

SCGAN: Saliency Map-guided Colorization with Generative Adversarial Network

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List

1 Background

2 Motivation

3 Methodology (SCGAN)

4 Optimization

5 Comparison with State of the Art

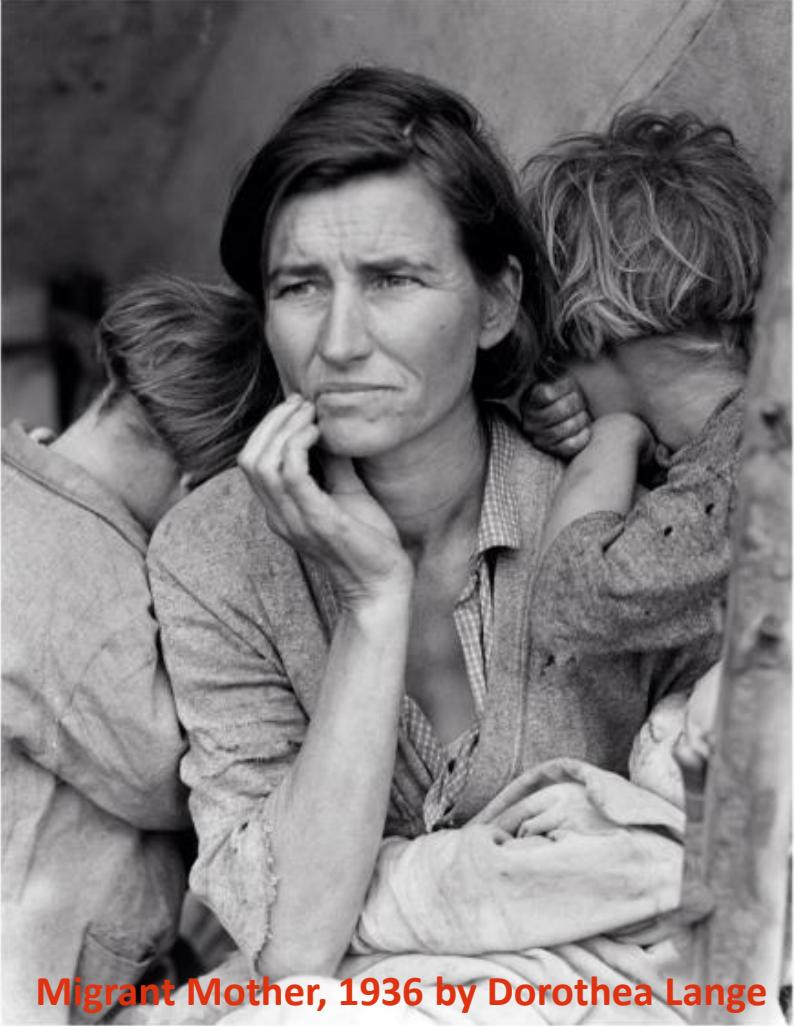
6 Ablation Study

7 Discussion of Saliency Map-guidance Method

8 Other Applications: Multispectral and Legacy Images

9 Limitation and Future Work

1 Background: What is Colorization?

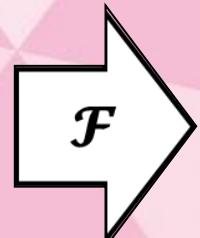
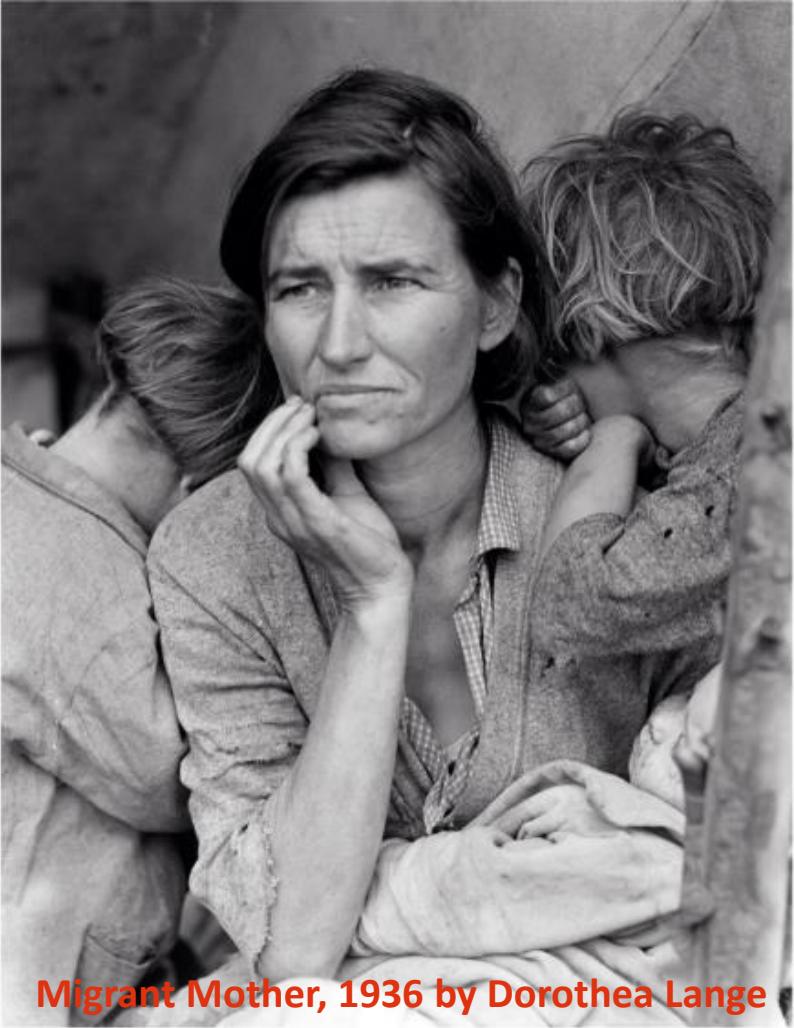


?



SCGAN Result

1 Background: What is Colorization?



SCGAN
IEEE TCSVT
2020



SCGAN Result

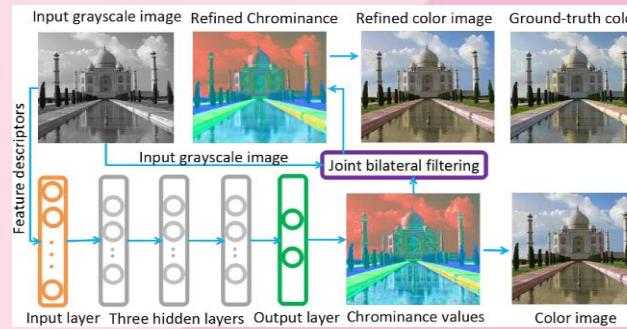
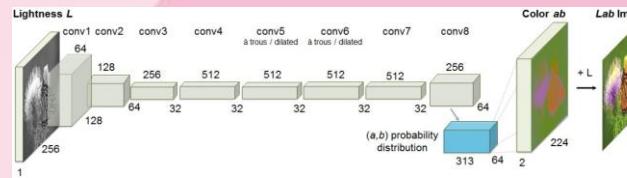


Parametric

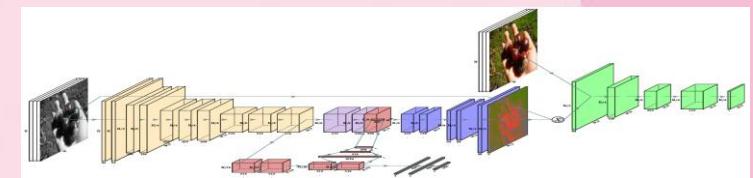
Non-parametric

Colorful Image Colorization, ECCV, 2016

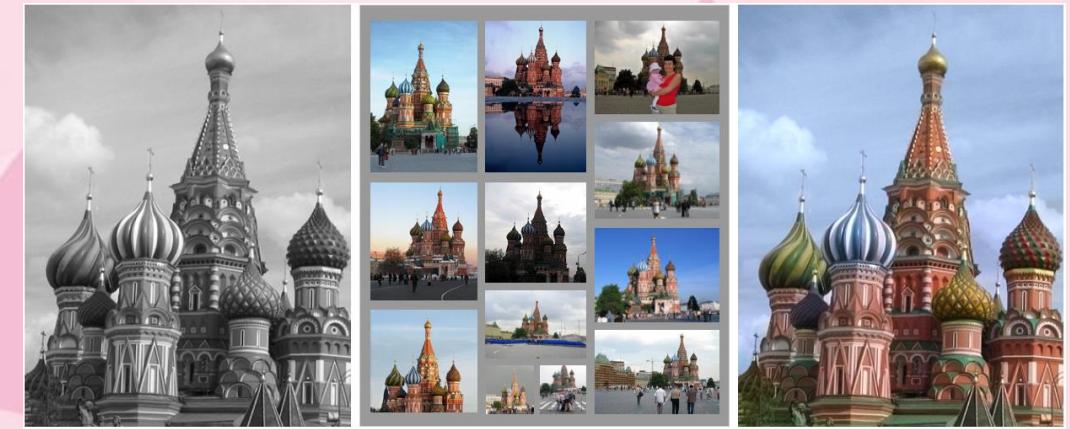
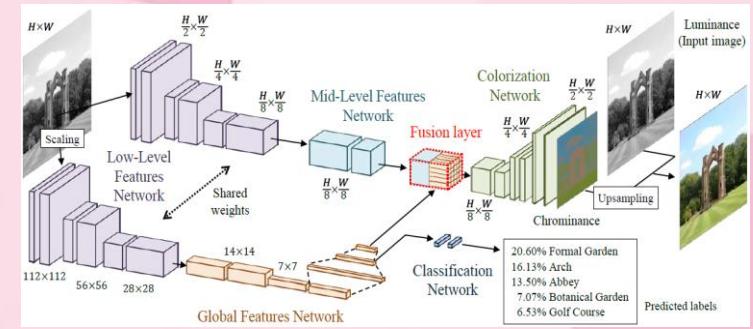
Deep Colorization, CVPR, 2015



