GLADNet: Low-Light Enhancement Network with Global Awareness

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FOR-LQ Workshop at FG'18
May 19, 2018

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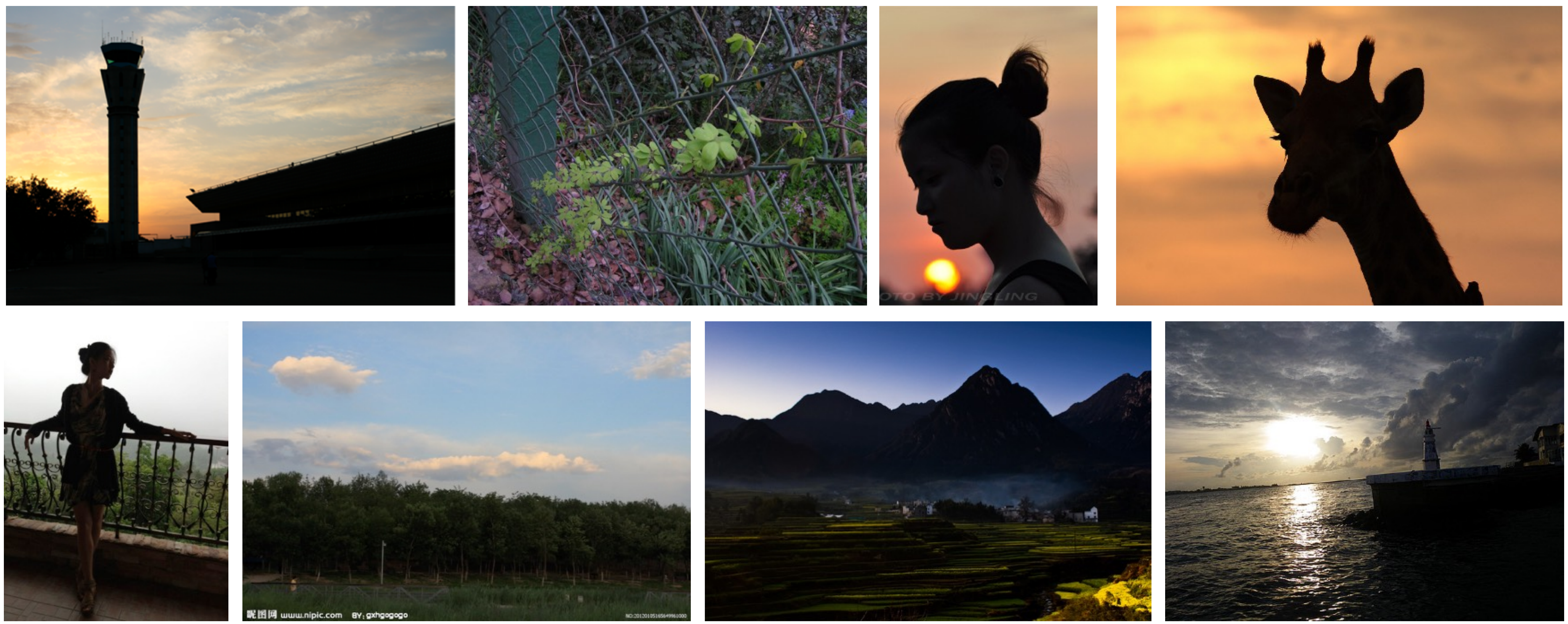
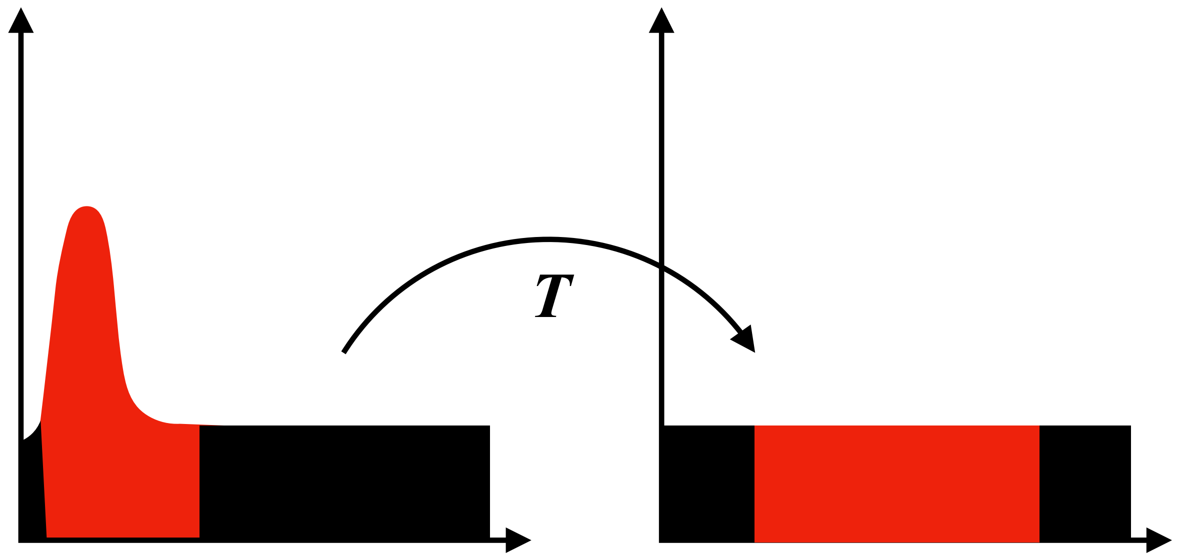
Low-Light

