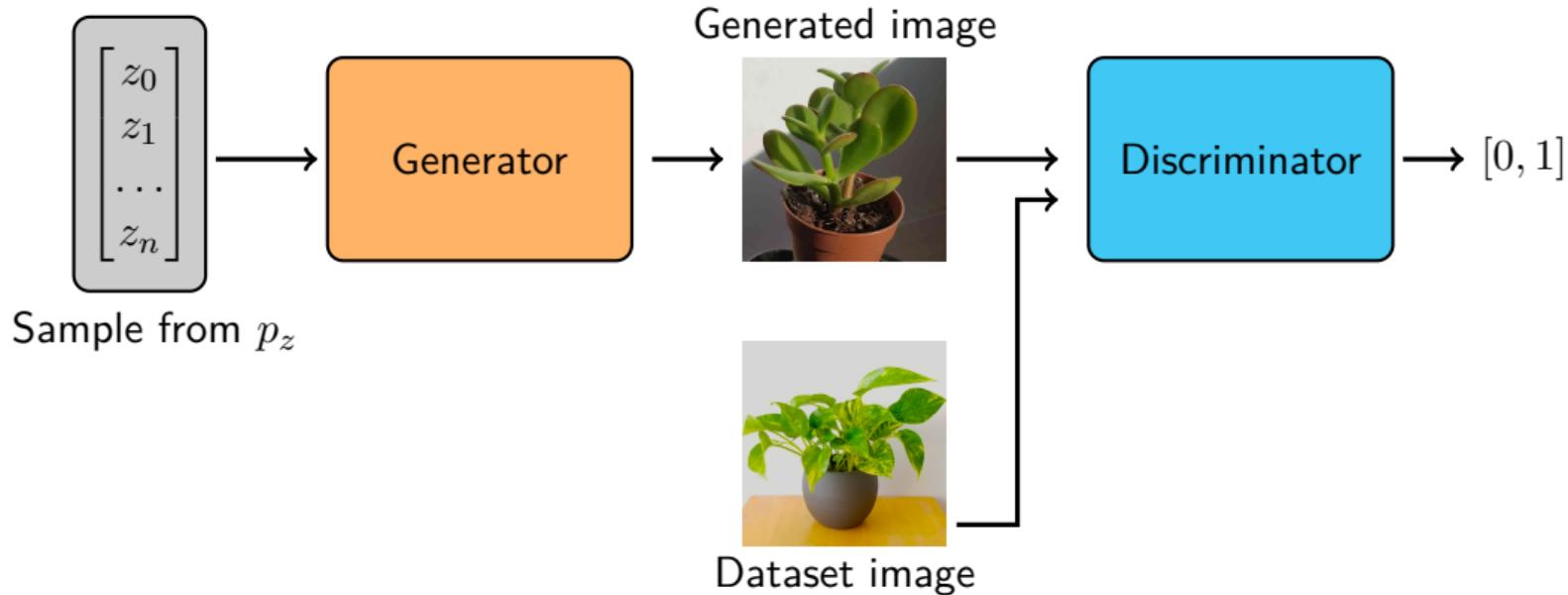
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Generative Adversarial Networks (GANs)

Generation

- The generator G_{θ_G} takes a random noise vector z as input and outputs an image $G_{\theta_G}(z)$.
- The discriminator D_{θ_D} takes an image x as input and outputs a probability $D_{\theta_D}(x)$ that the image is real.
- Minimax game problem:

$$\min_{\theta_G} \max_{\theta_D} V(G_{\theta_G}, D_{\theta_D}) = \min_{\theta_G} \max_{\theta_D} \mathbb{E}_x[\log D_{\theta_D}(x)] + \mathbb{E}_z[\log(1 - D_{\theta_D}(G_{\theta_G}(z)))]$$



Generative Adversarial Networks (GANs)

Image colorization or upscaling

Change the generator to fit the colorization/upscaling problem using conditional GANs:

- Replace the noise vector z by a grayscale/lows-res image z .
- The generator G_{θ_G} takes a grayscale/lows-res image z as input and outputs an enhanced image $G_{\theta_G}(z)$.
- The discriminator receives both the enhanced image and the enhanced image (condition) as input, and outputs a probability $D_{\theta_D}(x|z)$ that the image is real.

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Goal: build a pipeline transforming a grayscale and low-res image into a colorized, high-res image.

Two different possibilities:

- **Two-step approach:** colorize and upscale the image using two networks trained separately.
- **Single-step approach:** colorize and upscale the image at the same time, using a single GAN trained.