ChromaGAN, WACV, 2020



Let there be Color!, ACM TOG, 2016



- Transferring Color to Greyscale Images, ACM TOG, 2002
- Colorization using optimization, ACM TOG, 2004
- Colorization by Example, EGSR, 2005
- Natural Image Colorization, EGSR, 2007
- Intrinsic Colorization, ACM TOG, 2008
- Image Colorization Using Similar Images, ACM MM, 2012

1 Background: Related Works

1 Background: Applications

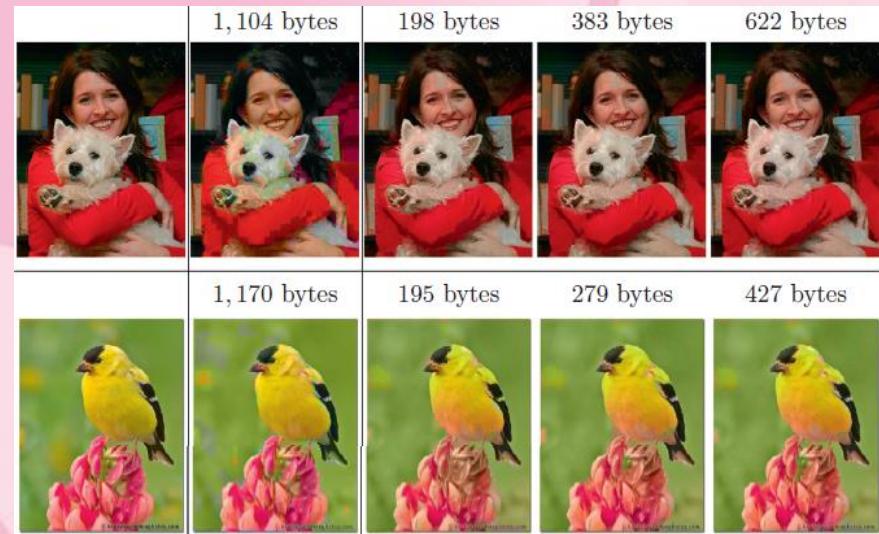
(1) Colorizing Legacy Photos



1 Background: Applications

(2) Image Compression

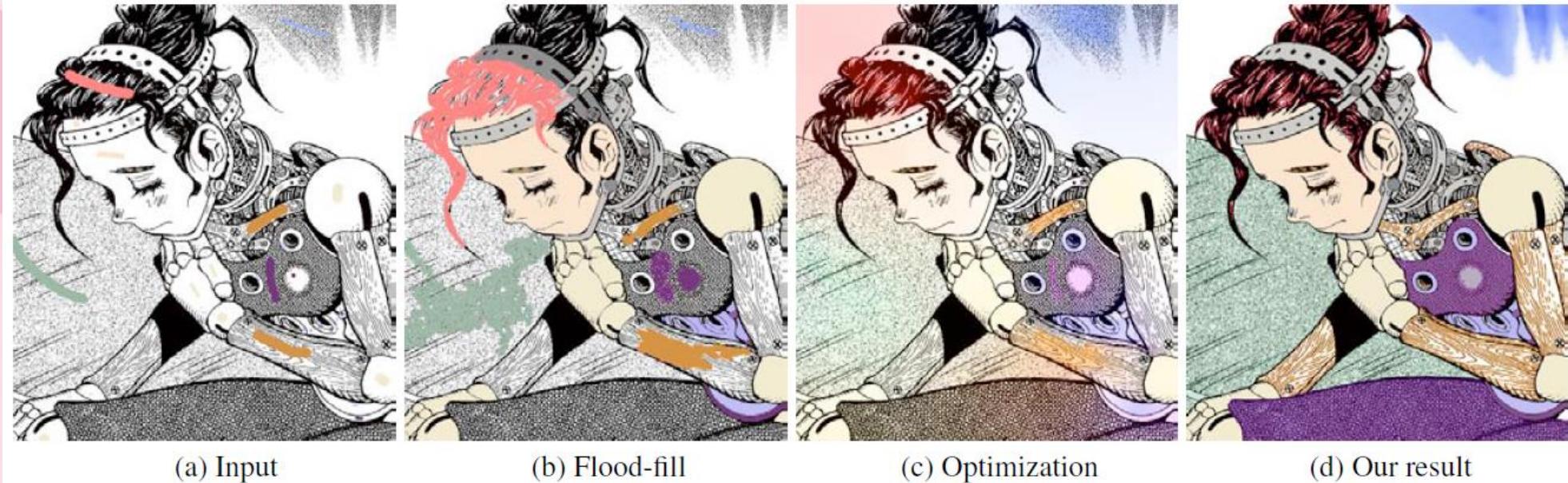
Image	JPEG [1]	Our approach		
	1,207 bytes	192 bytes	338 bytes	531 bytes
				



Multiple hypothesis colorization and its application to image compression, CVIU, 2017

1 Background: Applications

(3) Manga Colorization



Manga Colorization, ACM TOG, 2006

1 Background: Applications

(4) As a Proxy Task for other CV tasks

Learning a representation via (x, y) pairs

Classification

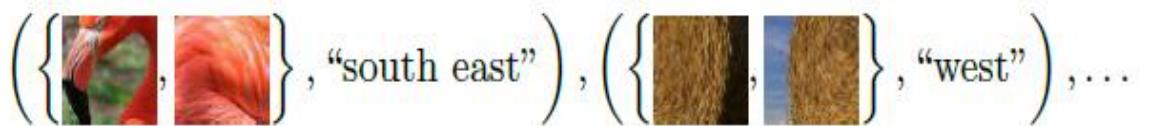


Self-supervision

Ex. 1: Inpainting (remove patch and then predict it)



Ex. 2: Context (given two patches, predict their spatial relation)

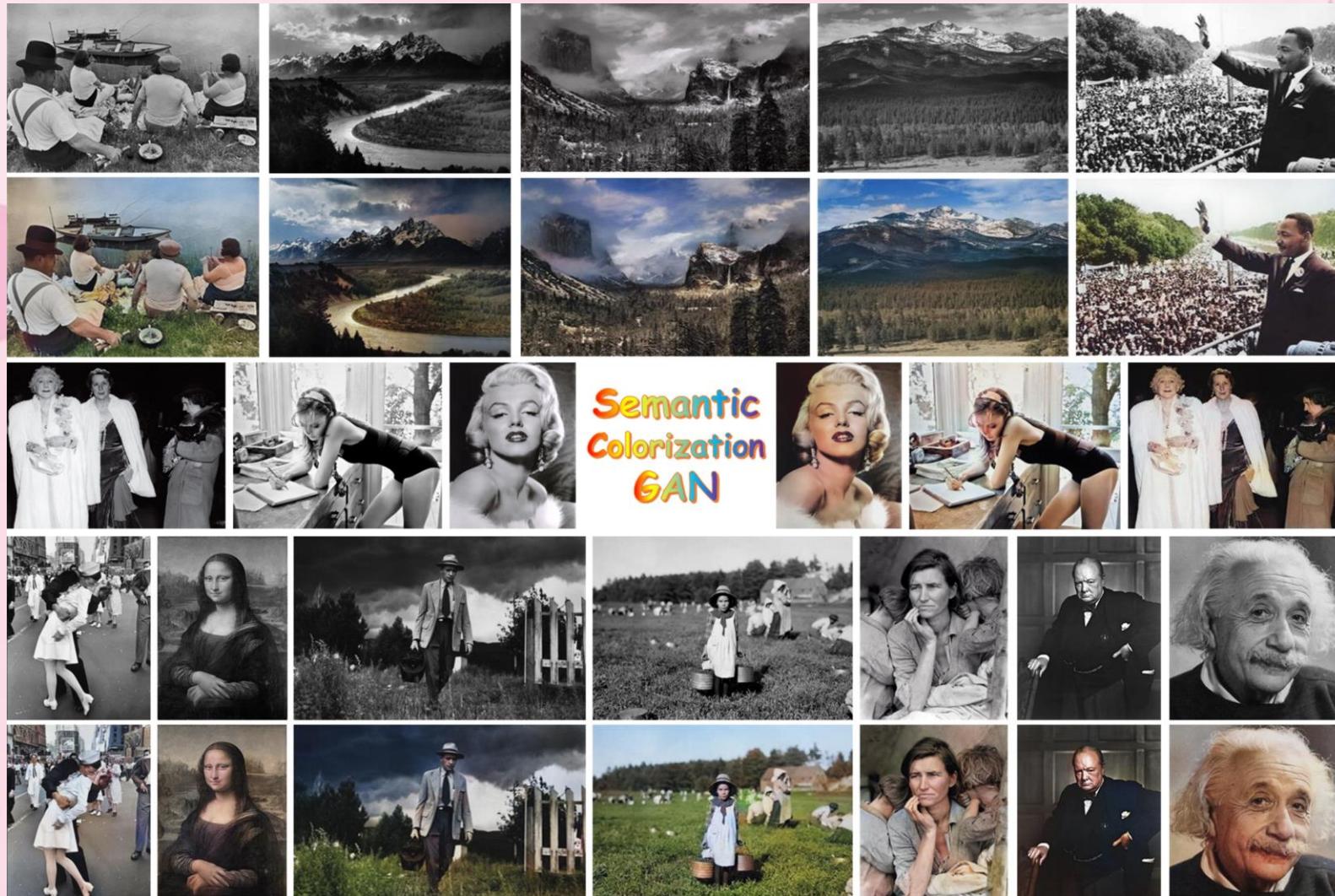


Ex. 3: Colorization (predict color given intensity)



Colorization as a Proxy Task for Visual Understanding, CVPR, 2017

1 Background: Representative Image



1 Background: Representative Image



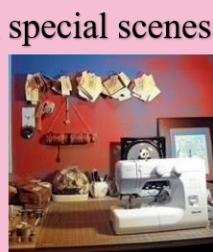
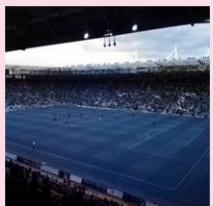
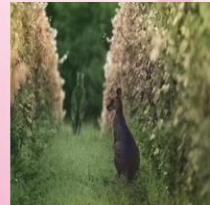
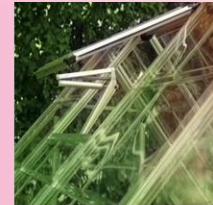
code can be found at:

<https://github.com/zhaoyuzhi/Semantic-Colorization-GAN>



2 Motivation

(1) There exist semantic confusion problem



2 Motivation

(2) There exist object intervention problem

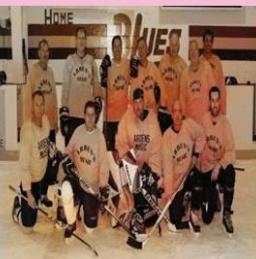
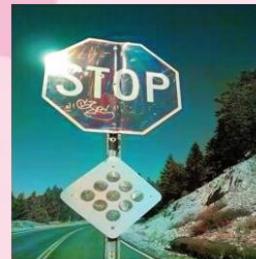
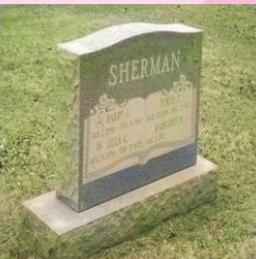
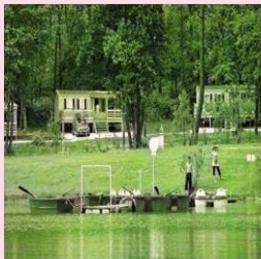


The grass / tree is green and interferes the surrounding objects

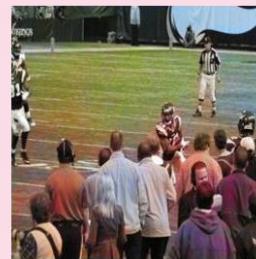
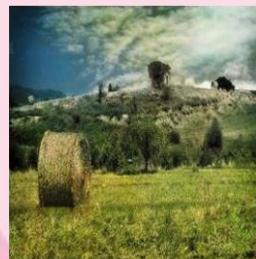
Most common object intervention problems



The sky is blue and interferes the surrounding objects



Other object intervention problems



2 Motivation

(3) Better Loss Function



+ GAN loss



+ GAN loss

(4) Some application does not have enough training data

2 Motivation

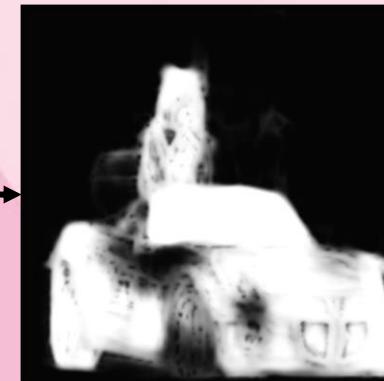
We propose to introduce a regularizer to enhance the colorization system: saliency map



Original colorization

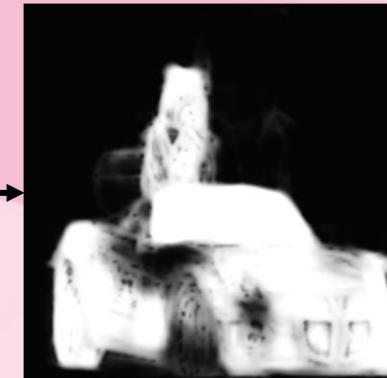


Saliency map branch
In our paper



2 Motivation

What is saliency map?

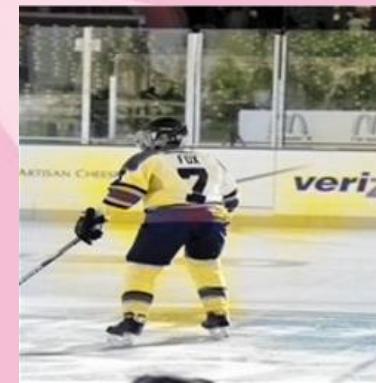
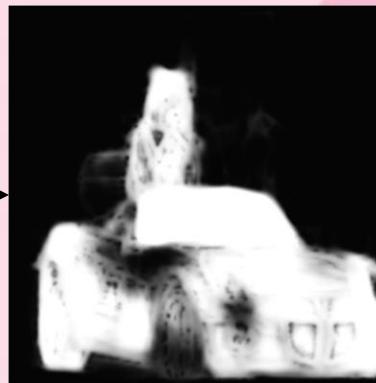


saliency map is the **visually important region** of an image, as a **weak binary segmentation map**

saliency map is also **unsupervised** when generation, thus adaptive to any datasets
(i.e., we can generate saliency maps for arbitrary images using SOTA saliency detection method)

2 Motivation

Why saliency map is useful to address those problems?

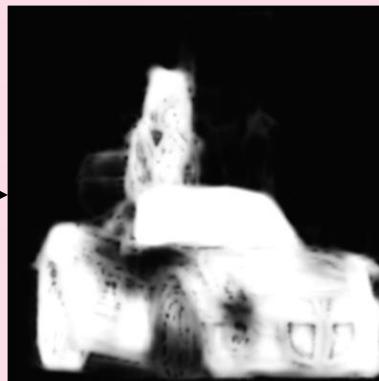


2 Motivation

Why saliency map is useful to address those problems?



RGB images



**Multispectral
images**



**NIR
images**



saliency map is also **unsupervised** when generation, thus adaptive to any datasets

2 Motivation

Why saliency map is useful to address those problems?

saliency map is also **unsupervised** when generation, thus adaptive to any datasets

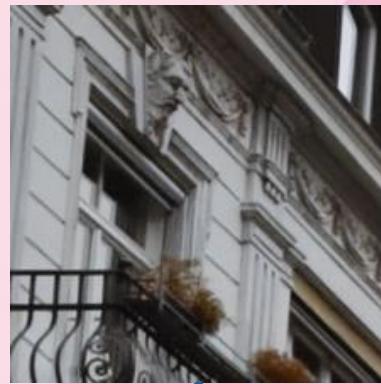
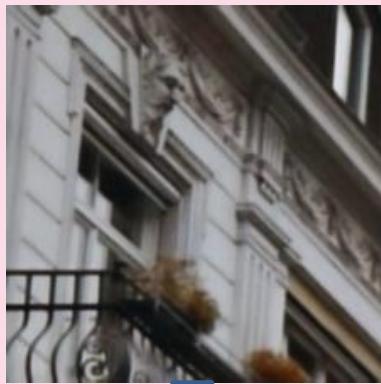
NIR images from a small dataset



2 Motivation

We **also** propose to use a GAN loss to sharpen image and make the output more colorful

GAN is a generative model that generates an image from noise. The proposed colorization framework is a conditional GAN that generates RGB images from grayscale images