- Insufficient illumination can severely degrade the quality of images.



Existing Low-Light Enhancement Methods

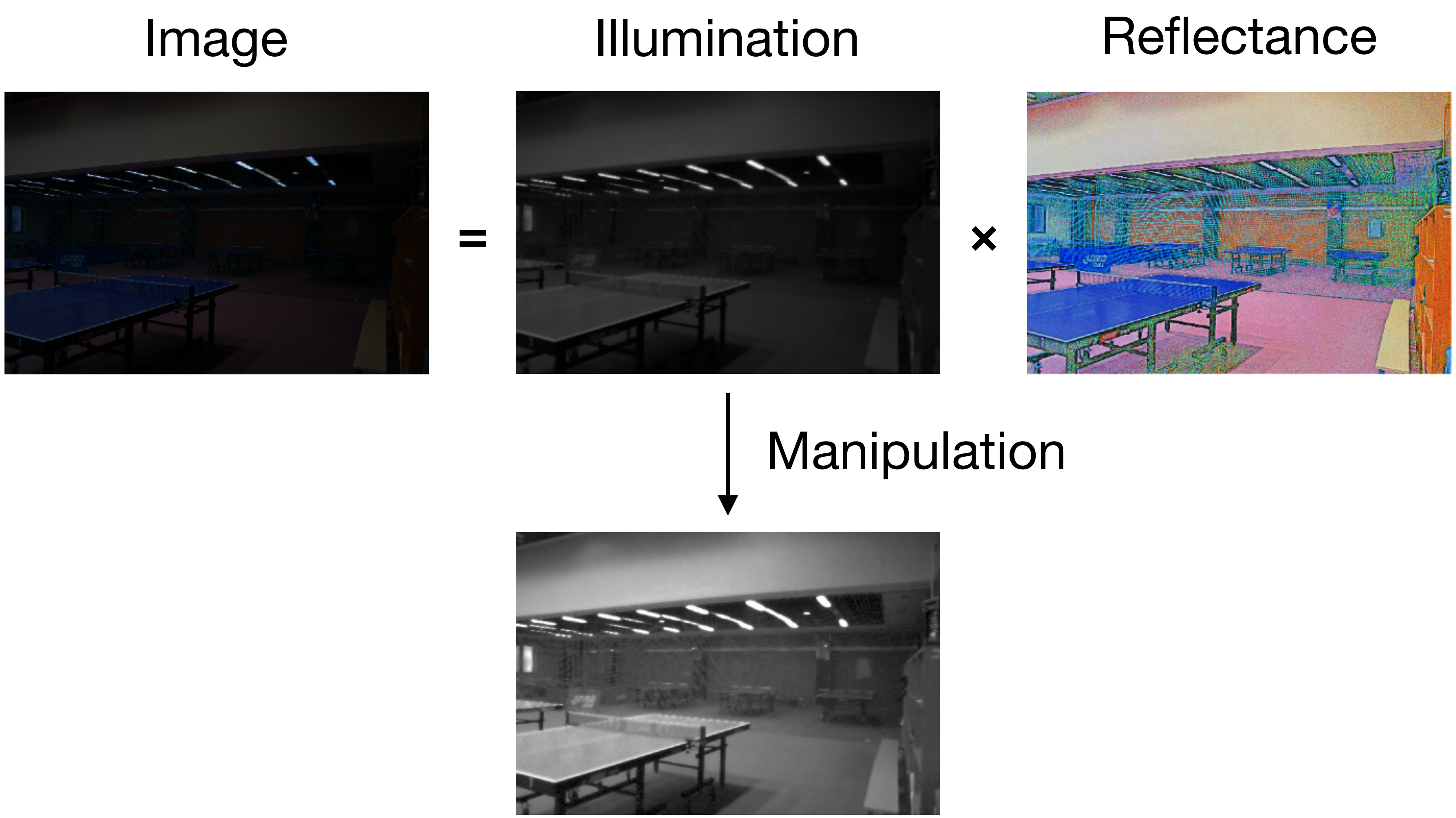
- Based on the histogram



Histograms of an image before and after equalization.