Using the LAB color space

Idea for colorization: instead of trying to learn the three RGB channels, learn only the two channels A and B of the LAB color space, given the channel L .

Idea for upscaling: learn to upscale the L channel, and use bicubic interpolation for the A and B channels.



Figure 1: Standard grayscale is very similar to the L channel

Generator model: U-Net

As a generator, we use the U-Net model, mostly used in segmentation tasks.

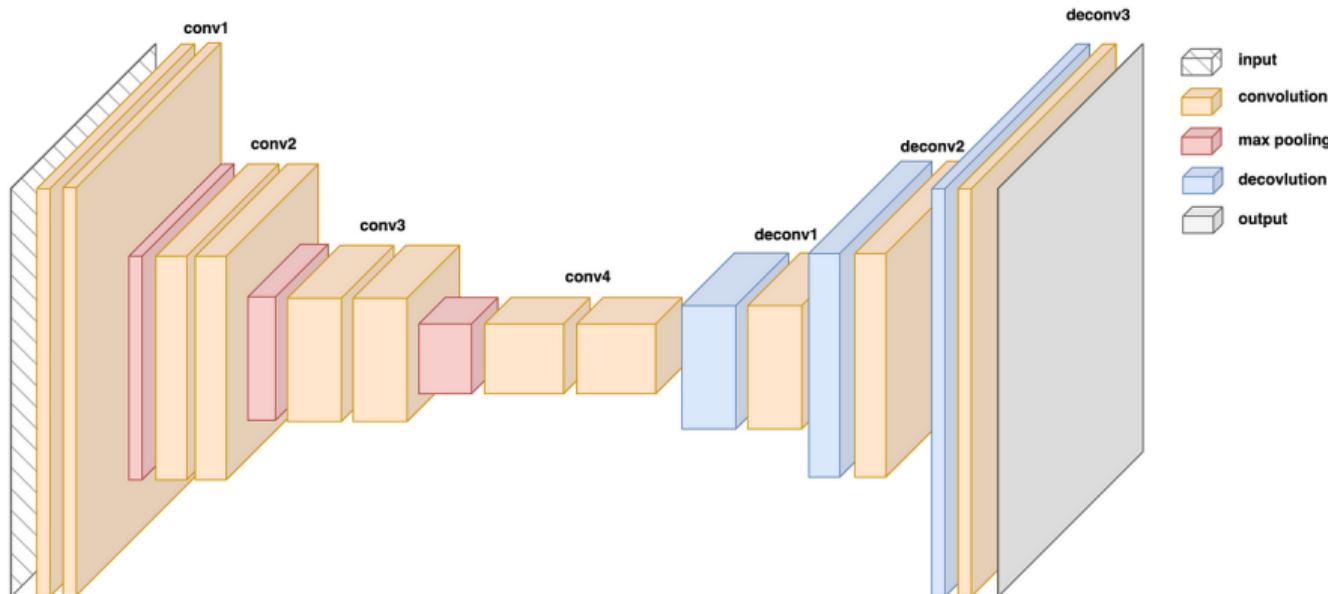


Figure 2: Architecture of the U-Net model

Upscaling model: ESPCN

As a generator, we use the ESPCN model.