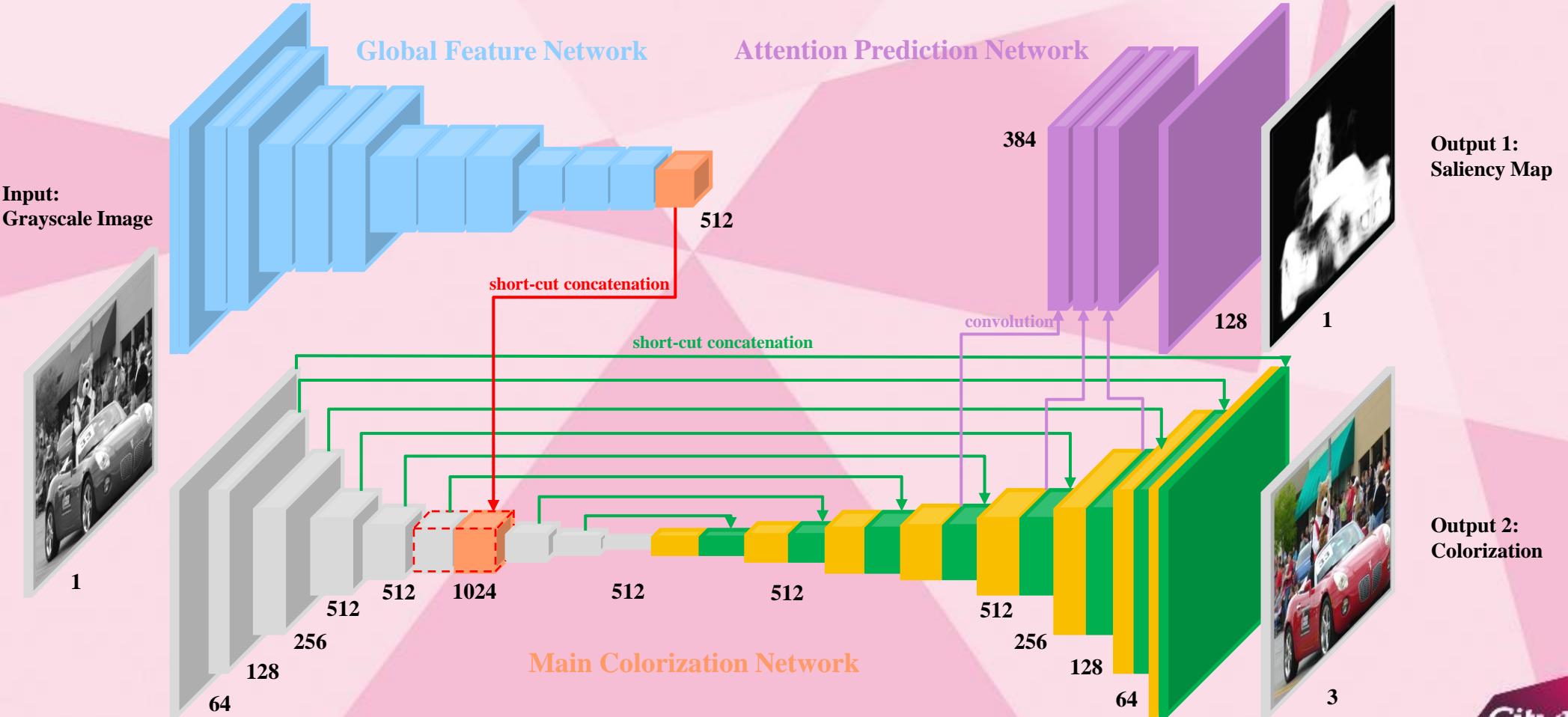


+ GAN loss



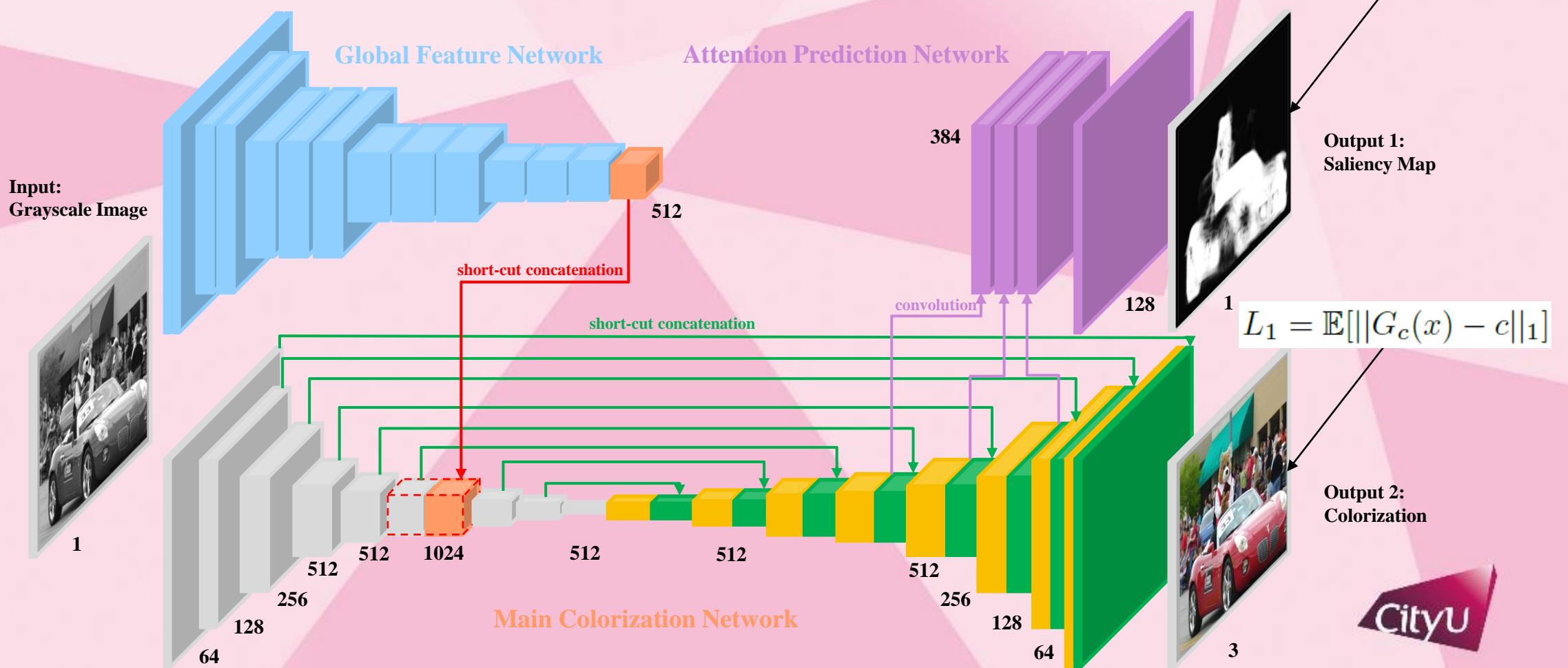
+ GAN loss

3 Methodology (SCGAN)



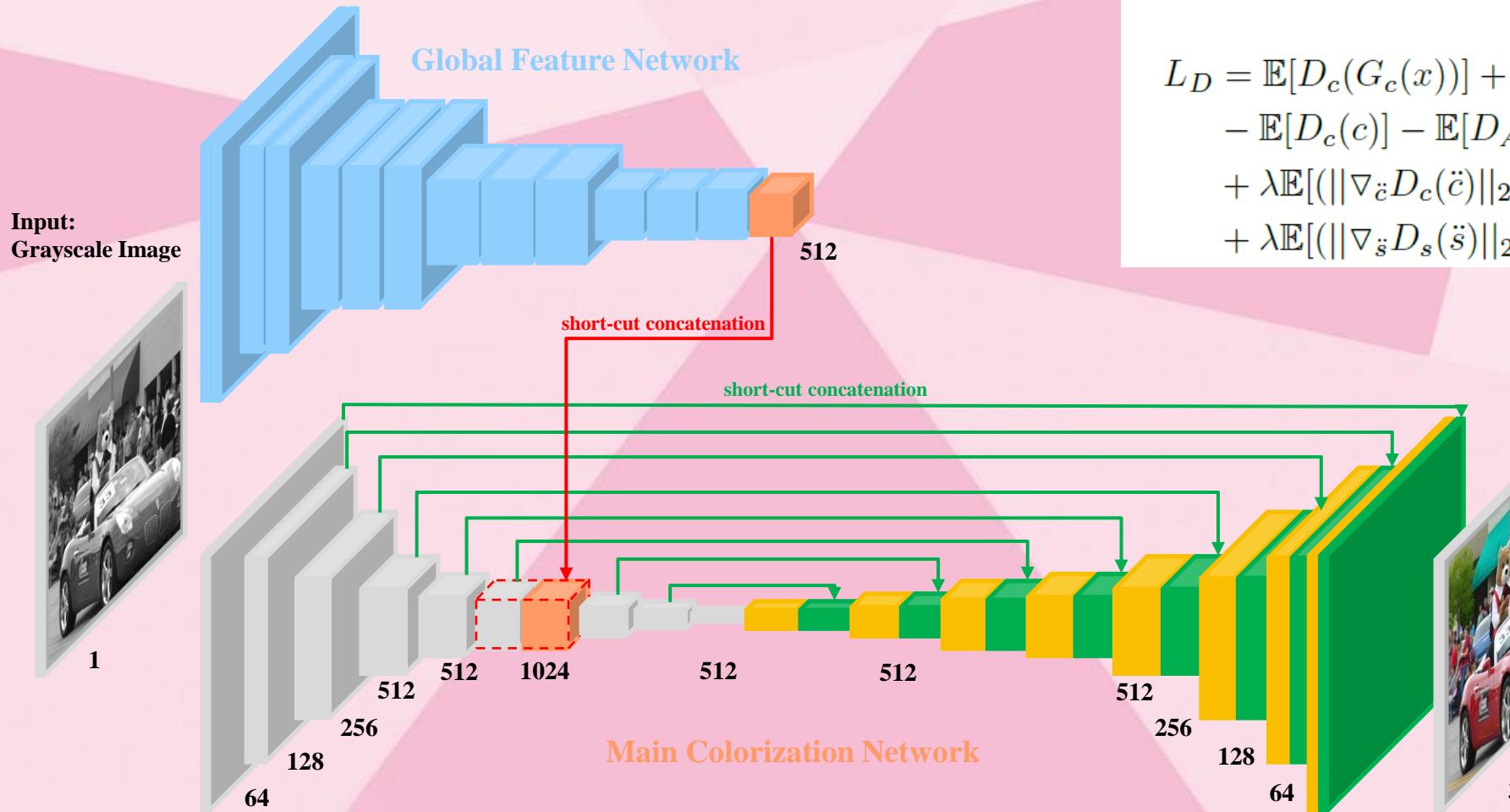
3 Methodology (SCGAN)