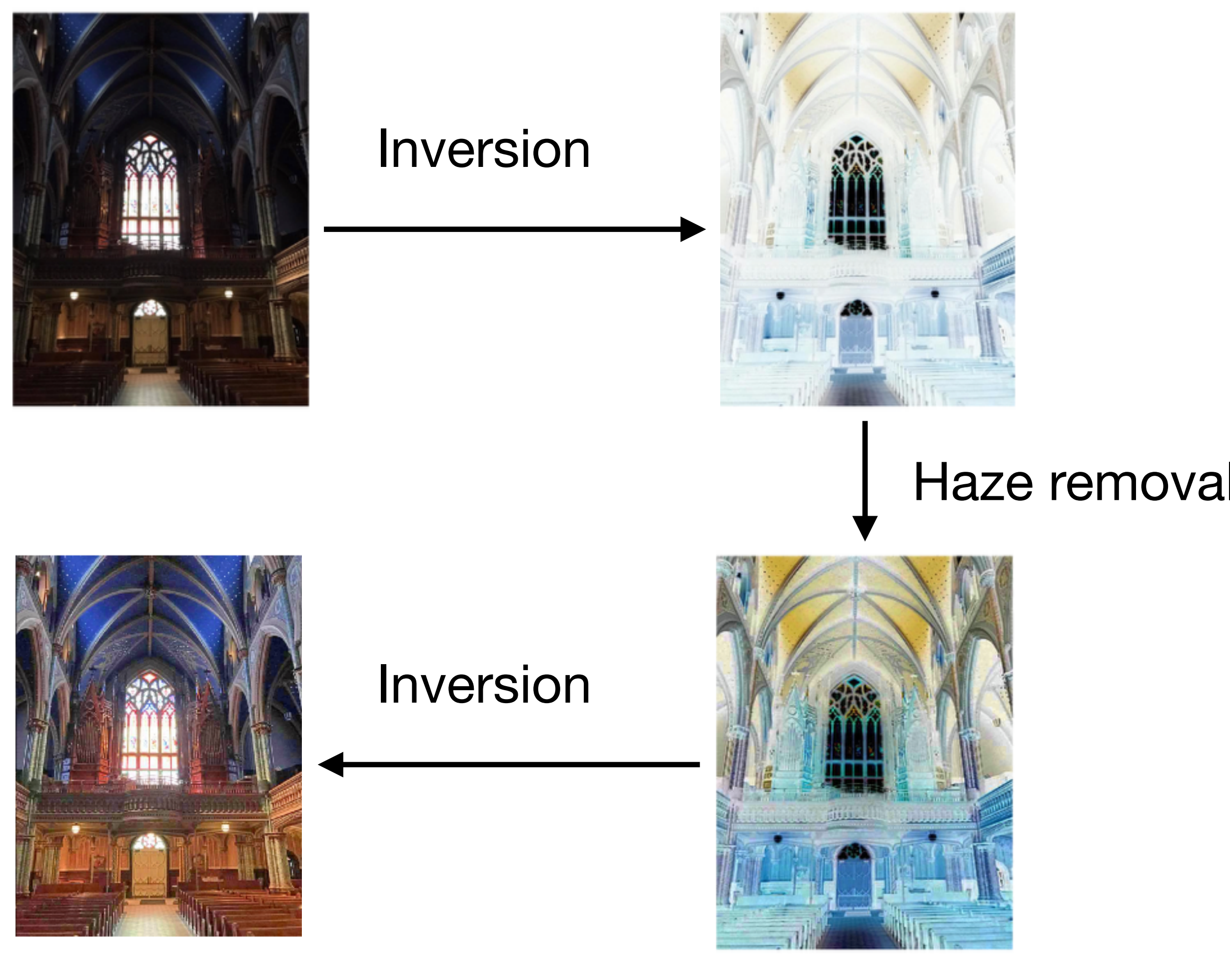
Existing Low-Light Enhancement Methods

- Based on the Retinex-model



