Guided Image Generation with Conditional Invertible Neural Networks
– Supplementary Material –

Contents

1 Architecture details – MNIST generation

The network consists of 24 segments with a conditional coupling block and random permutation each:

$$24 \times \begin{cases} \text{Cond. coupling block} \\ \text{Random permutation} \end{cases}$$

The Adam optimizer was used, with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-6}$, L2 weight decay 10^{-5}. The initial learning rate is 10^{-4}, exponentially decaying to 10^{-6}. The network requires roughly 2GB VRAM, at a large batch size 256, and can be easily trained on a single GPU. The affine coefficients s_j, t_j are produced jointly by a single MLP of the following form:

Fully connected	$392 + 10 \rightarrow 512$
ReLU	
Fully connected	$512 \rightarrow 512$
ReLU	
Fully connected	$512 \rightarrow 784$ ($\equiv [s_j, t_j]$)

2 Architecture details – Colorization

The network uses 5 resolution levels, segmenting the latent space into 4 partitions. Each conditional coupling block uses a separate head on top of the feature extraction network, except for the lowest resolution level, which only uses a single head for all coupling blocks. We produce the multiplicative and additive affine coefficients s_j, t_j jointly though a single network ('Coefficient functions' below). All convolutions, unless otherwise specified, use kernel size 3, stride 1, and padding 1. The Adam optimizer was used, with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-6}$, L2 weight decay 10^{-5}. The initial learning rate is $1.6 \cdot 10^{-4}$, reducing by a factor 0.2 when reaching a plateau. A batch size of 16 fits within 8GB VRAM, and we train with a batch size of $3 \times 16 = 48$ on 3 GPUs.

2.0.1 Level 1 (2x64x64 Px)

$4\times$ { Cond. coupling block; Random orthog. 1x1 conv. }

Reshape

$2\times$ { Random orthog. 1x1 conv.; Coupling block (Uncond.) }

Conditional coefficient functions:

Convolution	1 + 32 $\rightarrow$ 32 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	32 $\rightarrow$ 32 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	32 $\rightarrow$ 2 Ch. ($\equiv [s_j, t_j]$)

Unconditional coefficient functions:

Convolution	4 $\rightarrow$ 64 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	64 $\rightarrow$ 64 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	64 $\rightarrow$ 8 Ch., 1×1 Kernel

Conditioning heads:

Convolution	256 $\rightarrow$ 32 Ch.
Batch normalization	

2.0.2 Level 2 (8x32x32 Px)

$6\times$ { Cond. coupling block; Random orthog. 1x1 conv. }

Reshape

$2\times$ { Random orthog. 1x1 conv.; Coupling block (Uncond.) }

Split off 16 channels as $z^{(1)}$

Conditional coefficient functions:

Convolution	4 + 64 $\rightarrow$ 64 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	64 $\rightarrow$ 64 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	64 $\rightarrow$ 8 Ch.

Unconditional coefficient functions:

Convolution	16 $\rightarrow$ 128 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 128 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 32 Ch., 1×1 Kernel

Conditioning heads:

Convolution	256 $\rightarrow$ 128 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 64 Ch.
Batch normalization	

2.0.3 Level 3 (16x16x16 Px)

$6\times$ { Cond. coupling block; Random orthog. 1x1 conv. }

Reshape

$2\times$ { Random orthog. 1x1 conv.; Coupling block (Uncond.) }

Split off 32 channels as $z^{(2)}$

Conditional coefficient functions:

Convolution	8 + 128 $\rightarrow$ 128 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	128 $\rightarrow$ 128 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	128 $\rightarrow$ 16 Ch.

Unconditional coefficient functions:

Convolution	32 $\rightarrow$ 256 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 256 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 64 Ch., 1×1 Kernel

Conditioning heads:

Convolution	256 $\rightarrow$ 128 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 128 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 128 Ch.
Batch normalization	

2.0.4 Level 4 (32x8x8 Px)

$$6\times \left\{ \begin{array}{l} \text{Cond. coupling block} \\ \text{Random orthog. 1x1 conv.} \end{array} \right.$$

Reshape

$$2\times \left\{ \begin{array}{l} \text{Random orthog. 1x1 conv.} \\ \text{Coupling block (Uncond.)} \end{array} \right.$$

Split off 96 channels as $z^{(4)}$

Conditional coefficient functions:

Convolution	16 + 256 $\rightarrow$ 256 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	256 $\rightarrow$ 256 Ch.
Leaky ReLU	Slope $5 \cdot 10^{-2}$
Convolution	256 $\rightarrow$ 32 Ch.

Unconditional coefficient functions:

Convolution	64 $\rightarrow$ 256 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 256 Ch., 1×1 Kernel
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 128 Ch., 1×1 Kernel

Conditioning heads:

Convolution	256 $\rightarrow$ 128 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 128 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 256 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 256 Ch.
Batch normalization	

2.0.5 Level 5 (Fully conn. 512)

$$8\times \left\{ \begin{array}{l} \text{Cond. coupling block} \\ \text{Random permutation} \end{array} \right.$$

Result is $z^{(5)}$

Conditional coefficient functions:

Fully connected	256 + 512 $\rightarrow$ 512
ReLU	
Fully connected	512 $\rightarrow$ 512
ReLU	
Fully connected	512 $\rightarrow$ 512
ReLU	
Fully connected	512 $\rightarrow$ 512

Conditioning head (shared for all coupling blocks):

Convolution	256 $\rightarrow$ 128 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	128 $\rightarrow$ 256 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 256 Ch., Stride 2
Leaky ReLU	Slope 10^{-2}
Convolution	256 $\rightarrow$ 512 Ch., Stride 2
Global average pool	
Batch normalization	

3 Colorization – Ablations

In the following, we compare the following ablated versions of the cINN architecture:

1. No conditioning network at all, the grayscale image is used directly as conditioning input ('*No c.n.*').

2. The same VGG-like conditioning network as in the main paper, but it is only pretrained and then left fixed during the training of the cINN ('*Fixed c.n.*').

3. Both cINN and conditioning network are trained jointly, as in the main paper.

In general, we observe that it is critical that the conditioning network and the cINN are trained jointly. With a pretrained but fixed conditioning network, the generated images lack global coherence and exhibit exaggerated variance and artifacts.

The quantitaive scores for the ablated versions are as follows, computed in the same way as Table 1 in the main paper.

	No c.n.	Fixed c.n.	Jointly trained
MSE best of 8	4.06±0.04	3.37±0.04	3.53±0.04
Variance	41.1±0.3	58.0±0.4	35.2±0.3
FID	29.5±0.5	32.4±0.5	25.1±0.3
VGG top 5	82.9±0.5	80.8±0.6	85.0±0.5