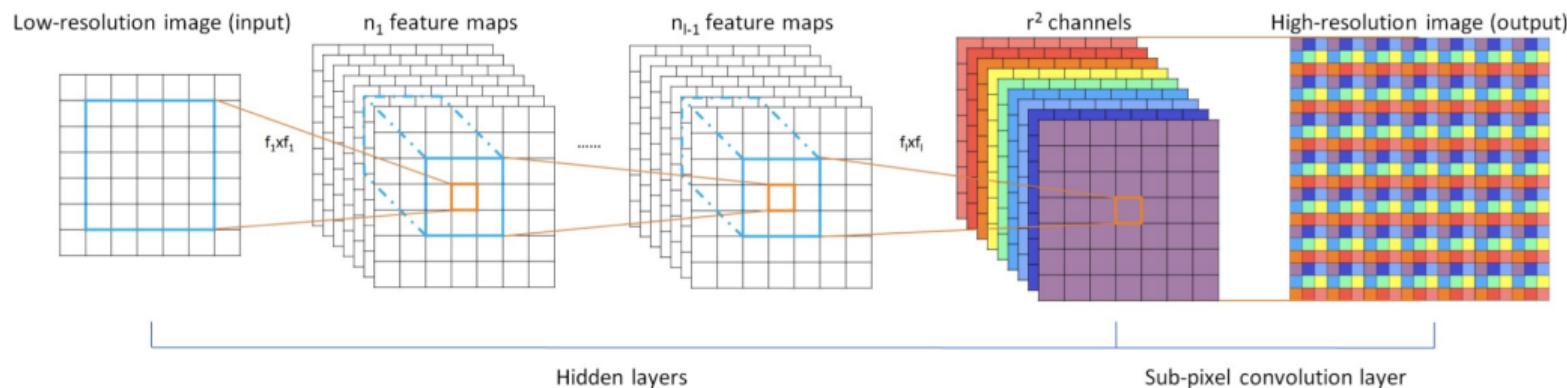


Figure 3: Architecture of the ESPCN model

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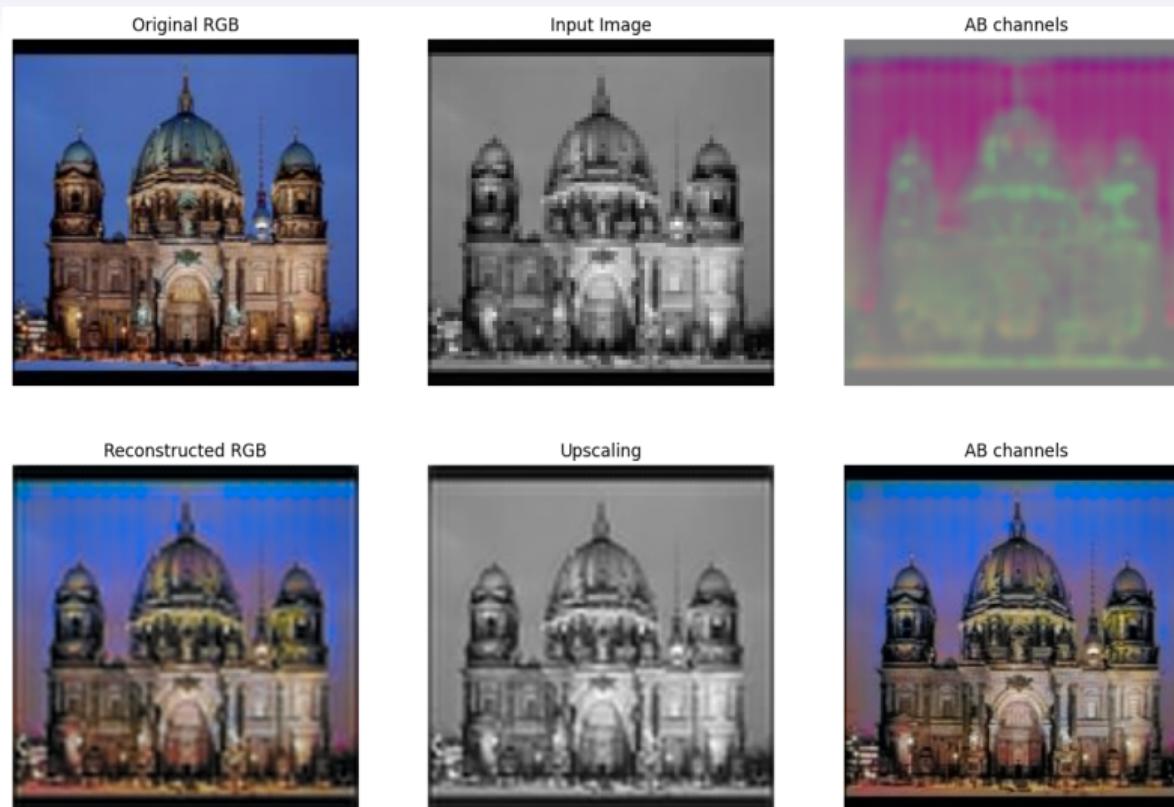


Figure 4: Colorization results for U-Net trained on Imagenette (separate training)