(1) Optimize SCGAN by joint losses



3 Methodology (SCGAN)

(2) GAN loss

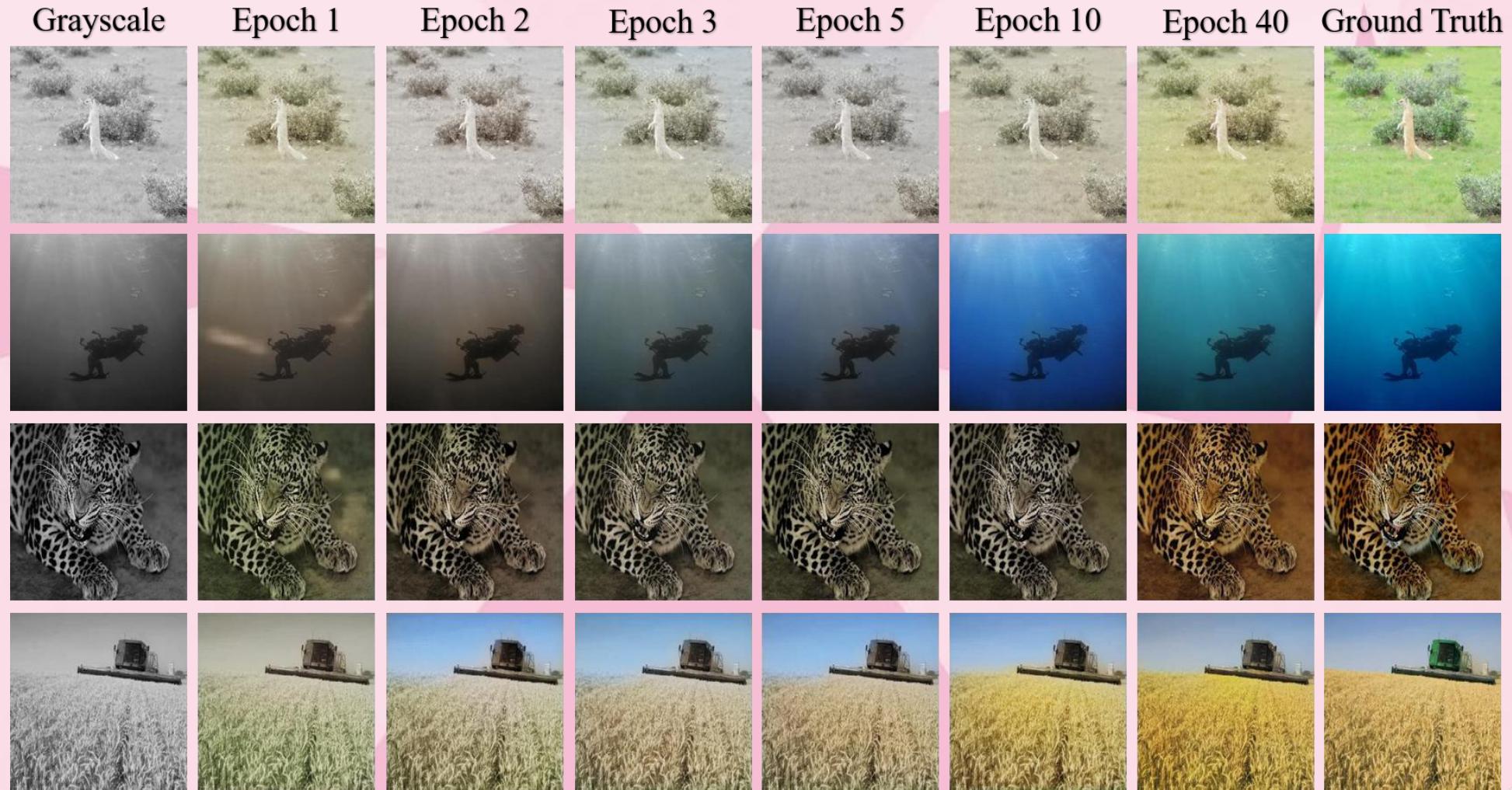


4 Optimization

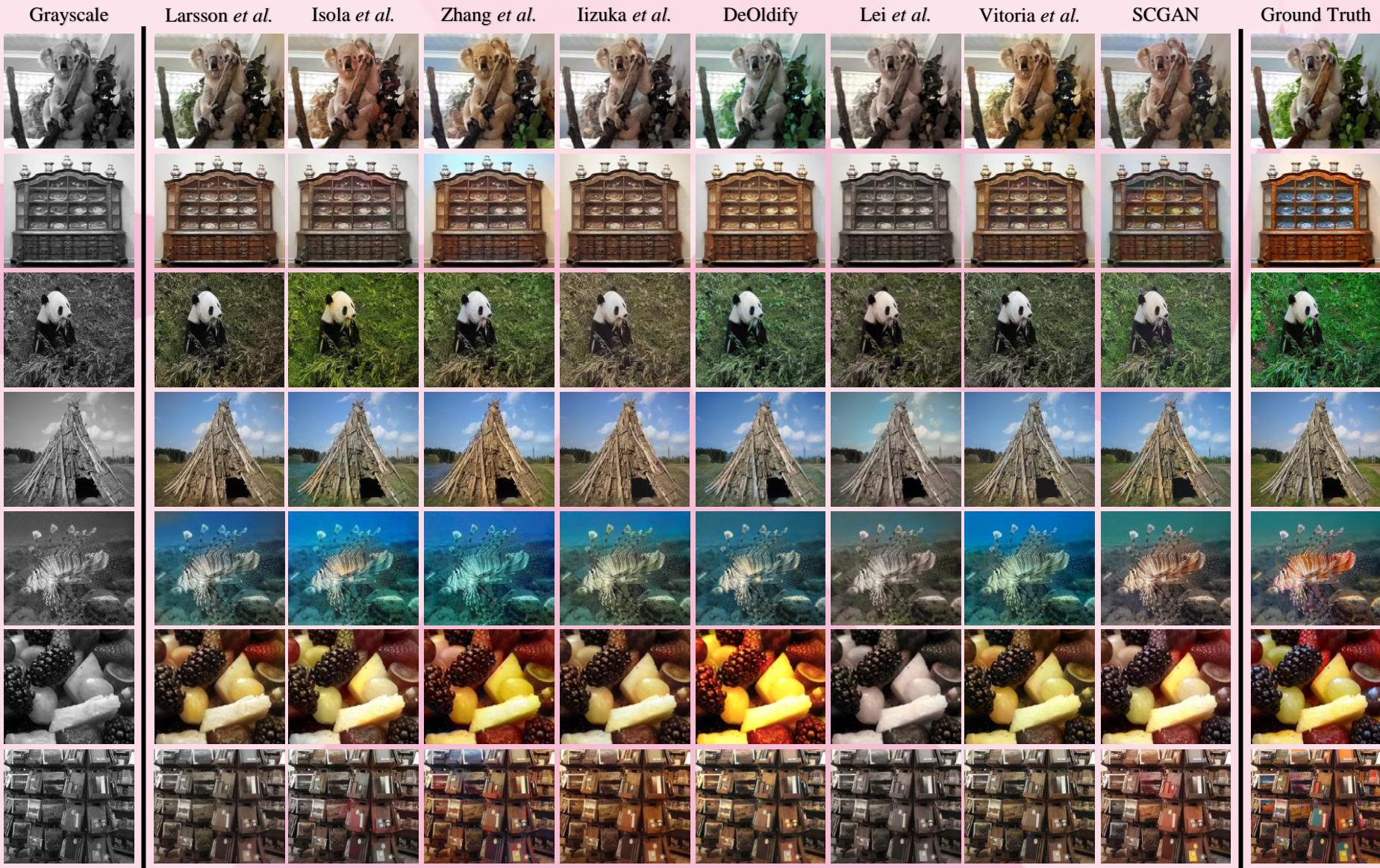
Details:

- (1) Dataset: 10% of ImageNet (where other methods use the entire dataset);**
- (2) Adam optimizer with Xavier initialization;**
- (3) Image patch 256×256 ;**
- (4) PyTorch 1.0.0 with Python 3.6.**

4 Optimization



5 Comparison with State of the Art



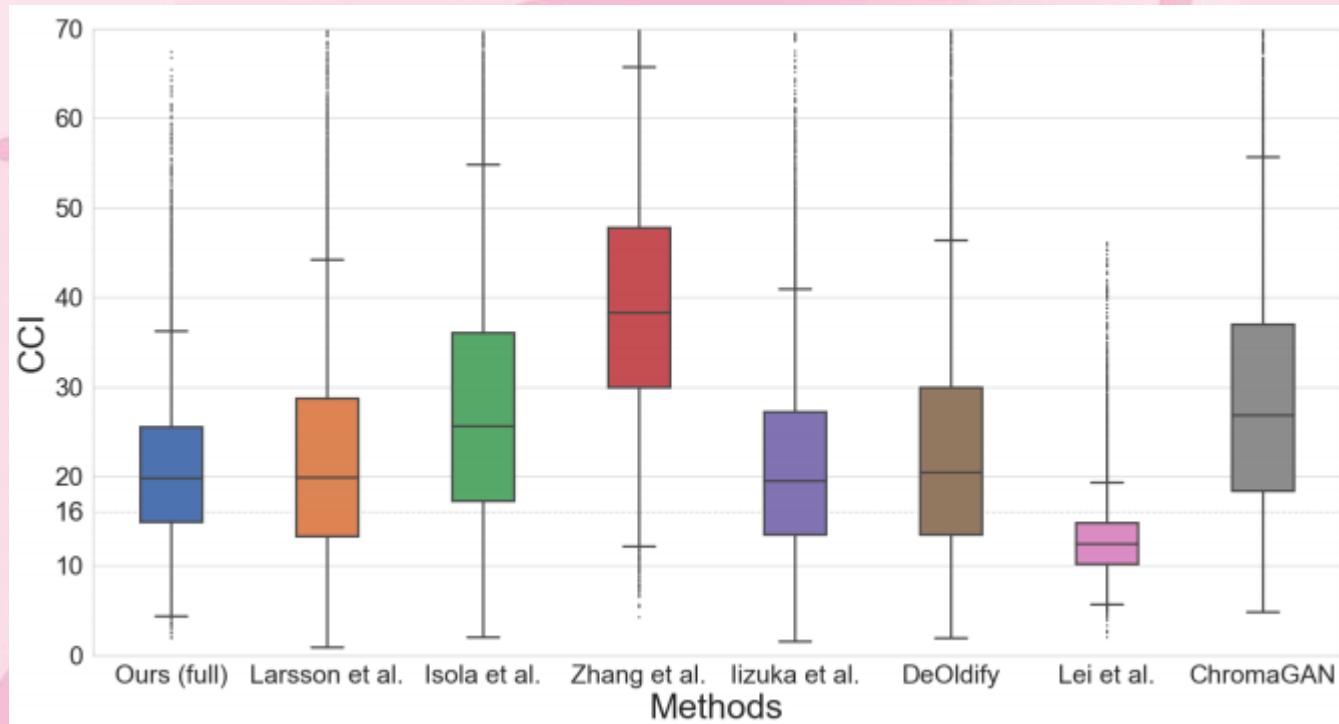
5 Comparison with State of the Art

Quantitative results

Method	PSNR	SSIM	Top-1 Accuracy	CCI Ratio	Color Naturalness	Color Bleeding Removal	Color Colorfulness
Ground Truth	/	1	63.44%	/	/	/	/
Grayscale	23.23	0.9394	49.78%	/	/	/	/
Larsson <i>et al.</i>	24.42	0.9229	55.16%	14.93%	9.14	8.58	8.22
Isola <i>et al.</i>	23.25	0.9386	52.29%	11.26%	8.56	7.93	8.96
Zhang <i>et al.</i>	22.49	0.9153	53.97%	3.300%	9.05	7.10	9.50
Iizuka <i>et al.</i>	24.32	0.9464	53.05%	19.60%	9.17	8.34	8.76
DeOldify	23.14	0.9194	53.45%	14.73%	9.20	8.57	9.01
Lei <i>et al.</i>	22.96	0.9146	51.46%	11.40%	8.02	7.14	7.45
Vitoria <i>et al.</i>	24.32	0.9273	53.65%	11.24%	9.03	8.24	9.17
SCGAN	23.80	0.9473	53.47%	21.41%	9.32	8.68	9.04