No conditioning network

Fixed conditioning network

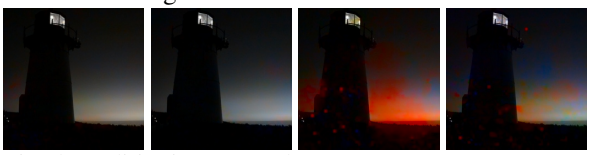
Jointly trained conditioning network

No conditioning network

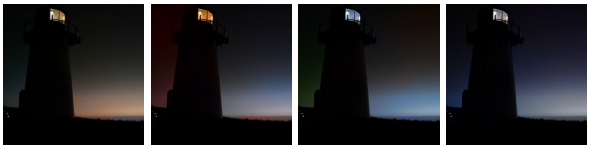
Fixed conditioning network

Jointly trained conditioning network

No conditioning network



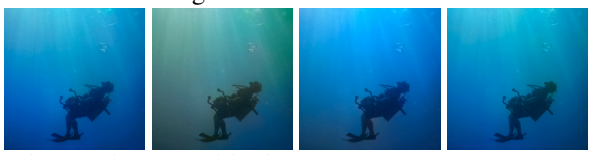
Fixed conditioning network



Jointly trained conditioning network

No conditioning network

Fixed conditioning network



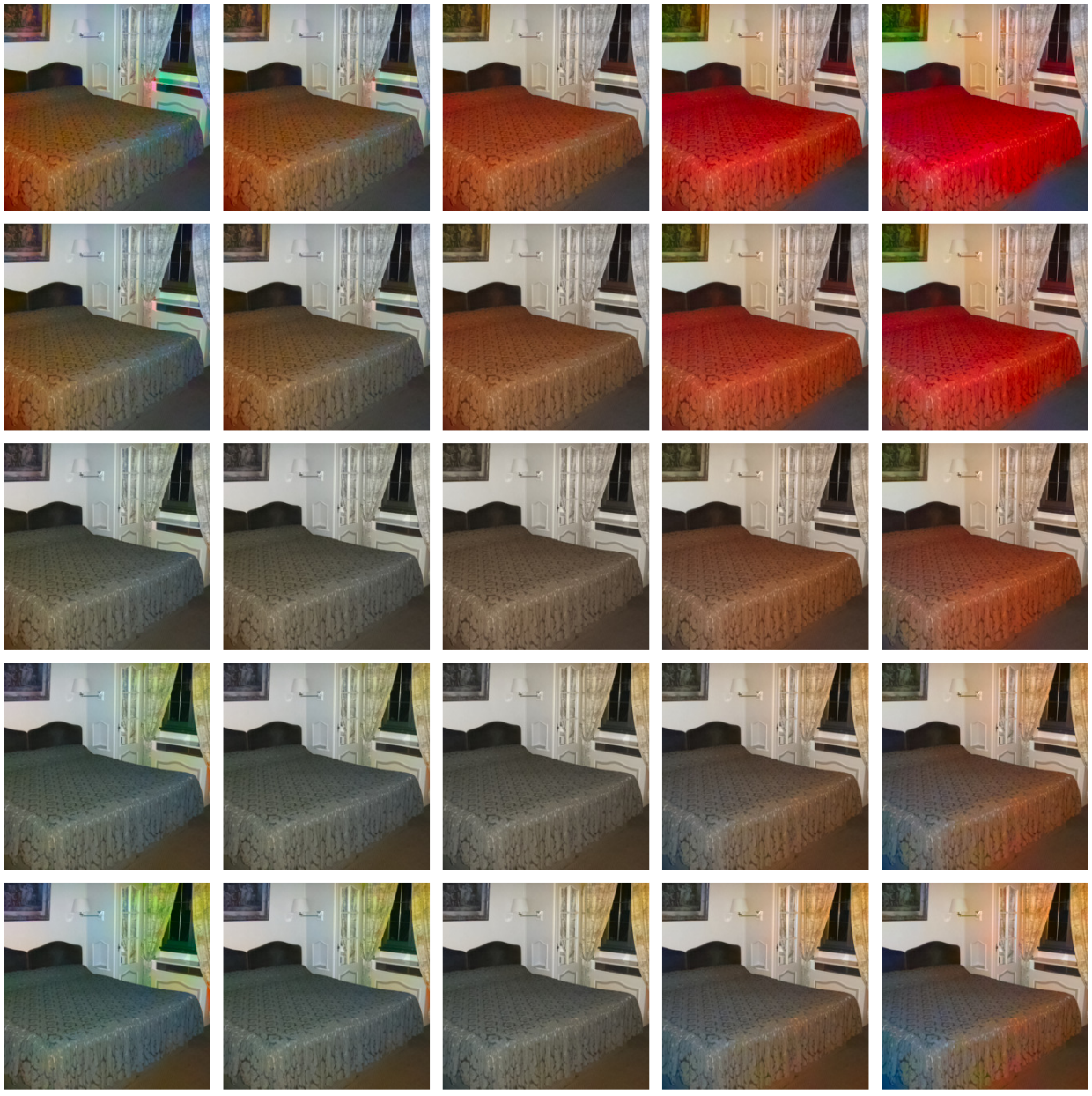
Jointly trained conditioning network

4 Colorization – Interpolations

In the following, we show 2-dimensional interpolations in latent space. Two random latent vectors $\mathbf{z}^{(1)}$, $\mathbf{z}^{(2)}$ are linearly combined:

$$\mathbf{z}^* = a_1\mathbf{z}^{(1)} + a_2\mathbf{z}^{(2)}$$

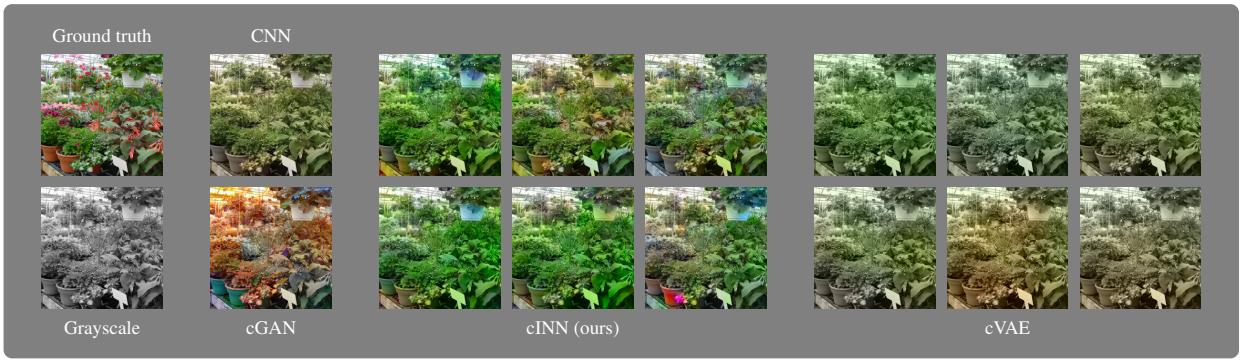
with varying $a_1, a_2 \in [-0.9 \dots 0.9]$ across each axis of a grid. The center image has $\mathbf{z}^* = 0$. Note that the images in the corners have a larger magnitude than trained for, $\|z^*\|_2 \approx 1.3\,\mathbb{E}\big[\|\mathbf{z}\|_2\big]$, leading to some oversaturation artifacts, as in Fig. 12 of the main paper.

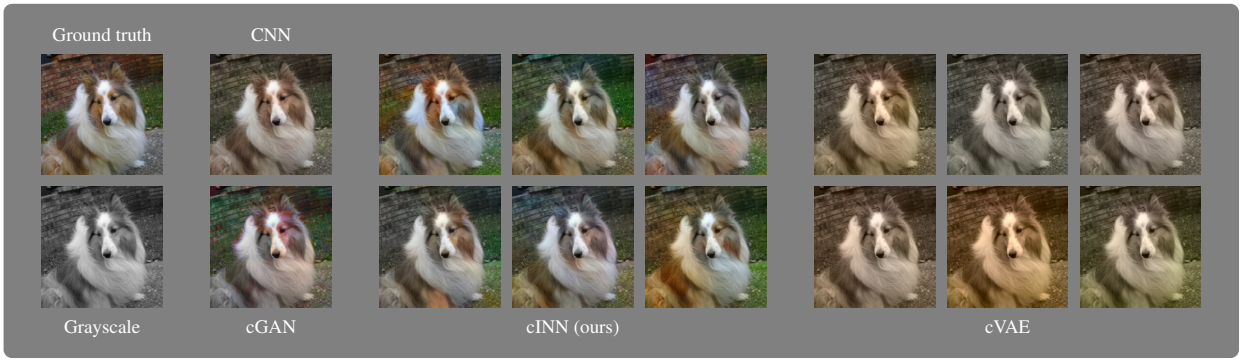


5 Colorization – Additional examples

On the following pages, we provide some additional colorized images, as well as comparisons to alternative methods. All images are taken from the ImageNet 2012 validation set, and all methods were trained on ImageNet 2012. As we do not observe any significant diversity for the cGAN, we only provide a single sample.

5.1 General examples

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cGAN
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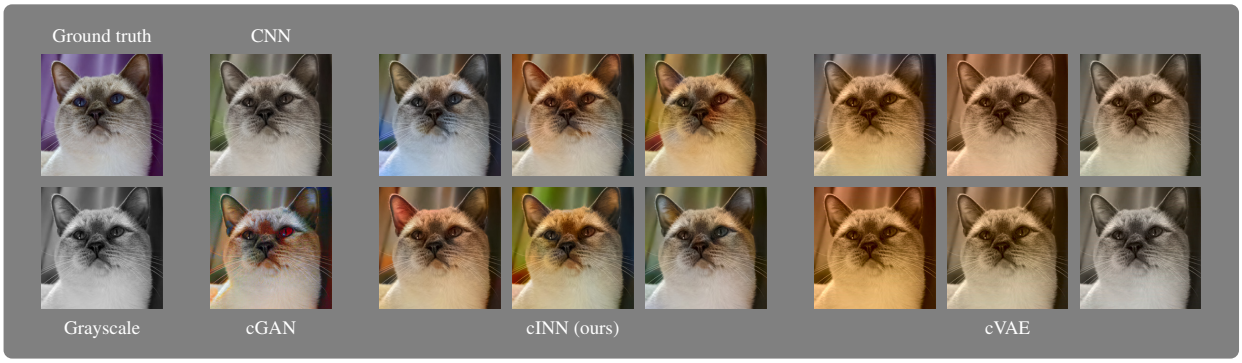
cVAE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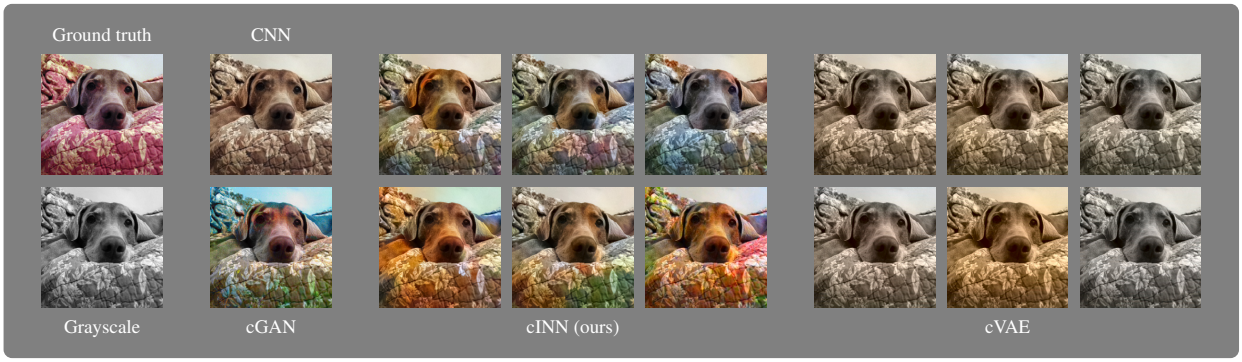
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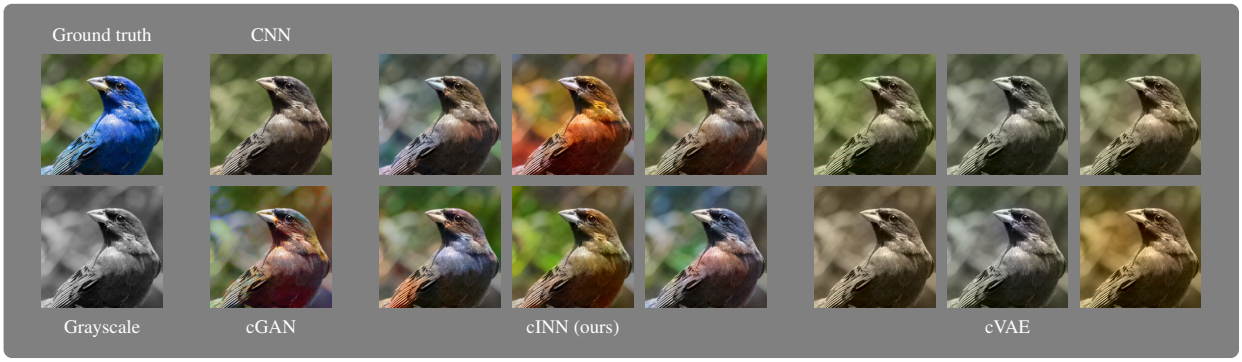
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cVAE