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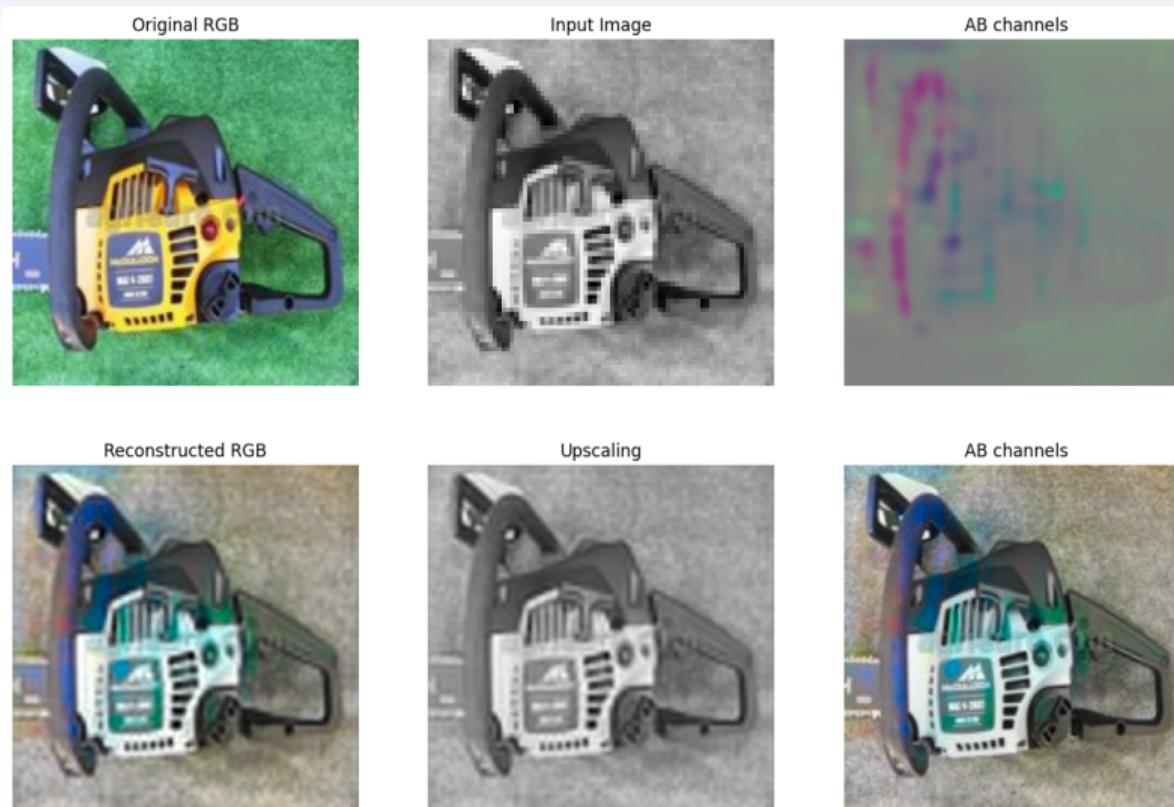


Figure 5: Colorization results for U-Net trained on Imagenette (separate training)