5 Comparison with State of the Art

Quantitative results



5 Comparison with State of the Art

Grayscale



Zhang *et al.*



Vitoria *et al.*



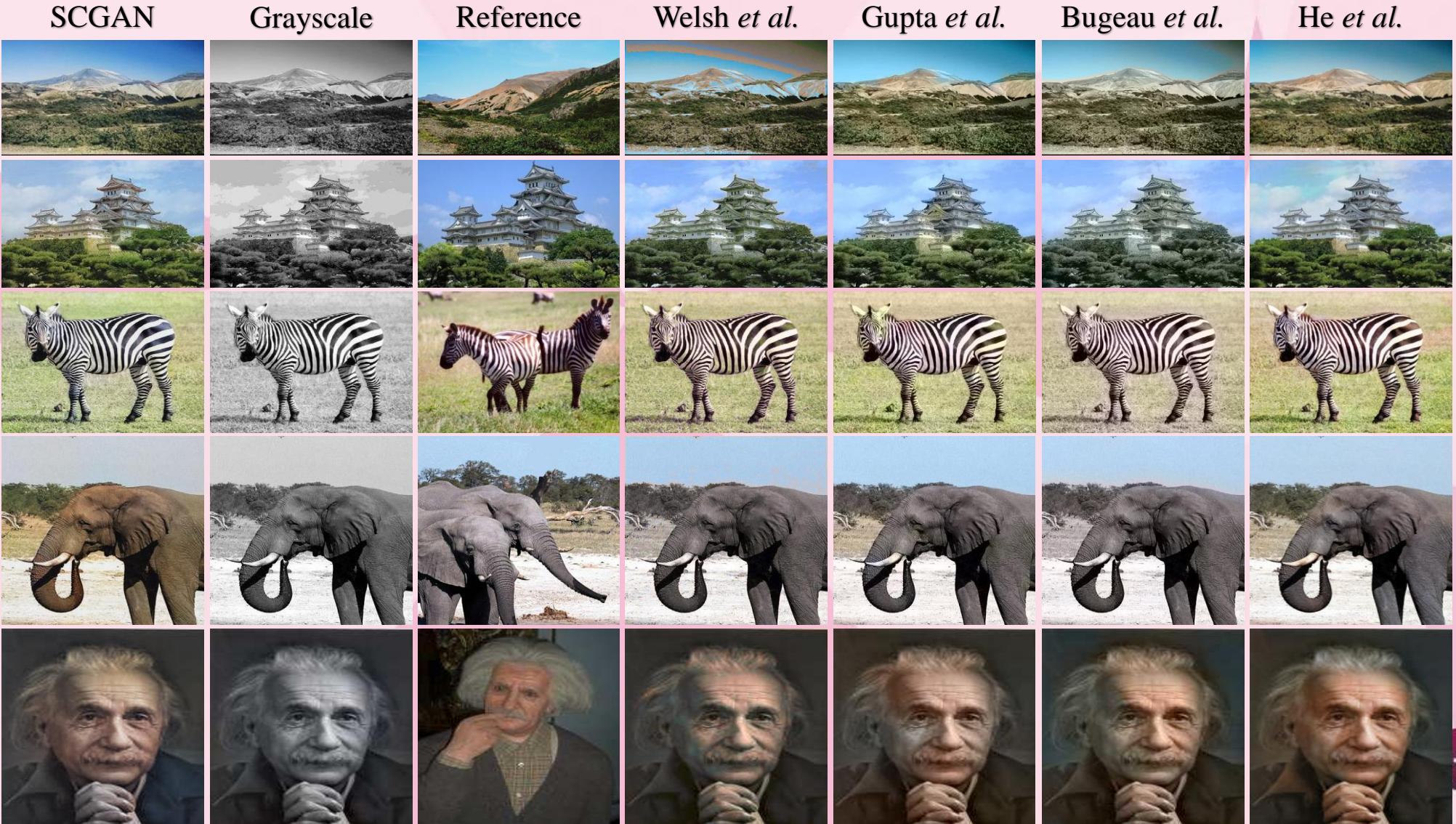
SCGAN



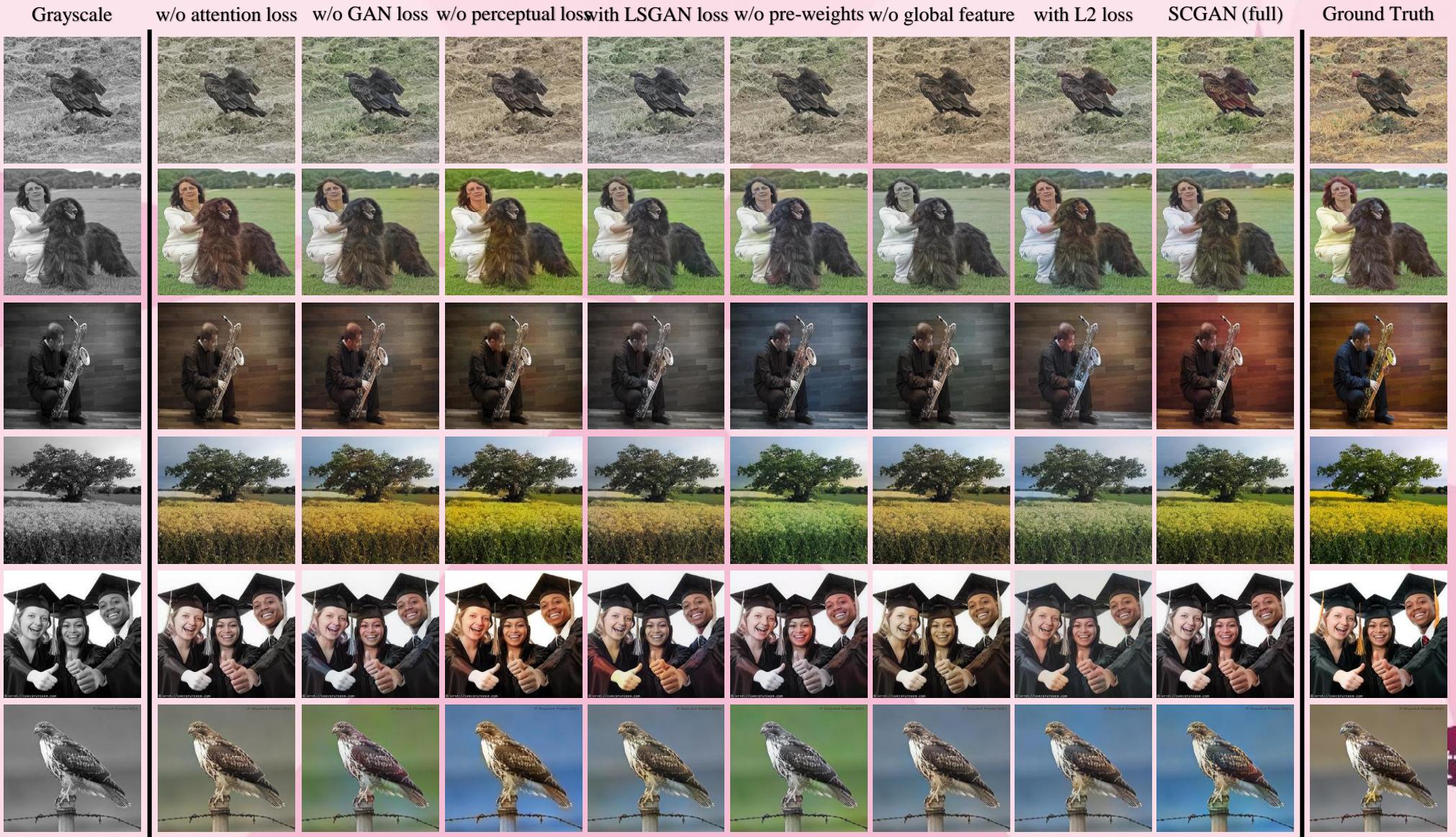
SCGAN



5 Comparison with State of the Art



6 Ablation Study



6 Ablation Study

Quantitative results

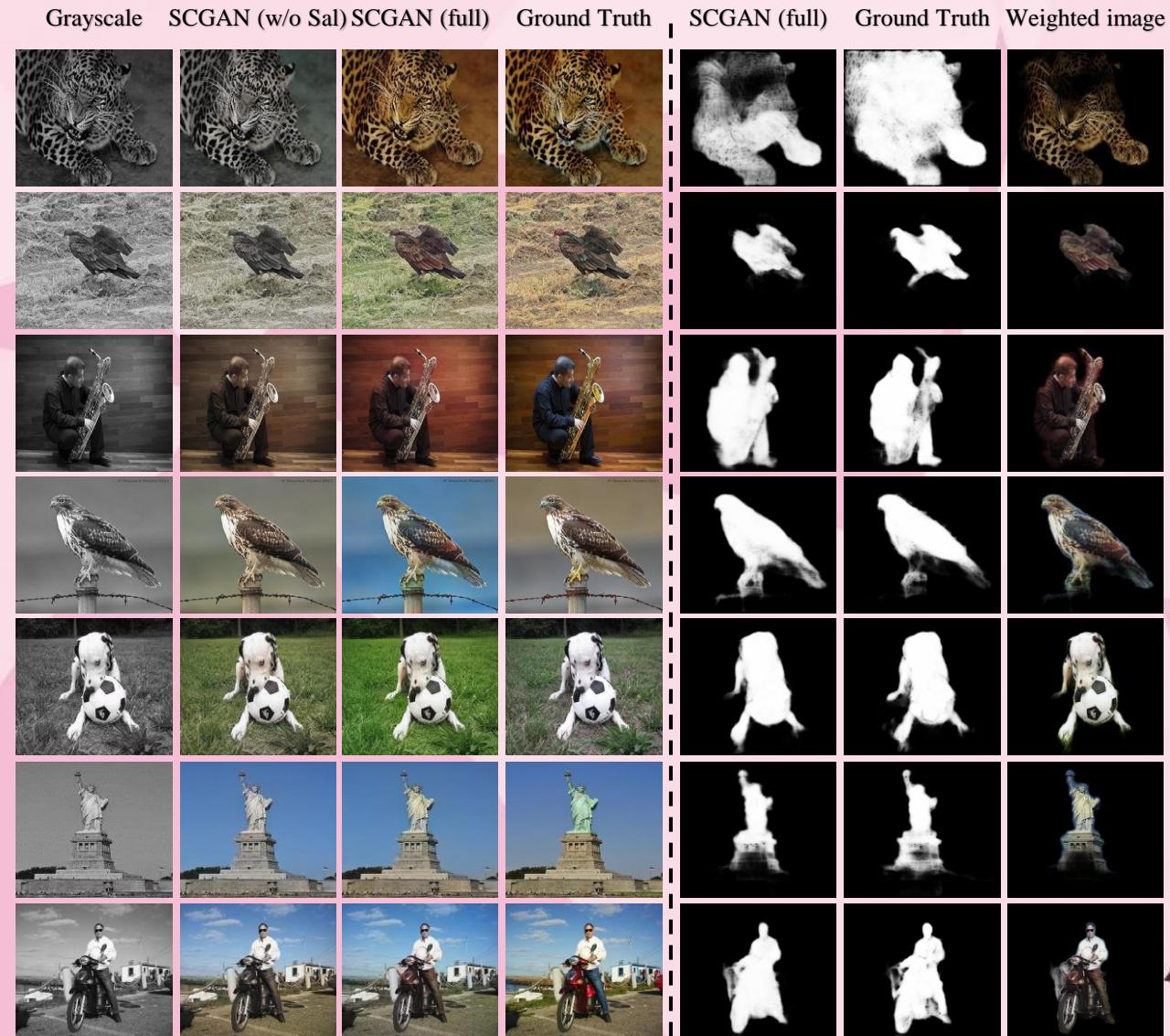
Method	PSNR	SSIM	Top-1 Acc	CCI Ratio
w/o attention loss	23.81	0.9368	52.34%	18.56%
w/o GAN loss	23.28	0.9305	52.89%	20.45%
w/o perceptual loss	23.80	0.9443	52.11%	21.31%
with LSGAN loss	23.46	0.9390	53.42%	20.86%
w/o pre-weights	23.15	0.9280	52.59%	18.20%
w/o global feature	23.61	0.9356	52.16%	17.55%
with L2 loss	23.67	0.9436	53.26%	19.58%
SCGAN (full)	23.80	0.9473	53.47%	21.41%