Ground truth
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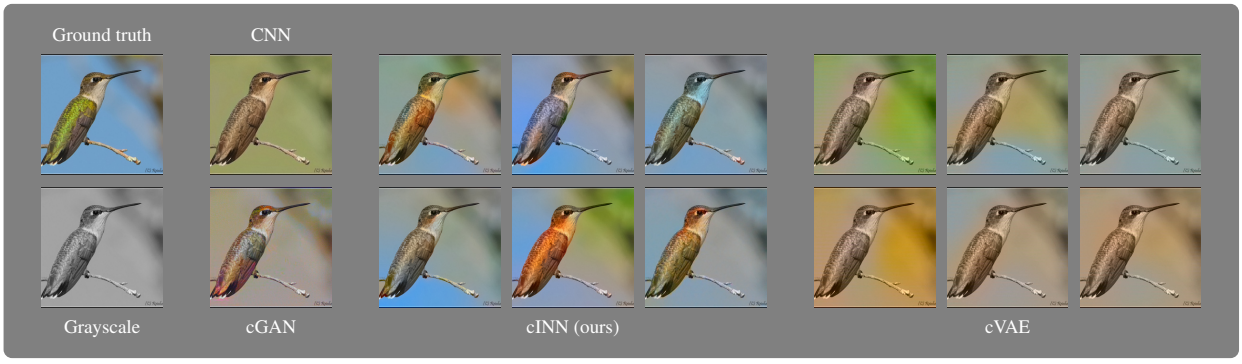
Grayscale
cGAN
cINN (ours)
cVAE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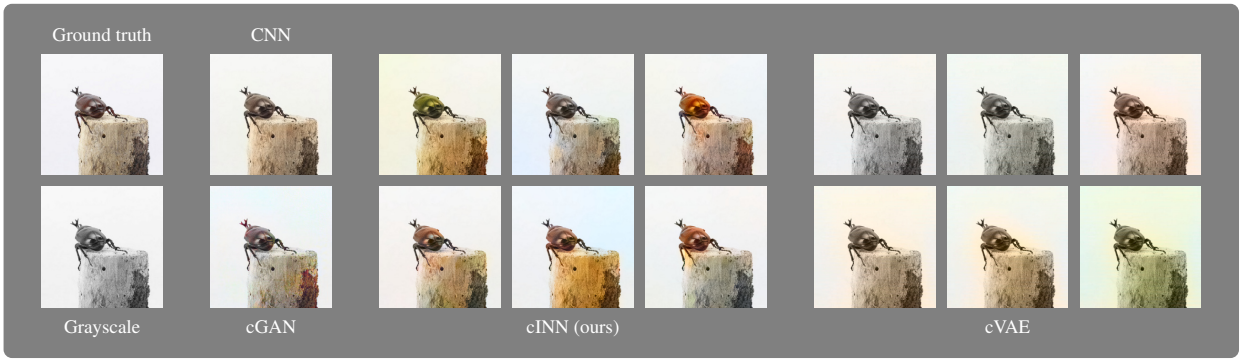
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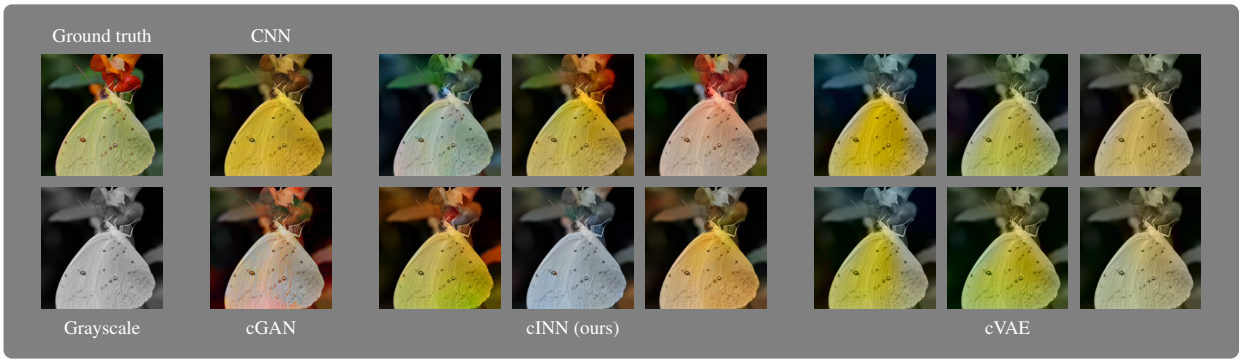
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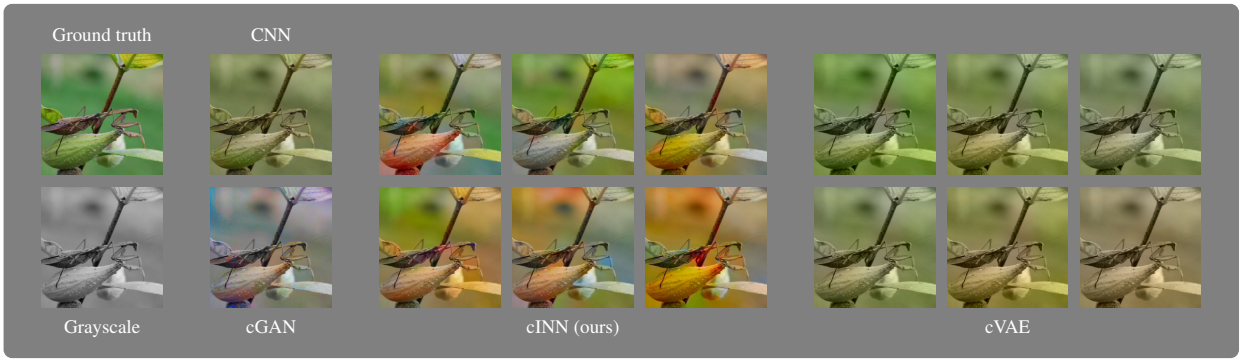
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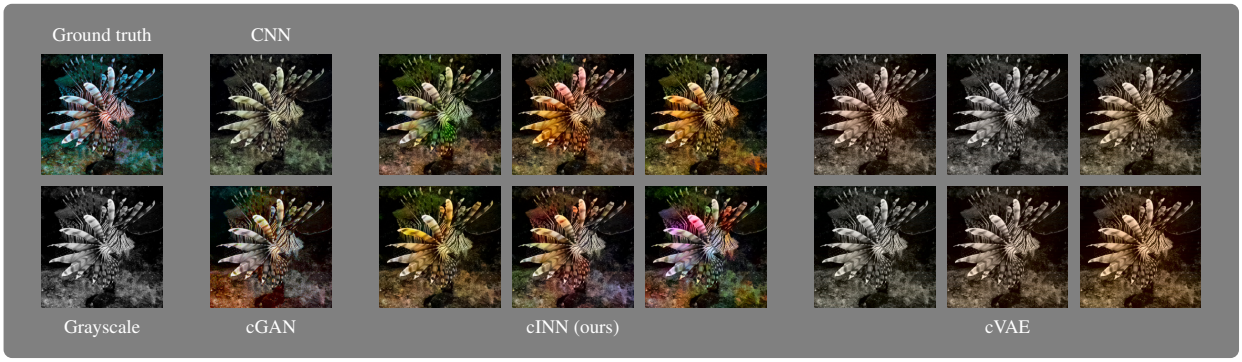
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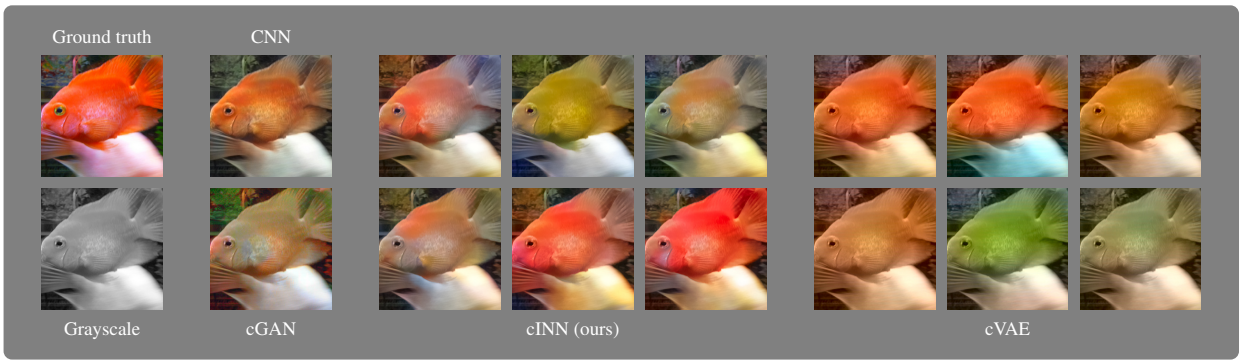
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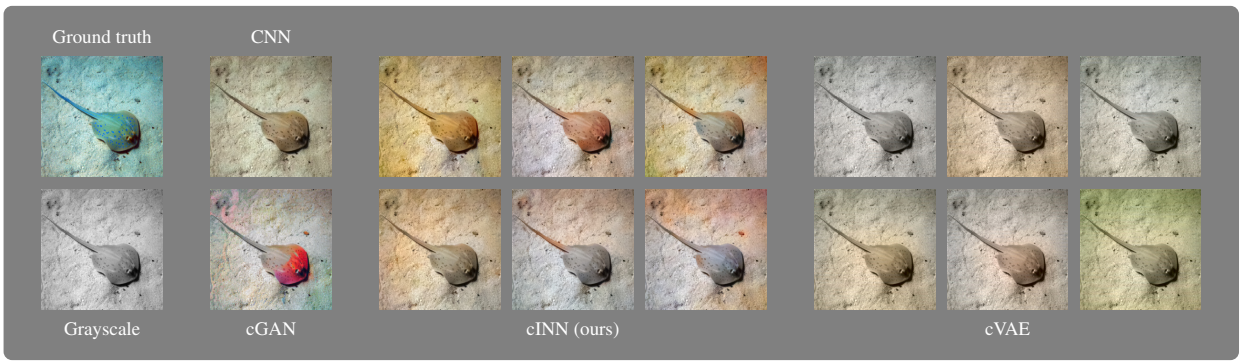
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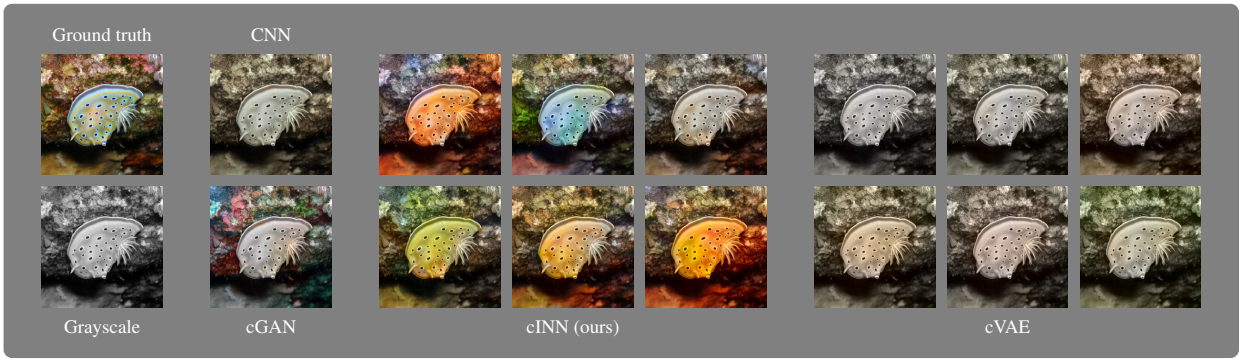