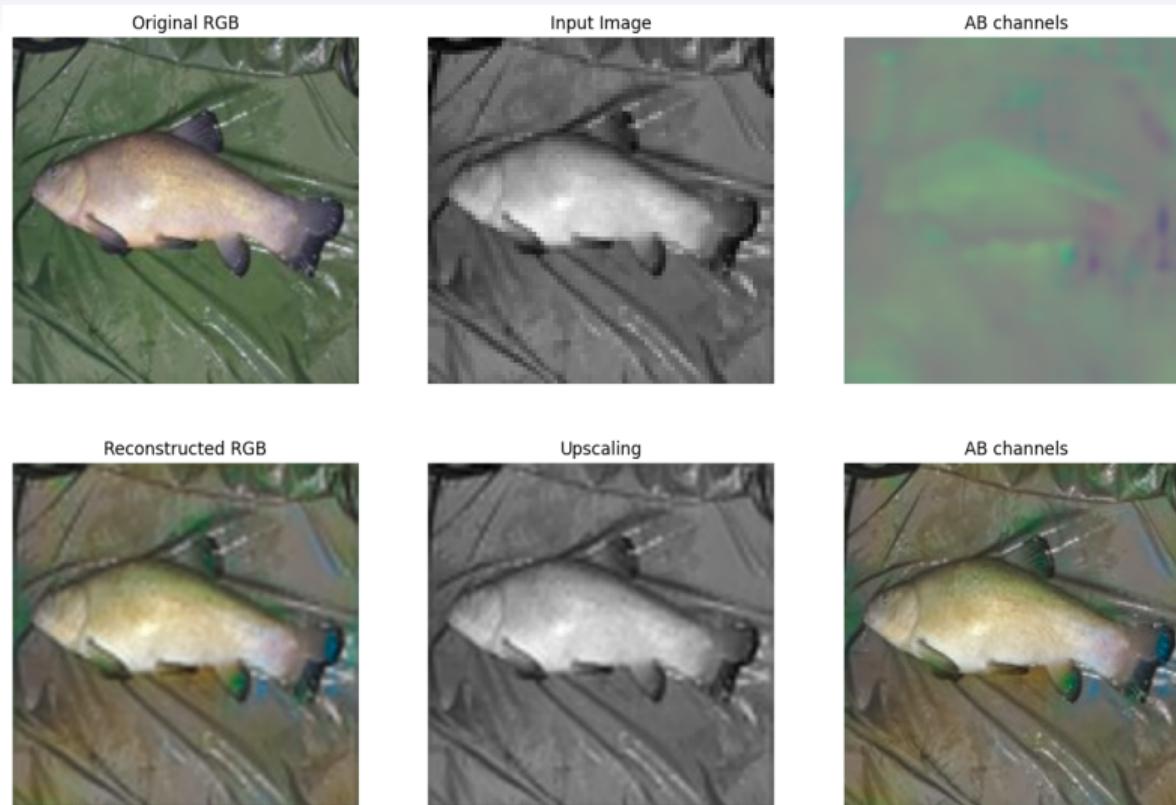


Figure 6: Colorization results for U-Net trained on Imagenette (separate training)

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Figure 7: Colorization results for U-Net trained on Imagenette (separate training)

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Figure 8: Colorization results for U-Net trained on Imagenette (separate training)

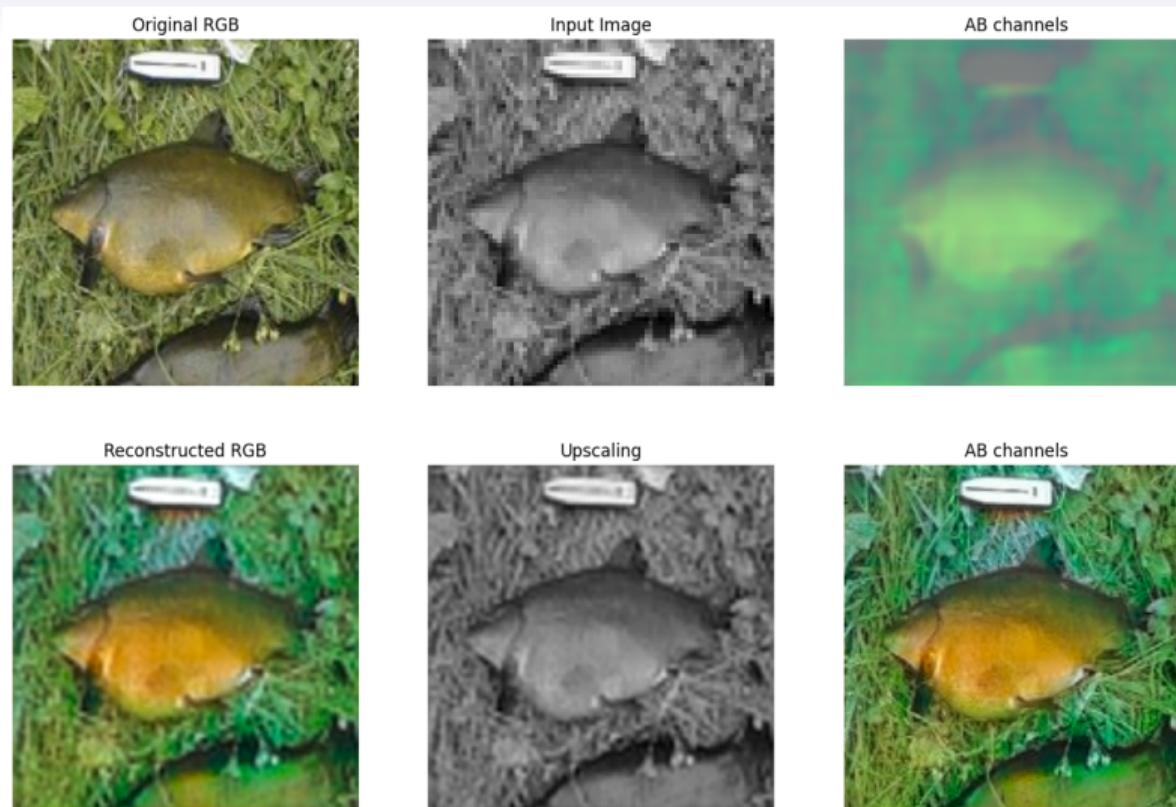


Figure 9: Colorization results for U-Net trained on Imagenette (separate training)