7 Discussion of Saliency Map-guidance Method

SCGAN trained with saliency map, i.e., SCGAN (full)

VS

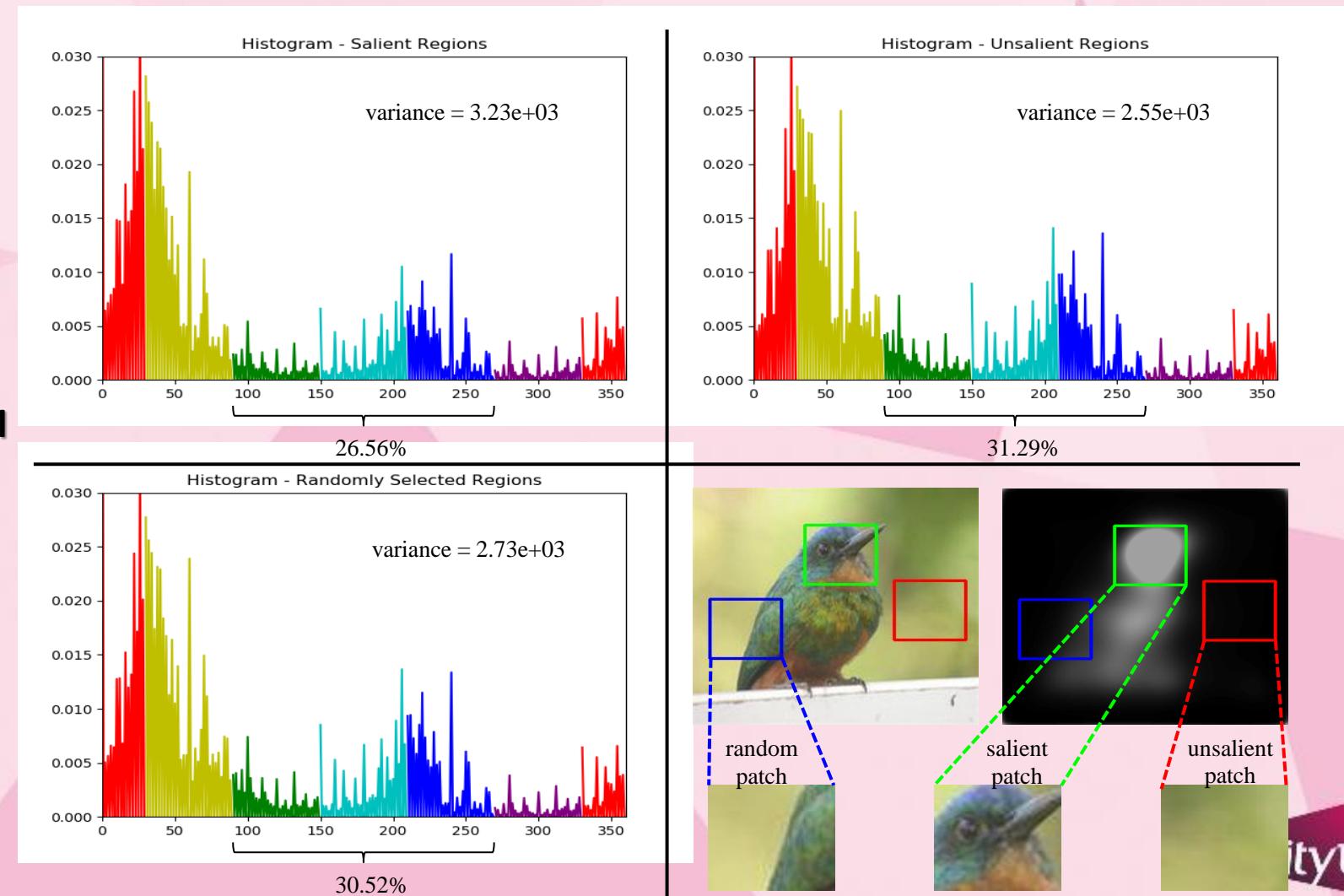
SCGAN trained without saliency map, i.e., SCGAN (w/o sal)



7 Discussion of Saliency Map-guidance Method

SCGAN trained with saliency map, i.e., SCGAN (full)

occupies more colorful regions, while less green and blue



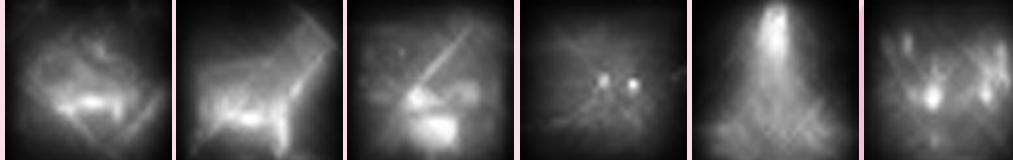
7 Discussion of Saliency Map-guidance Method

Two types of saliency maps: we use **object detection** saliency map

Training
grayscale
images



Saliency
maps from
fixation
prediction
[91]



Saliency
maps from
object
Detection [70]



Training
RGB
images



Validation
grayscale
images



Colorizations
from SCGAN with
saliency maps from
fixation
prediction [91]



Colorizations
from SCGAN with
saliency maps
from object
detection [70]

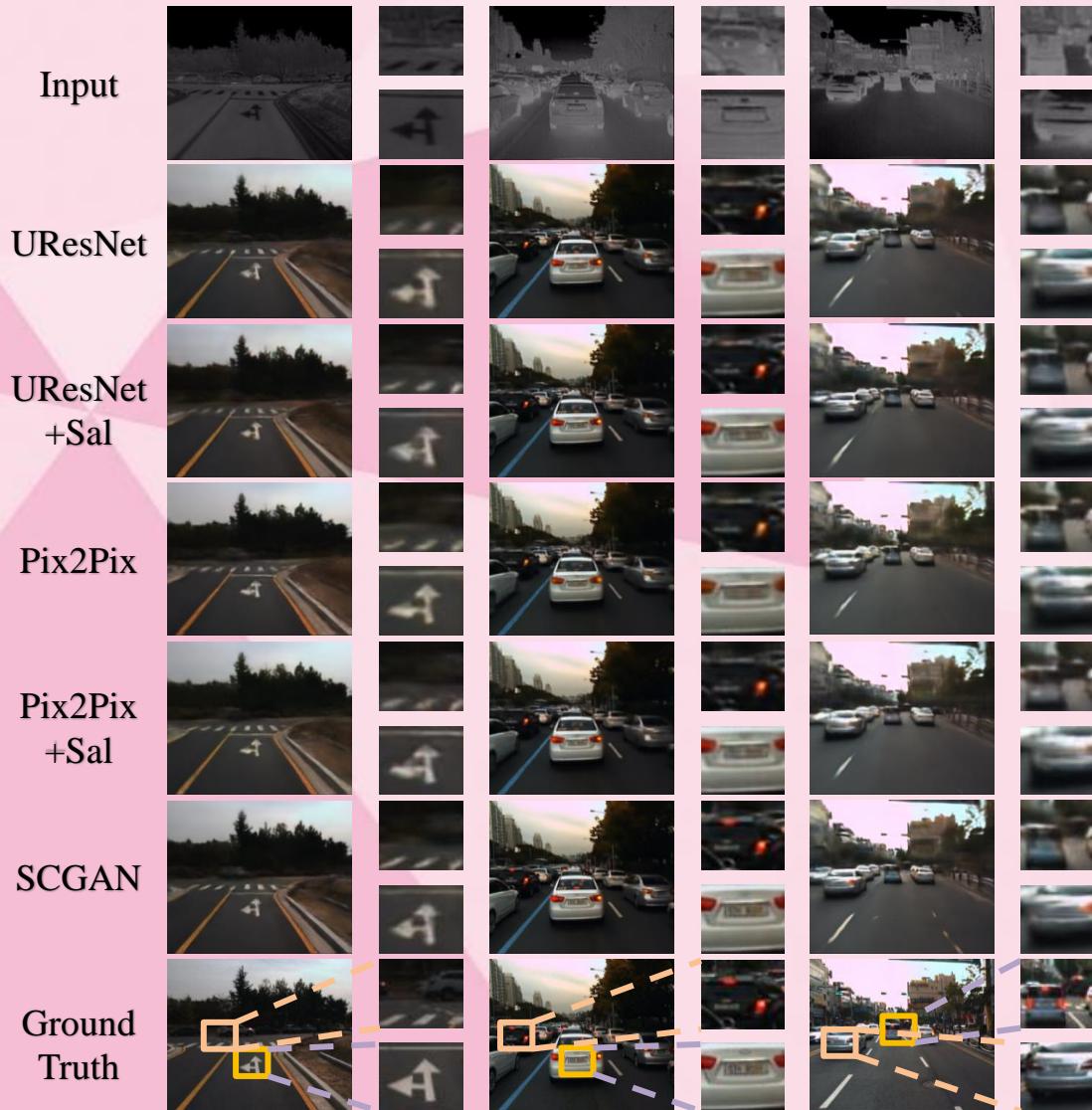


Ground
truth
validation
images



8 Other Applications: Multispectral and Legacy Images

**Multispectral images
with saliency map-
guidance method and
the proposed SCGAN**



8 Other Applications: Multispectral and Legacy Images

Multispectral images with saliency map-guidance method and the proposed SCGAN

Method	PSNR	SSIM	Saliency Map Guidance
Pix2Pix	23.55	0.8165	-
Pix2Pix+Sal	23.53	0.8164	✓
UResNet	23.66	0.8219	-
UResNet+Sal	23.72	0.8244	✓
SCGAN	24.59	0.8396	✓