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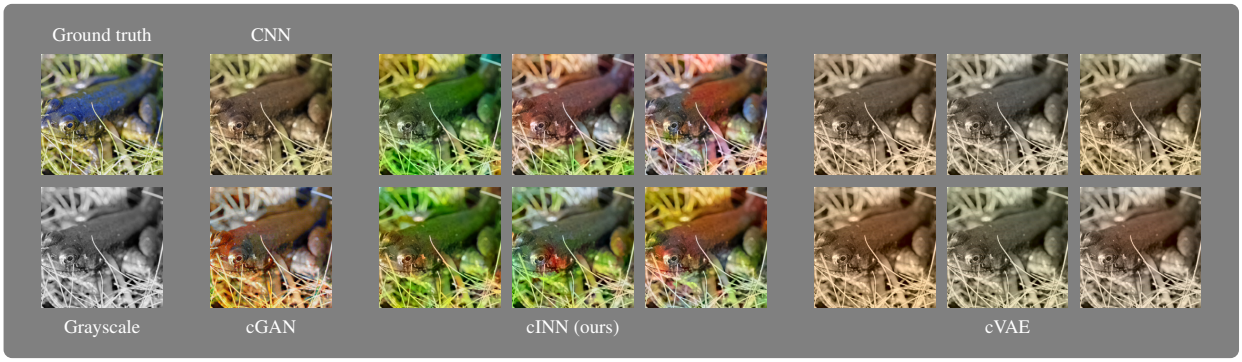
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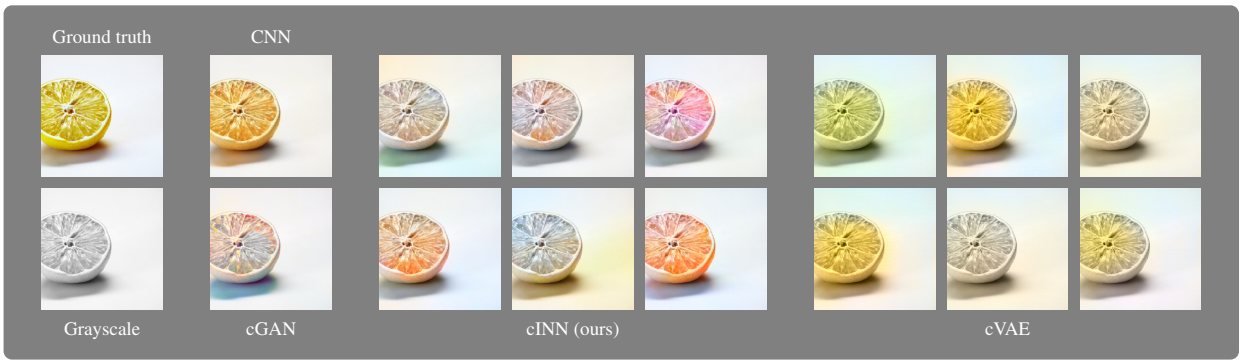
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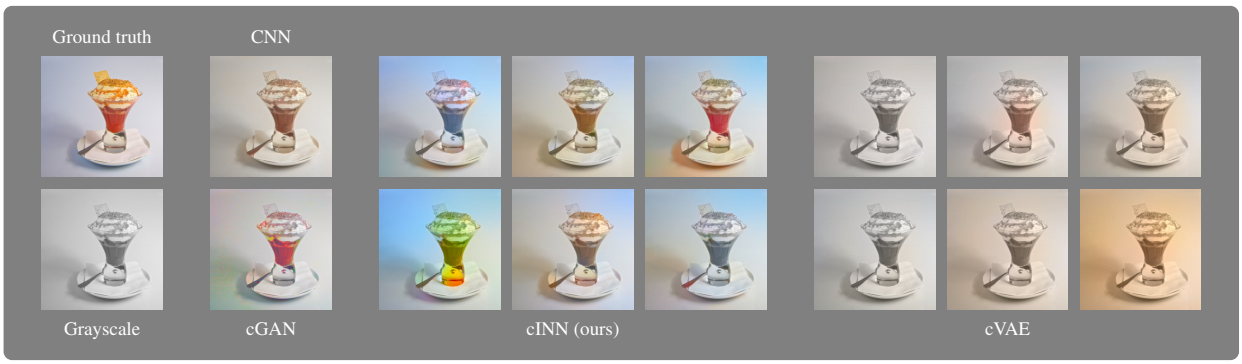
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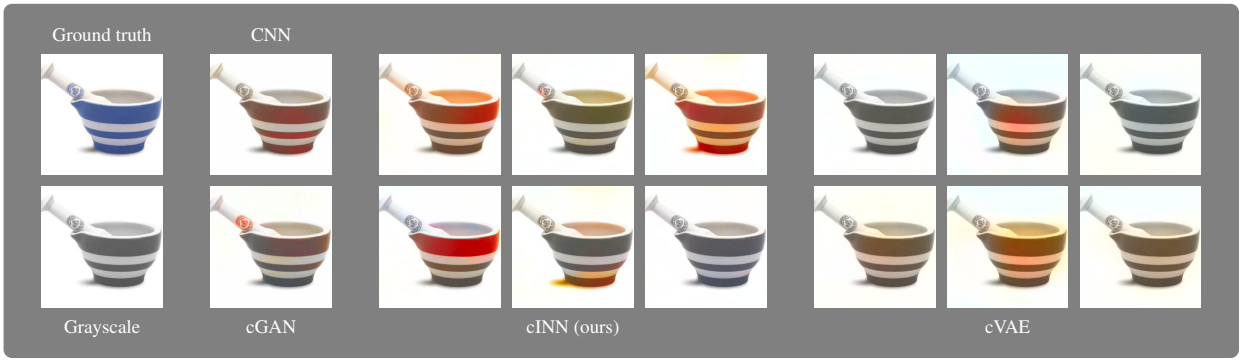
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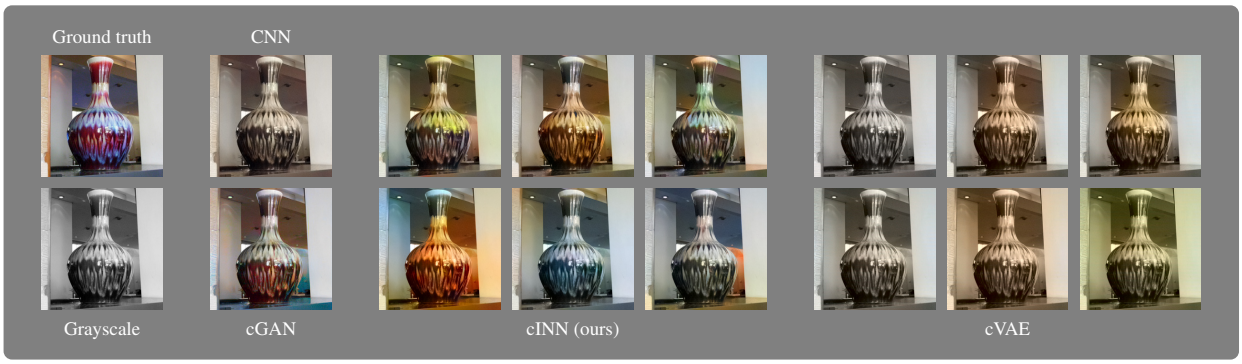
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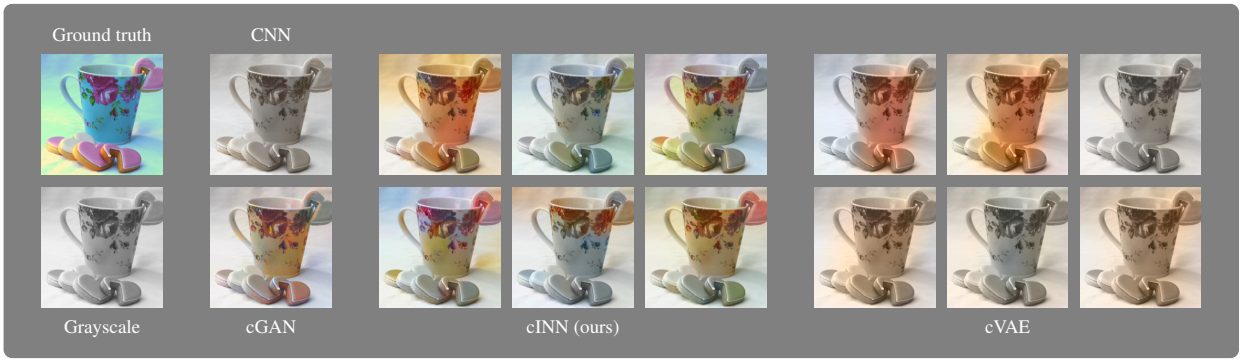
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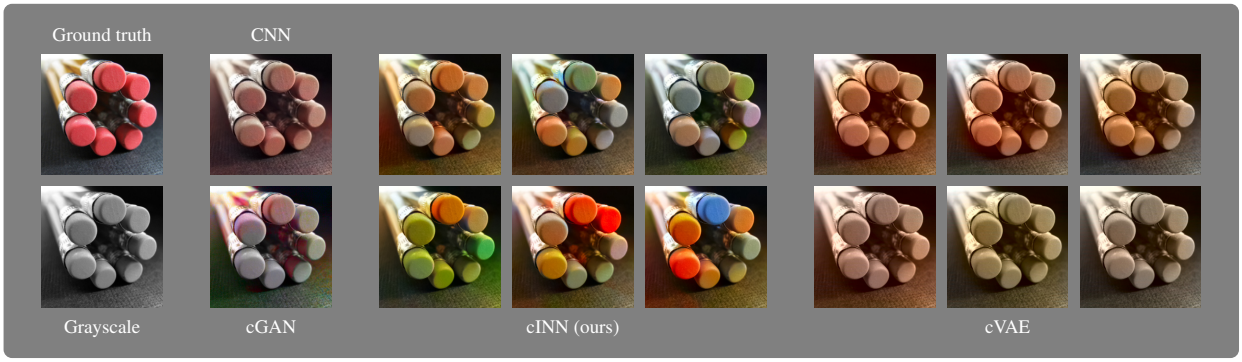
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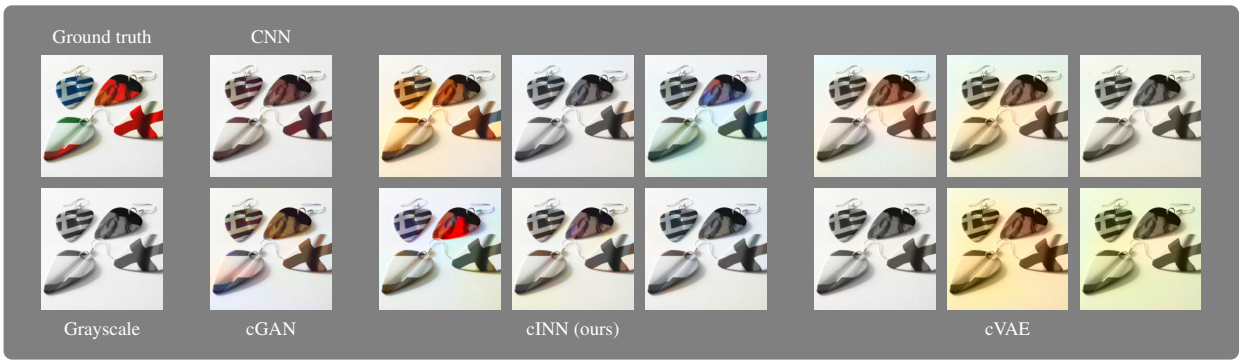