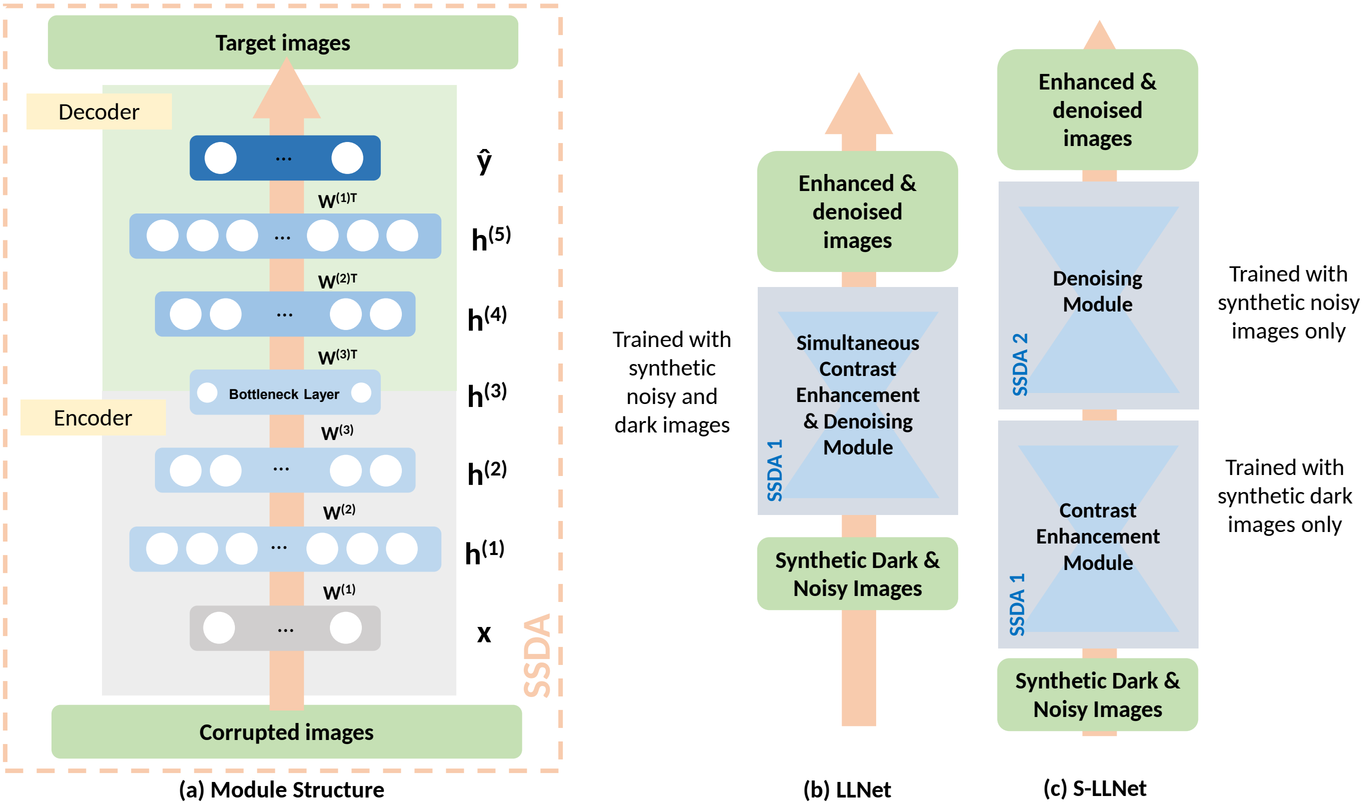
Existing Low-Light Enhancement Methods

- Based on the de-hazing techniques