8 Other Applications: Multispectral and Legacy Images

**Legacy images with
saliency map-guidance
method and the
proposed SCGAN**

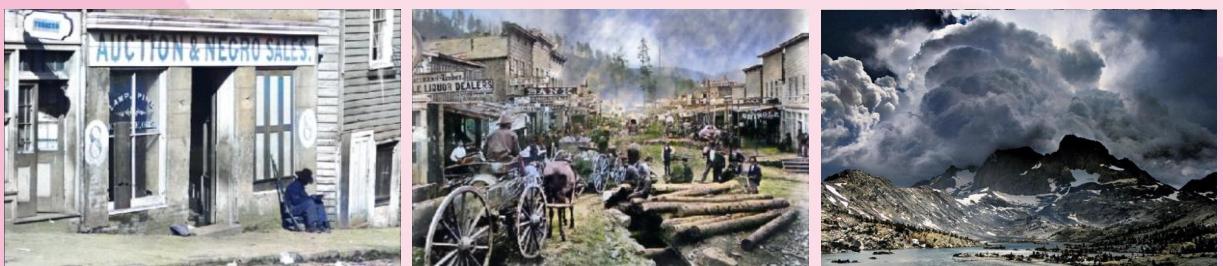
Grayscale



SCGAN



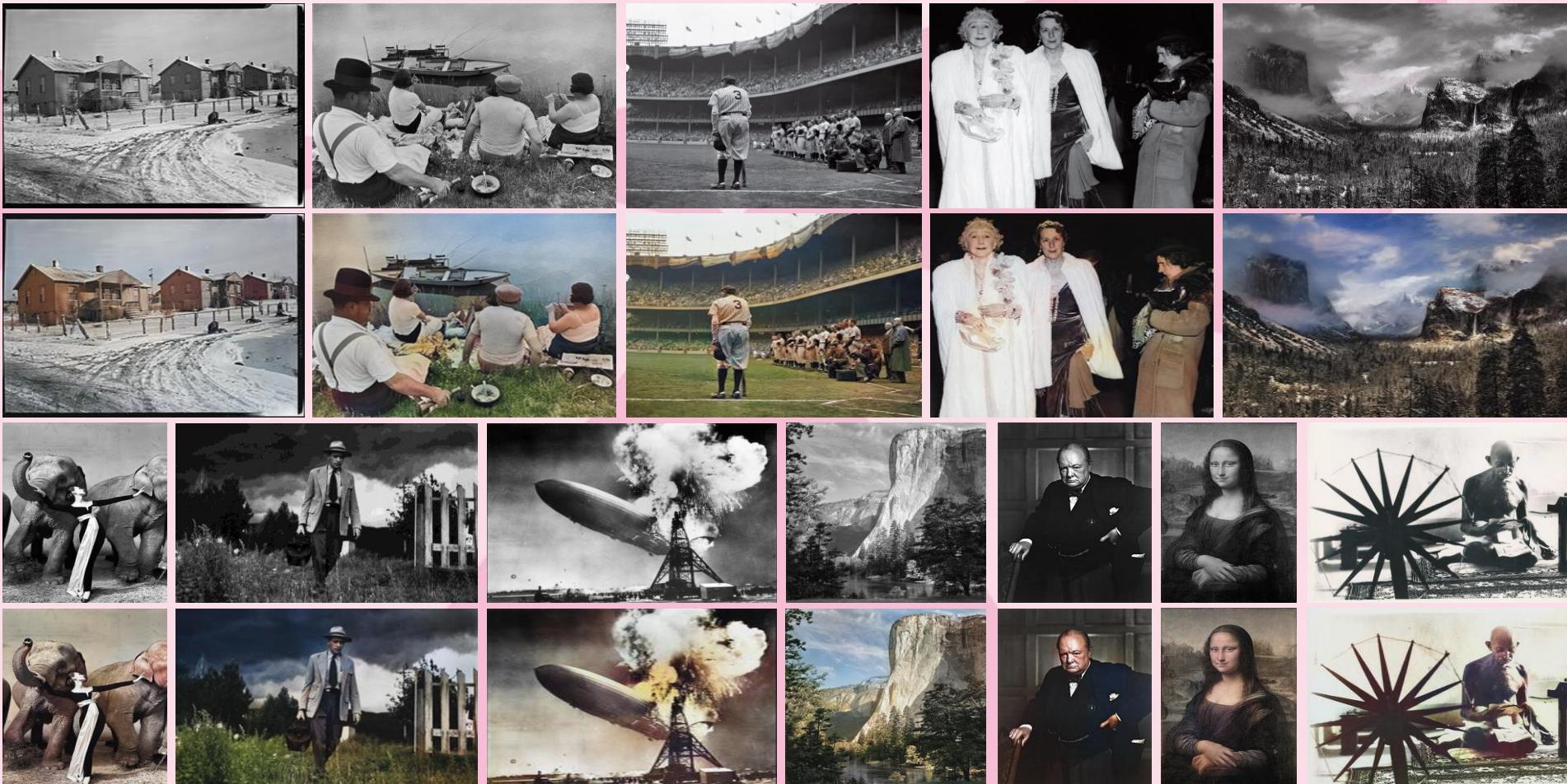
DeOldify



ColouriseSG



8 Other Applications: Multispectral and Legacy Images



8 Other Applications: Multispectral and Legacy Images

Legacy images with
saliency map-guidance
method and the
proposed SCGAN

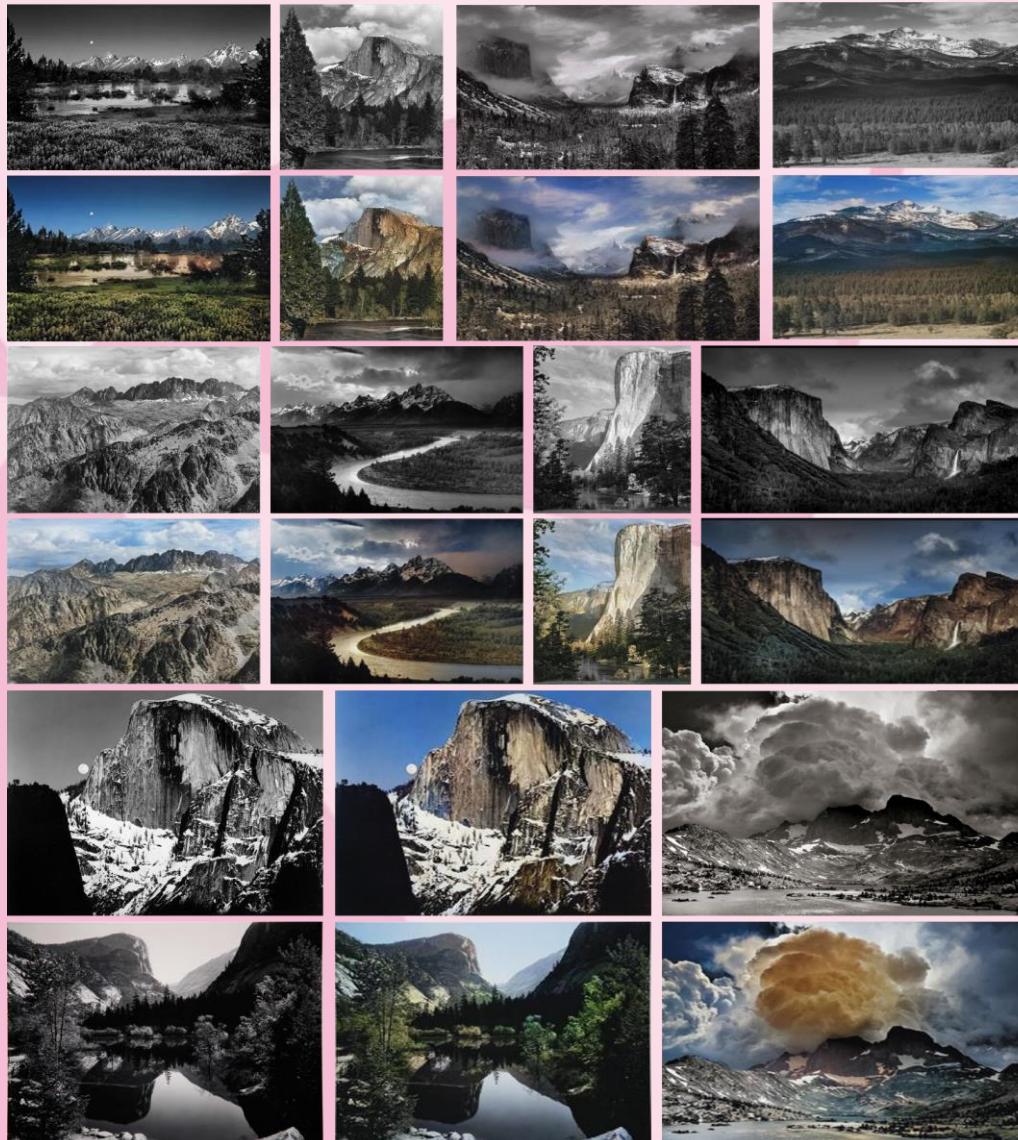
Portrait Photographs



8 Other Applications: Multispectral and Legacy Images

Legacy images with
saliency map-guidance
method and the
proposed SCGAN

Landscape Photographs



9 Limitation and Future Work

Grayscale



SCGAN



Ground Truth



full paper can be found at:

<https://ieeexplore.ieee.org/document/9257445/keywords#keywords>



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