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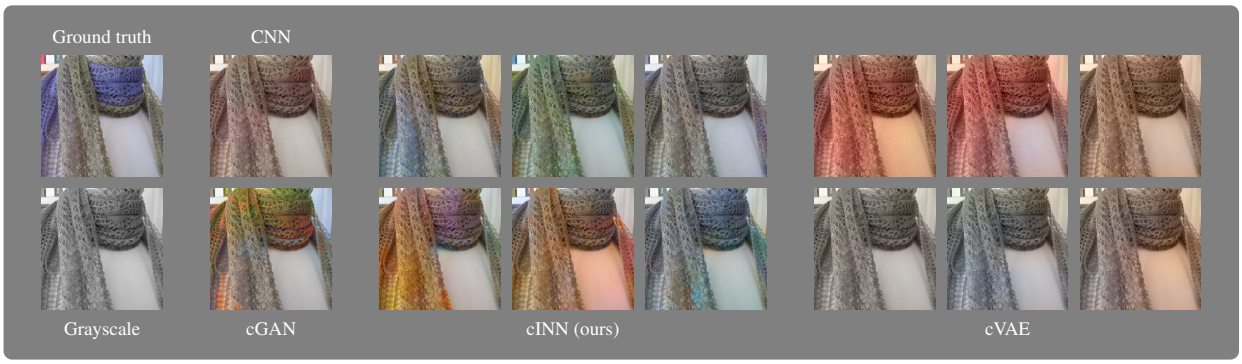
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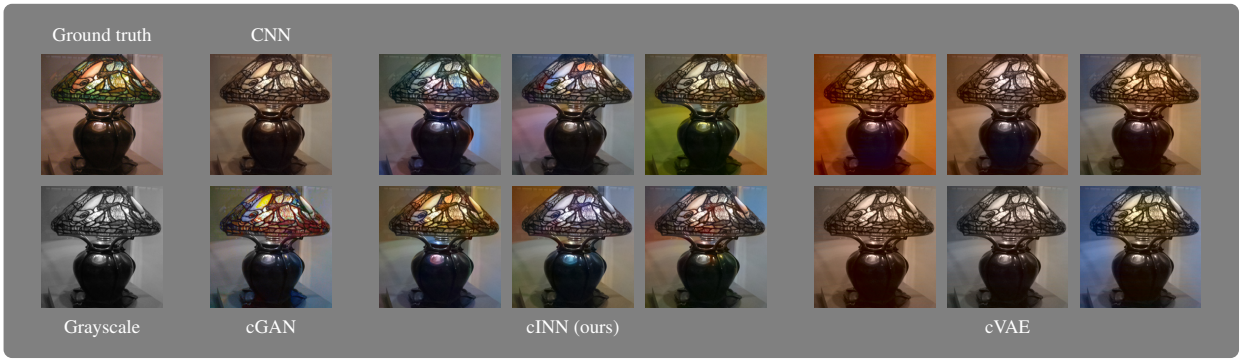
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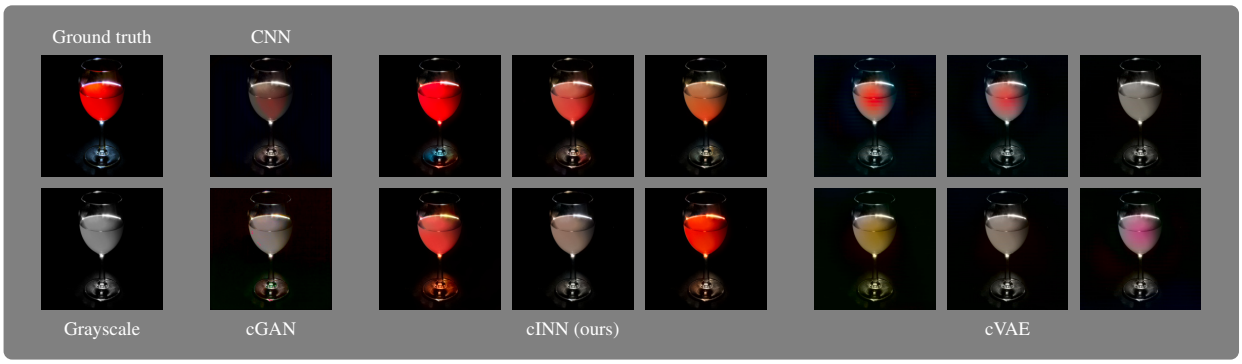
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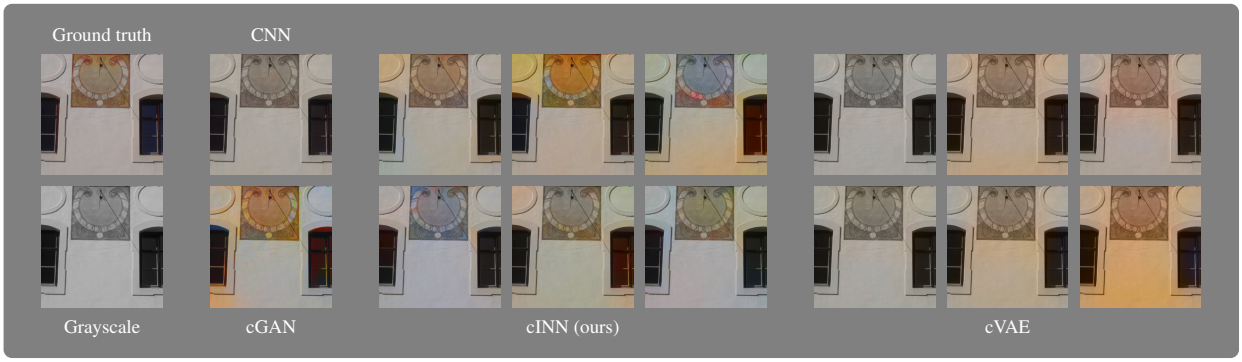
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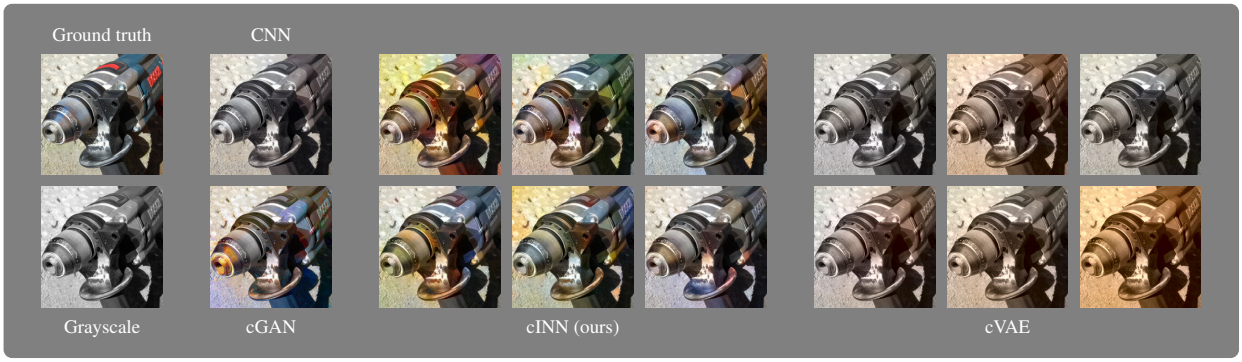
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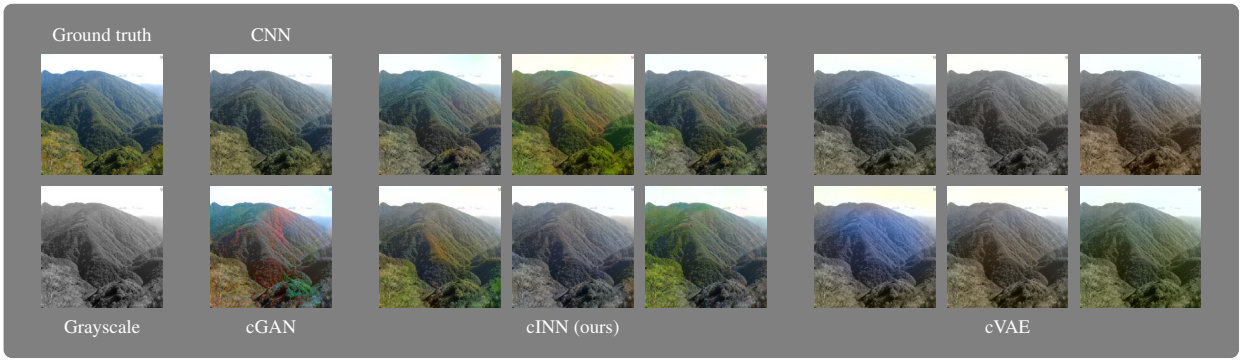
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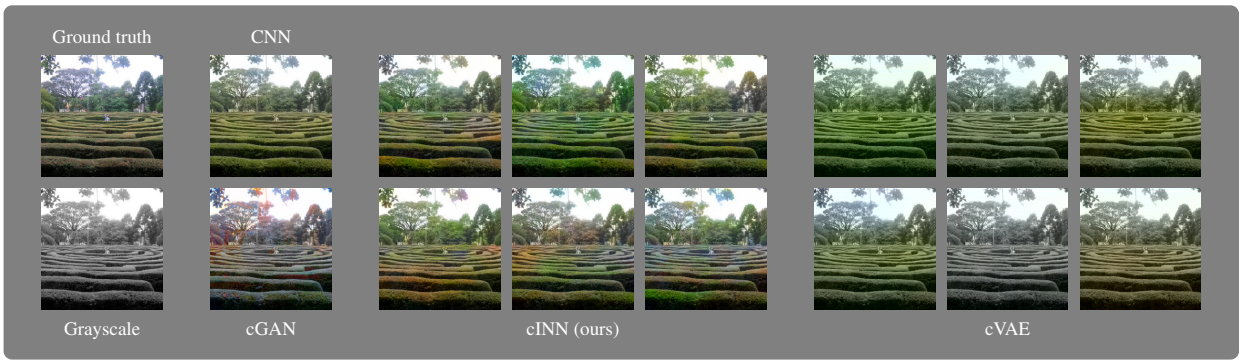
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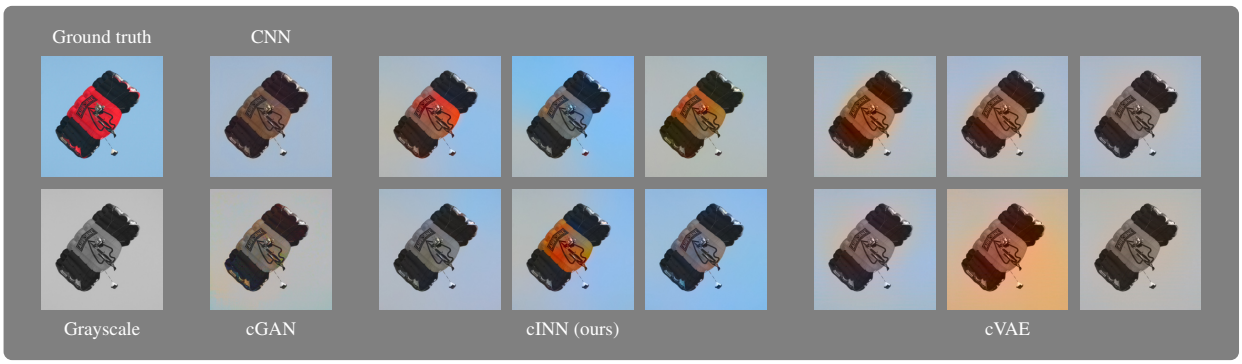
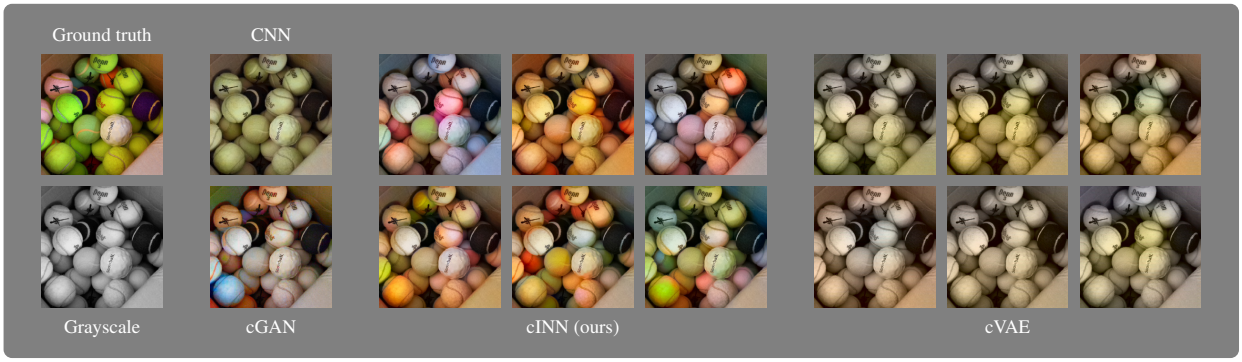
cINN (ours)
cVAE