Existing Low-Light Enhancement Methods

- Data-driven



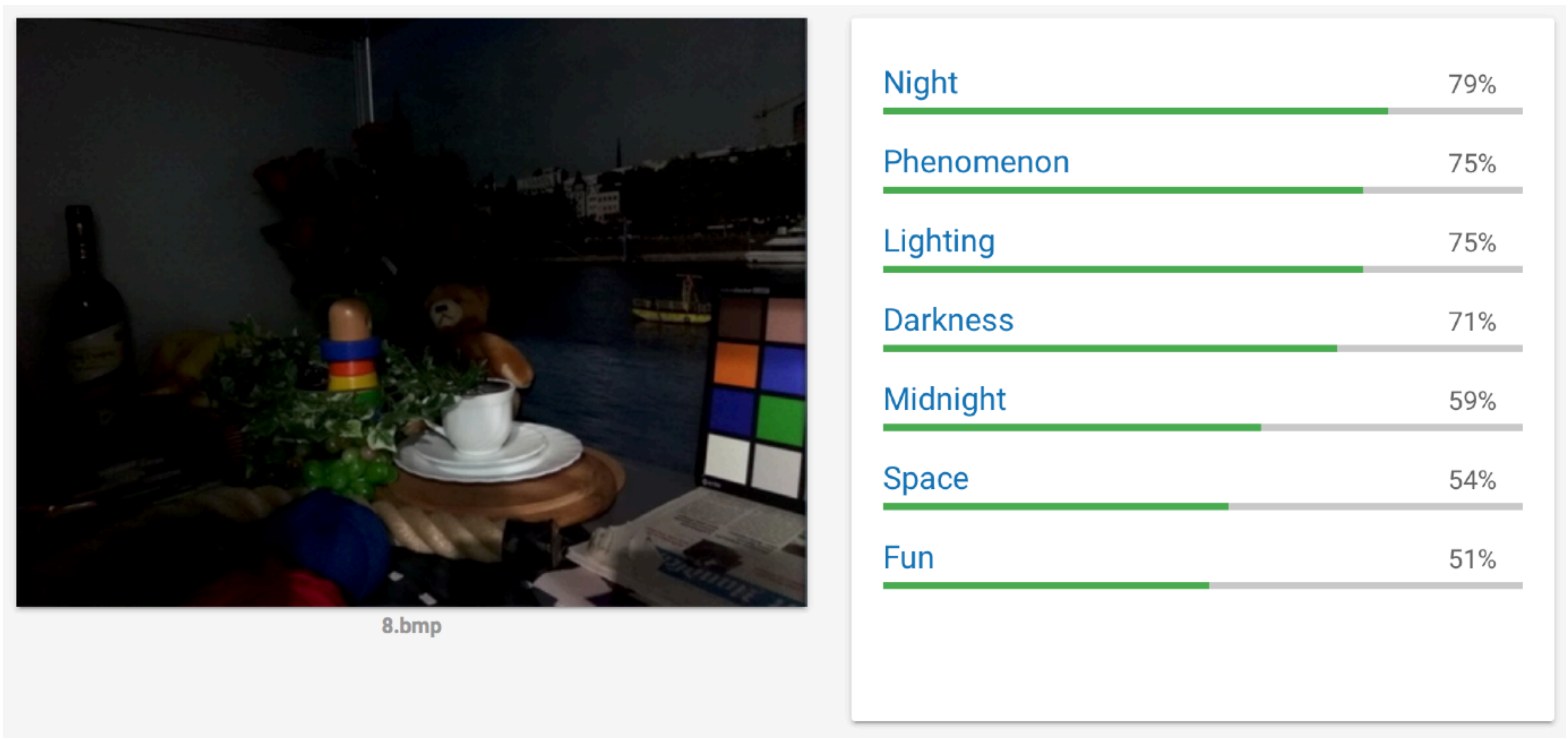
Architecture of the LLNet [8].