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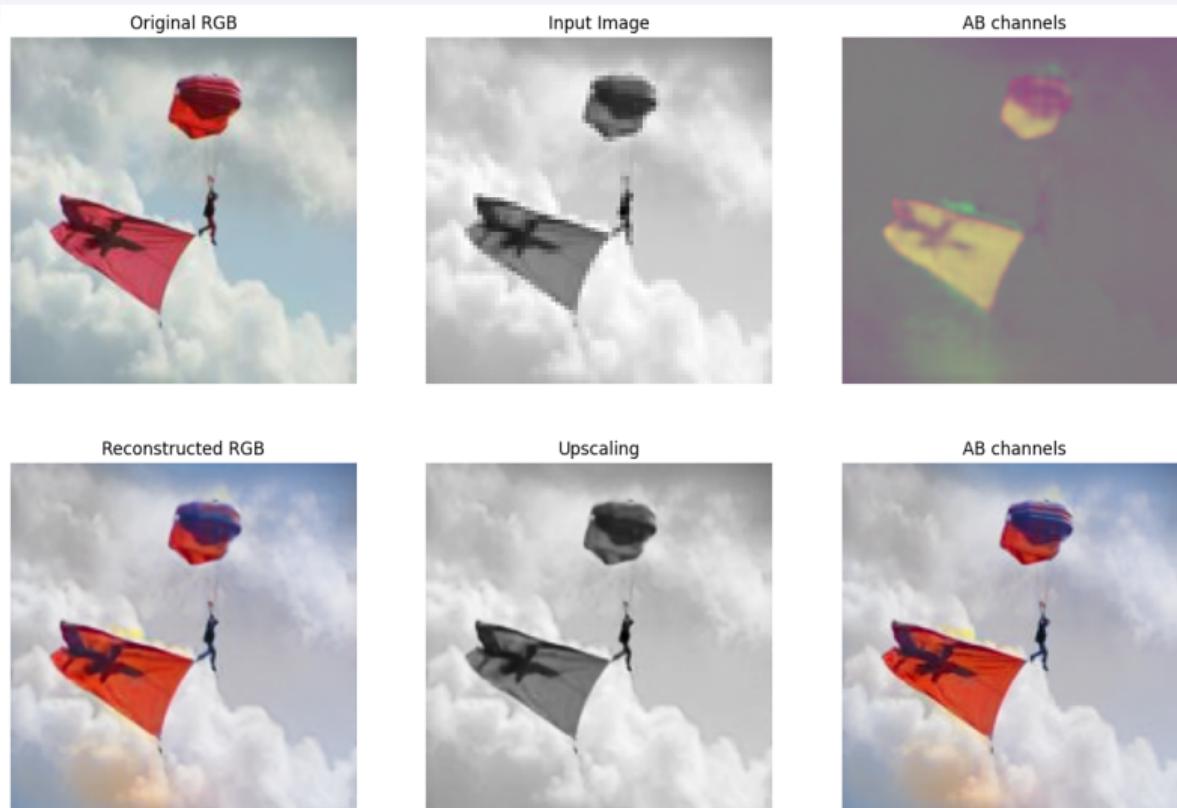


Figure 10: Colorization results for U-Net trained on Imagenette (joint training)

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Figure 11: Colorization results for U-Net trained on Imagenette (joint training)