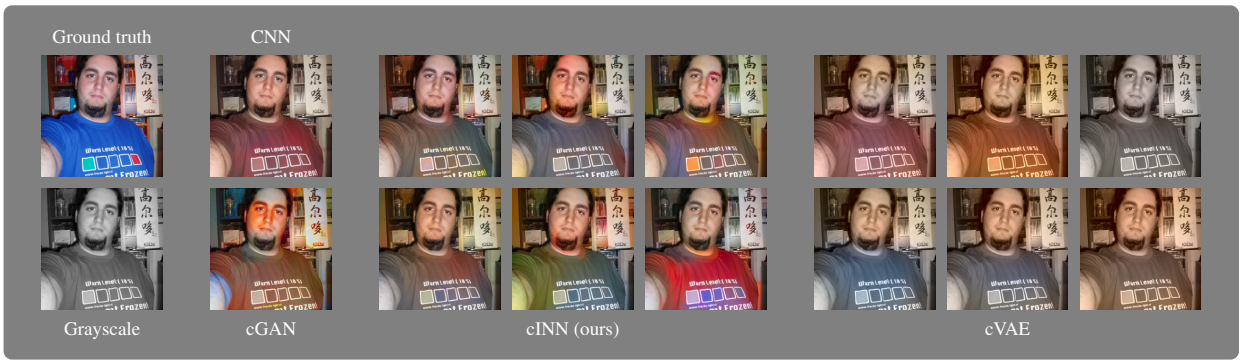

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

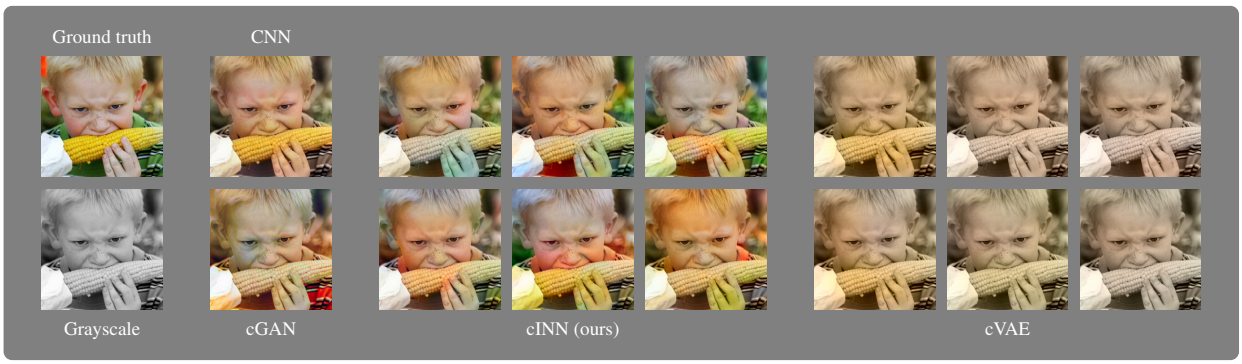


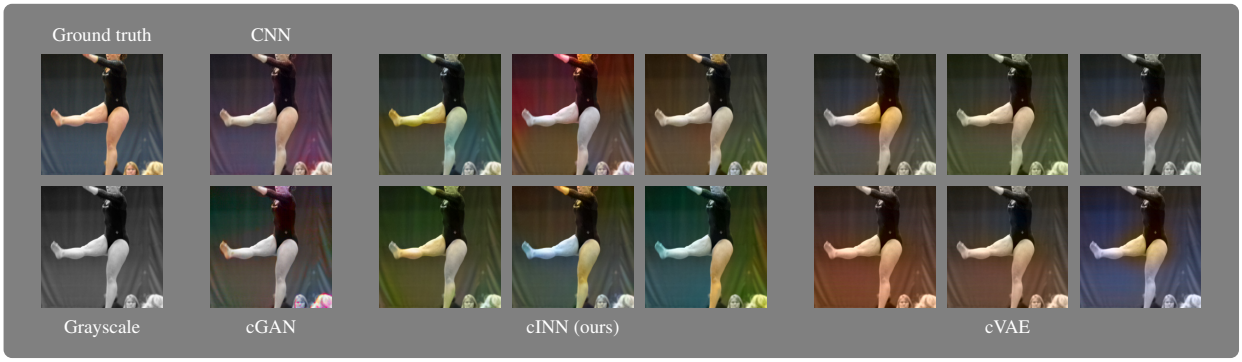
5.2 Humans

We find that the cINN often has difficulties generating convincing skin colors, as shown below. Clothing is colored in diverse ways, but not always with the correct connectivity and consistency.


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

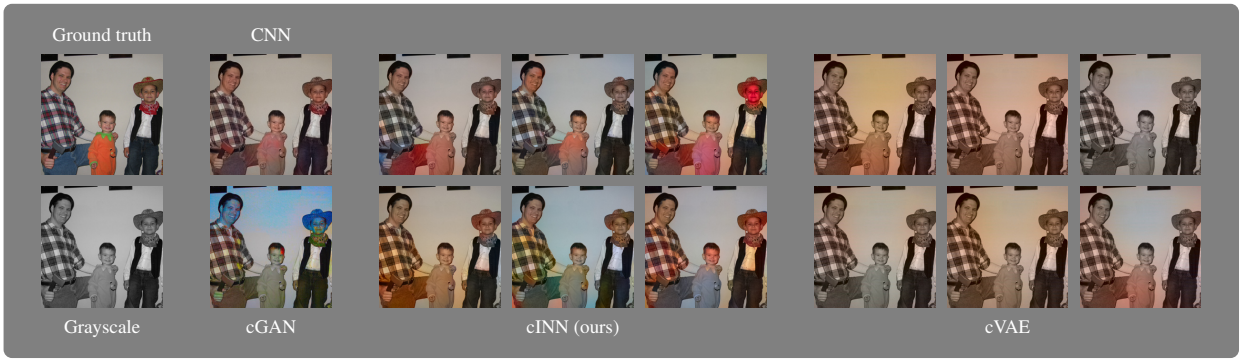

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

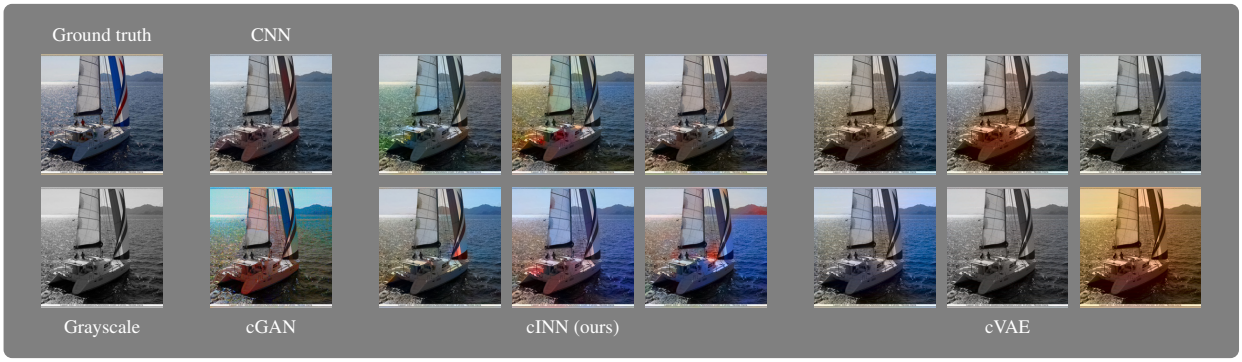

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE



5.3 Lacking consistency

The following failure cases exhibit a lack in consistency, in occluded objects, multi-part objects, or reflections.



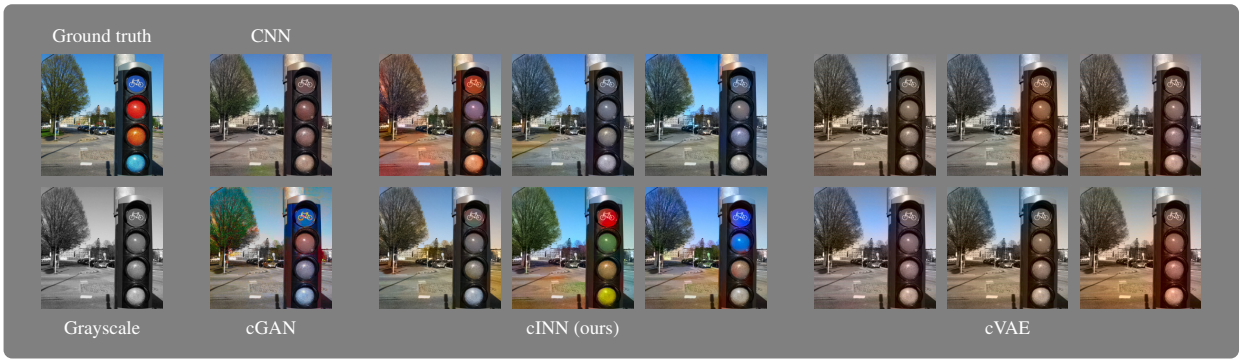

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

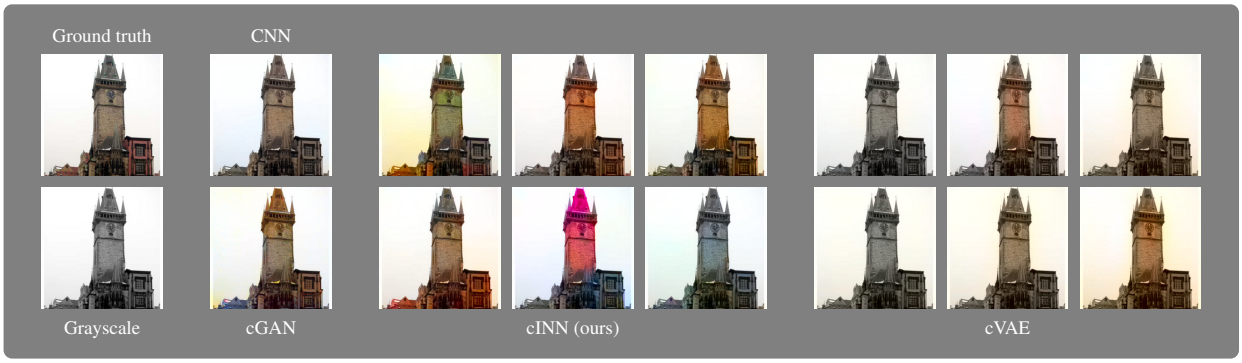

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

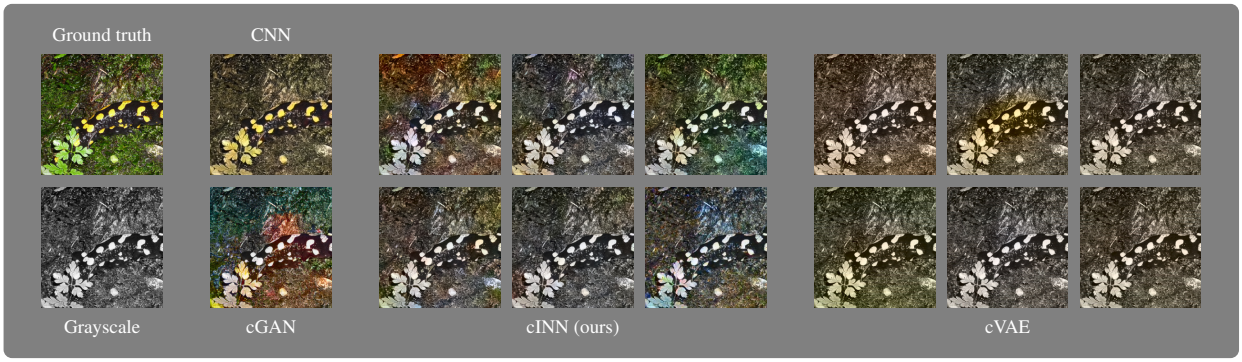
5.4 Color ignores semantic content

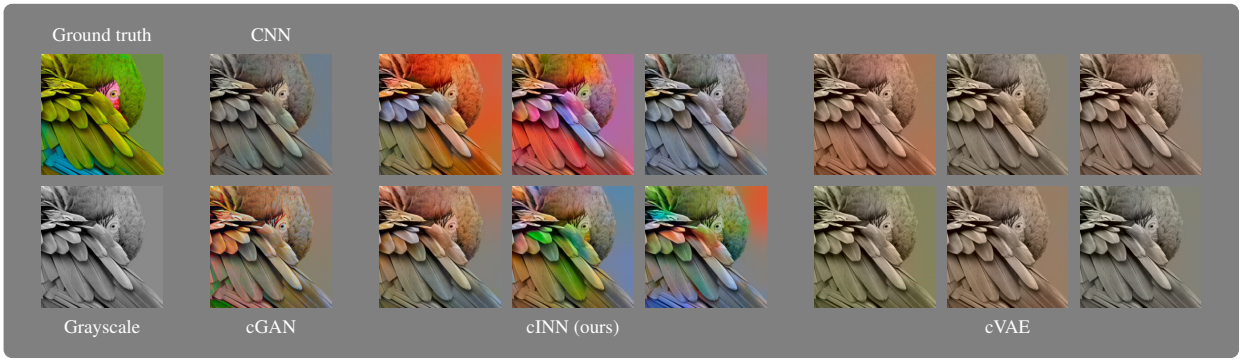
In the following examples, the semantic content of the image was not recognized, and the generated colors are clearly incorrect.