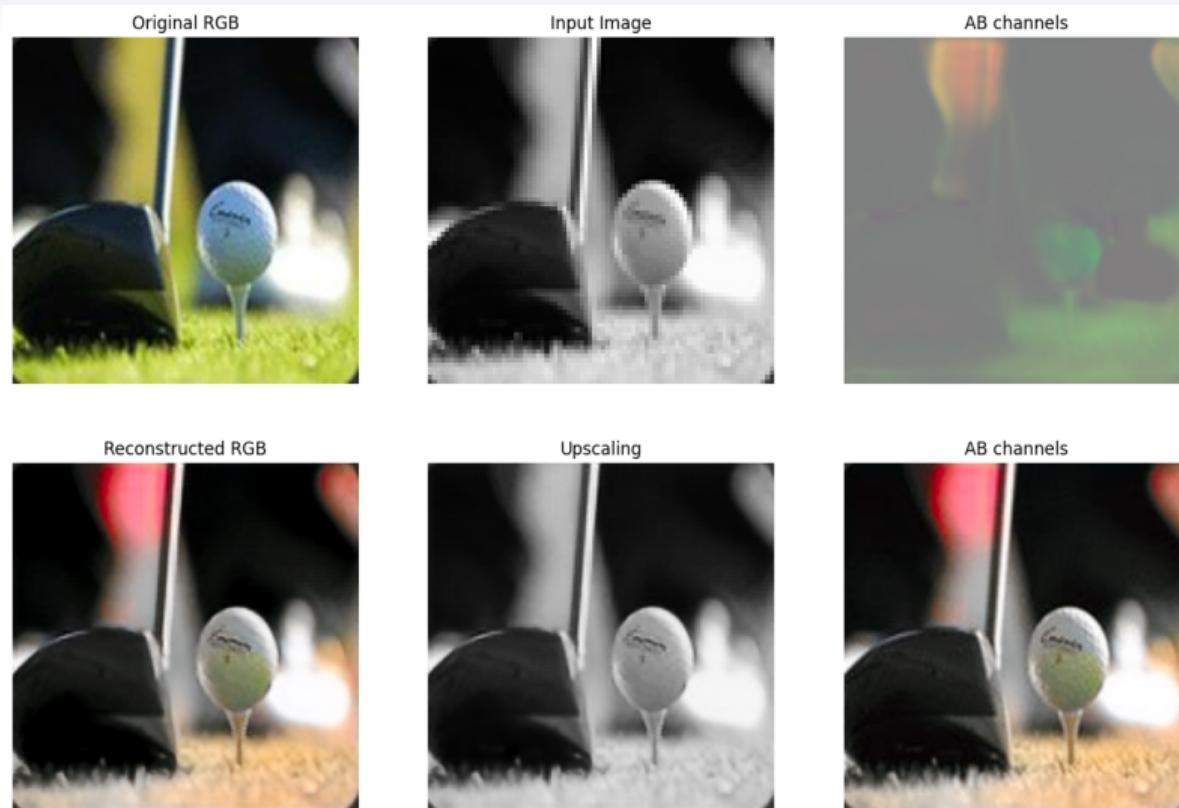


Figure 12: Colorization results for U-Net trained on Imagenette (joint training)

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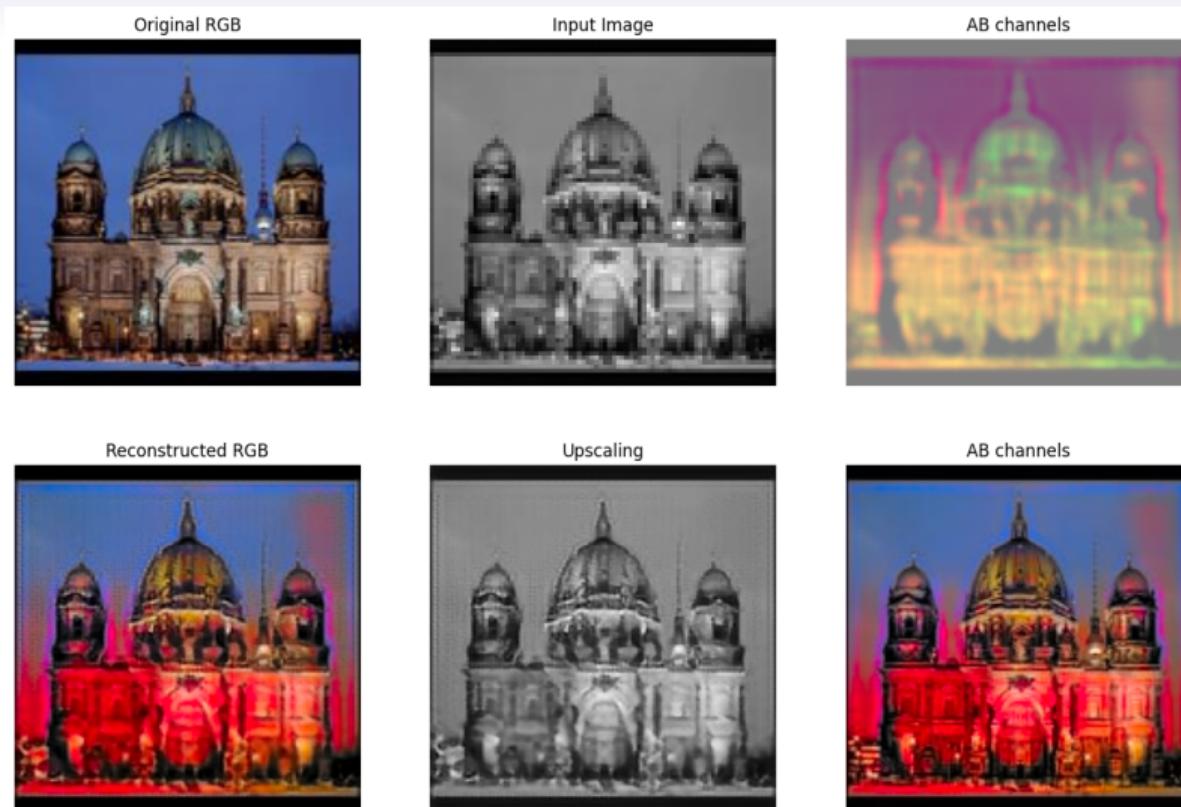