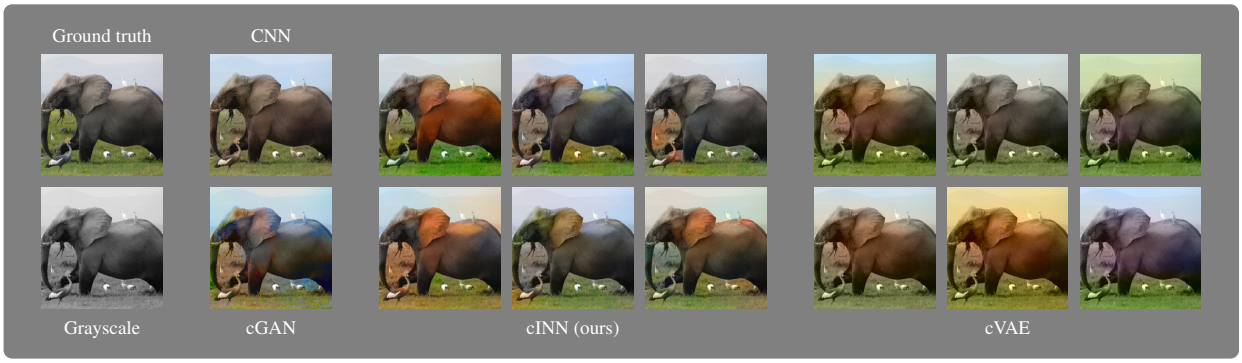



Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

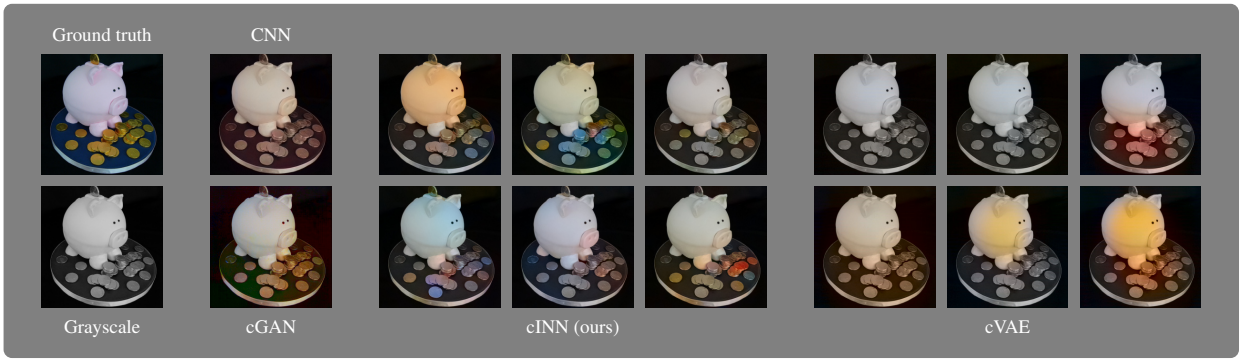

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

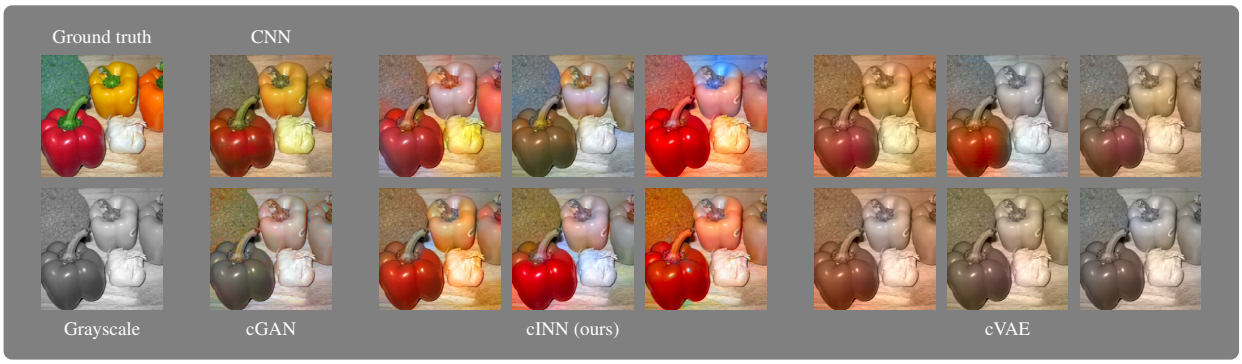

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

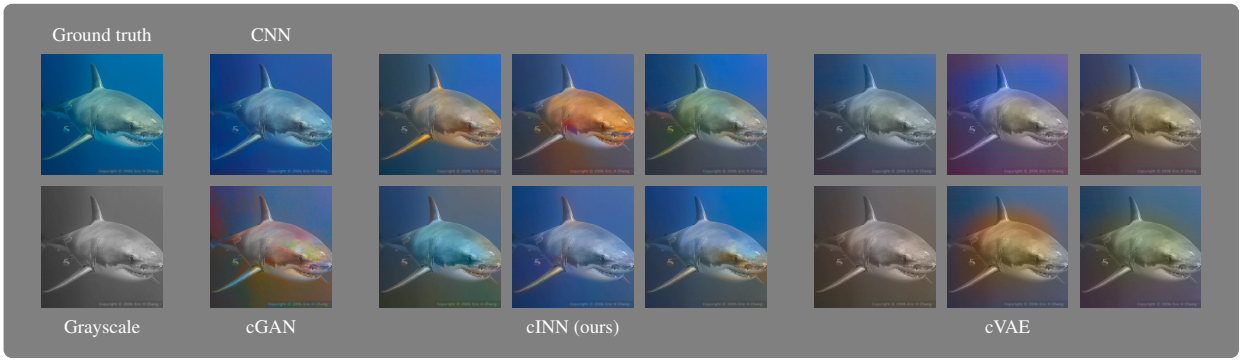

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

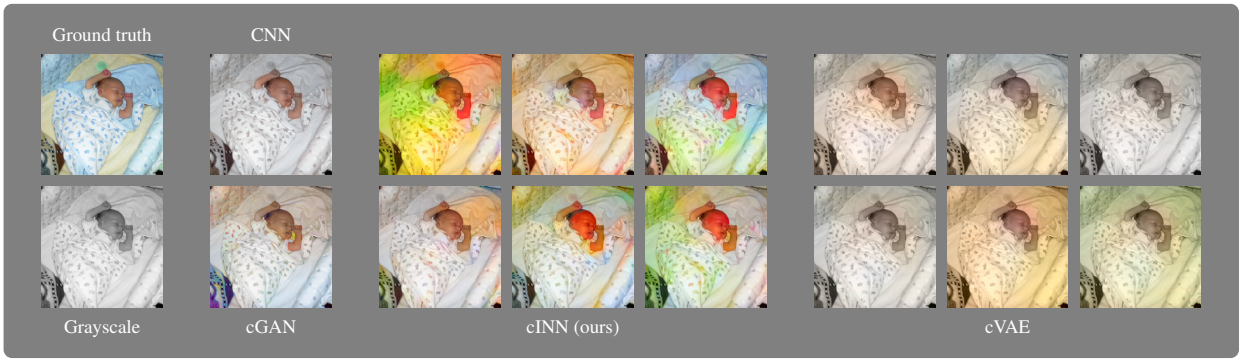

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

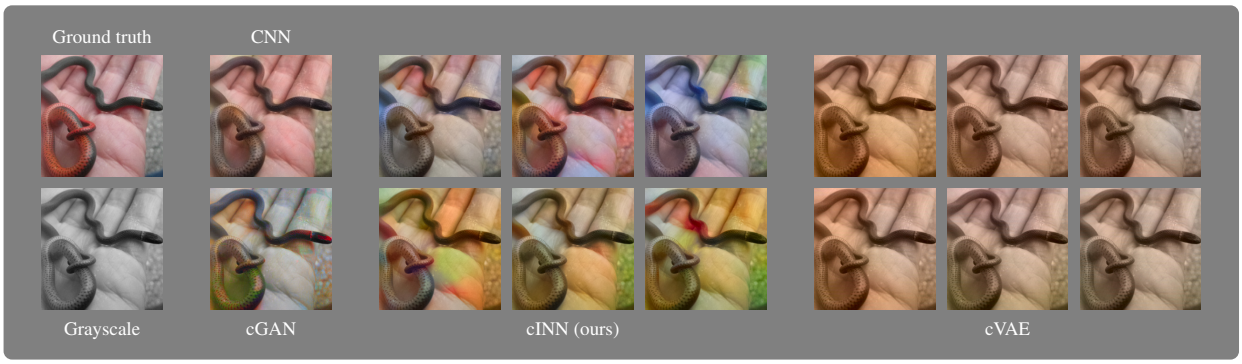


5.5 Outright failures

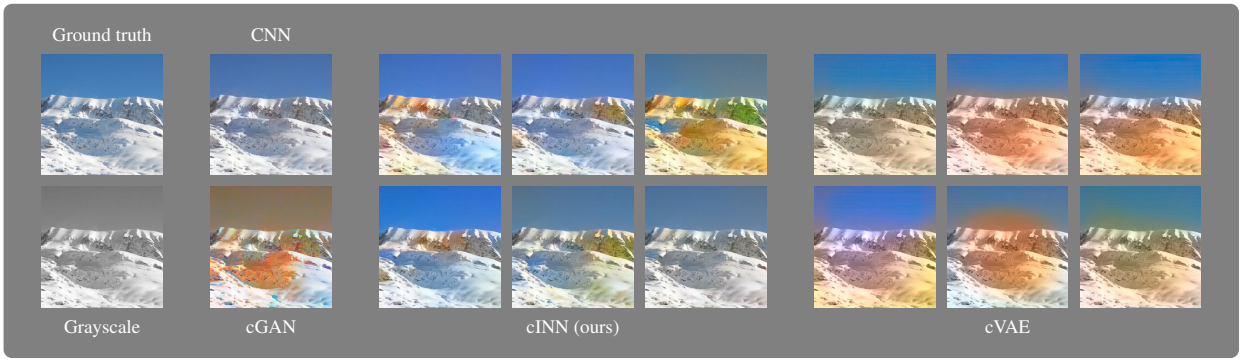
For the following images, the cINN fails completely, and generates colors with seemingly little or no connection to the grayscale image.

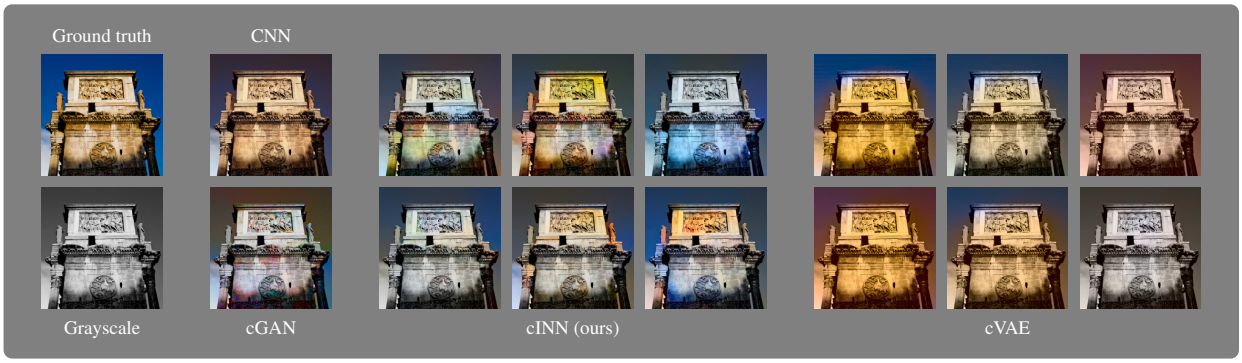



Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE

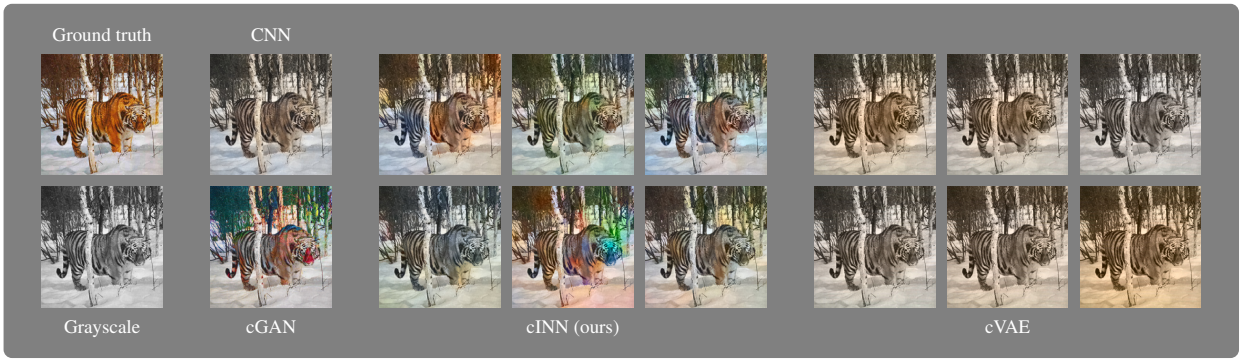

Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE


Ground truth
CNN
Grayscale
cGAN
cINN (ours)
cVAE