Figure 13: Colorization results for U-Net trained on Imagenette (joint training)

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Results



Original RGB



Input Image



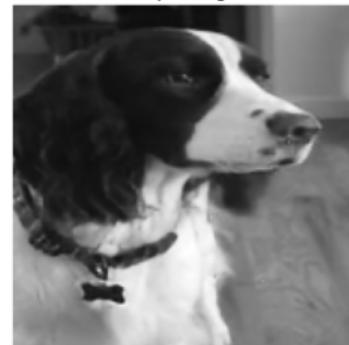
AB channels



Reconstructed RGB



Upscaling



AB channels

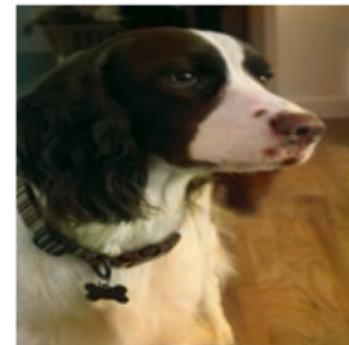


Figure 14: Colorization results for U-Net trained on Imagenette (joint training)

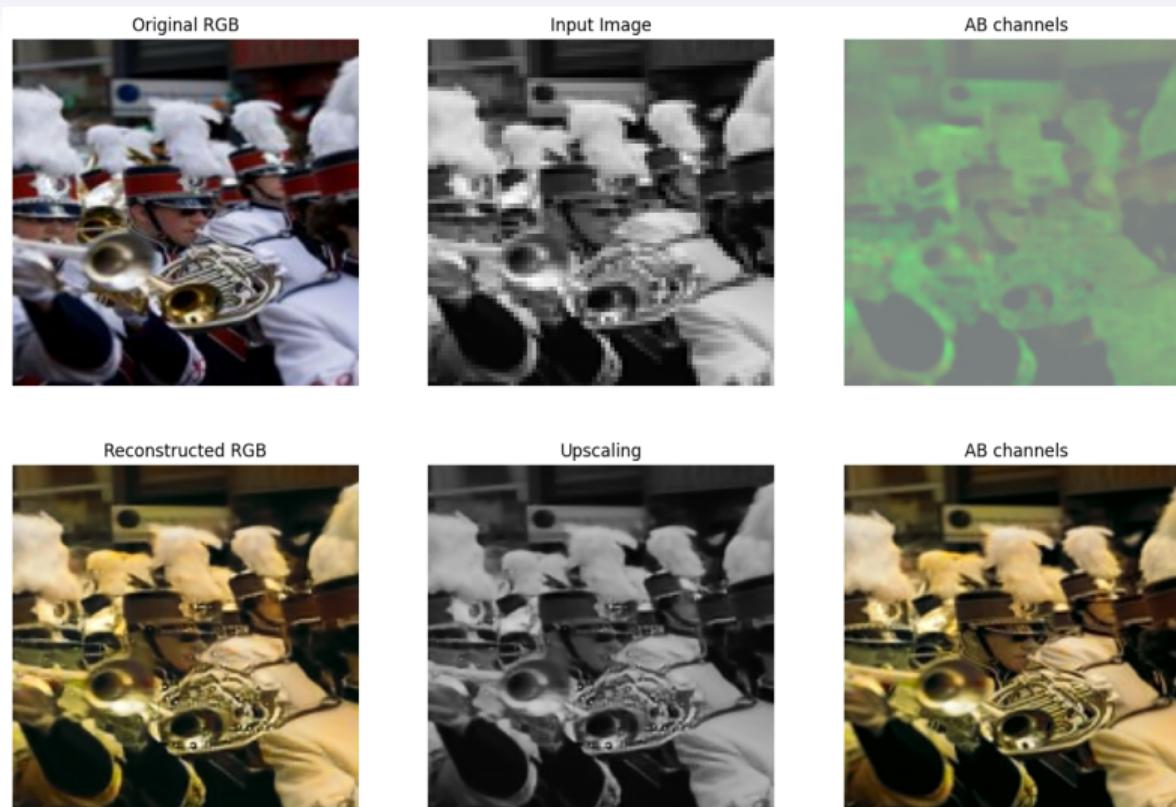


Figure 15: Colorization results for U-Net trained on Imagenette (joint training)



References

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2. Nazeri, Kamyar, Eric Ng, and Mehran Ebrahimi. "Image colorization using generative adversarial networks." *Articulated Motion and Deformable Objects: 10th International Conference, AMDO 2018, Palma de Mallorca, Spain, July 12-13, 2018, Proceedings* 10. Springer International Publishing, 2018.
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