Motivation

- Existing methods do not perform well in certain aspects
  - Partially over-exposed, artifacts, slow operation *etc.*

Motivation

- Visual recognition models suffer from low-illumination



Result by Google Cloud Vision API

Motivation

- Visual recognition models suffer from low-illumination

Compared with result on normal-light image

Wrong labels:

couch with 84%, *angle* with 56%

Score declining:

Bedroom from 96% to 80%,

Bedding from 81% to 51%

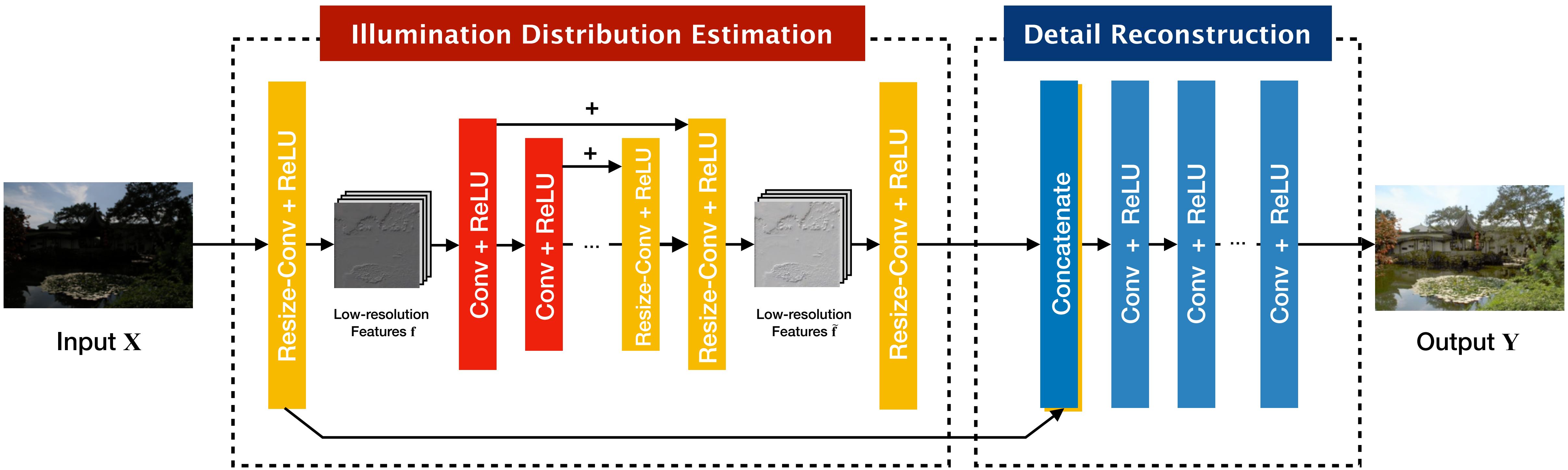
Result by Google Cloud Vision API

Contents

- Background
- Architecture of GladNet
- Training Dataset Generation
- Experiments

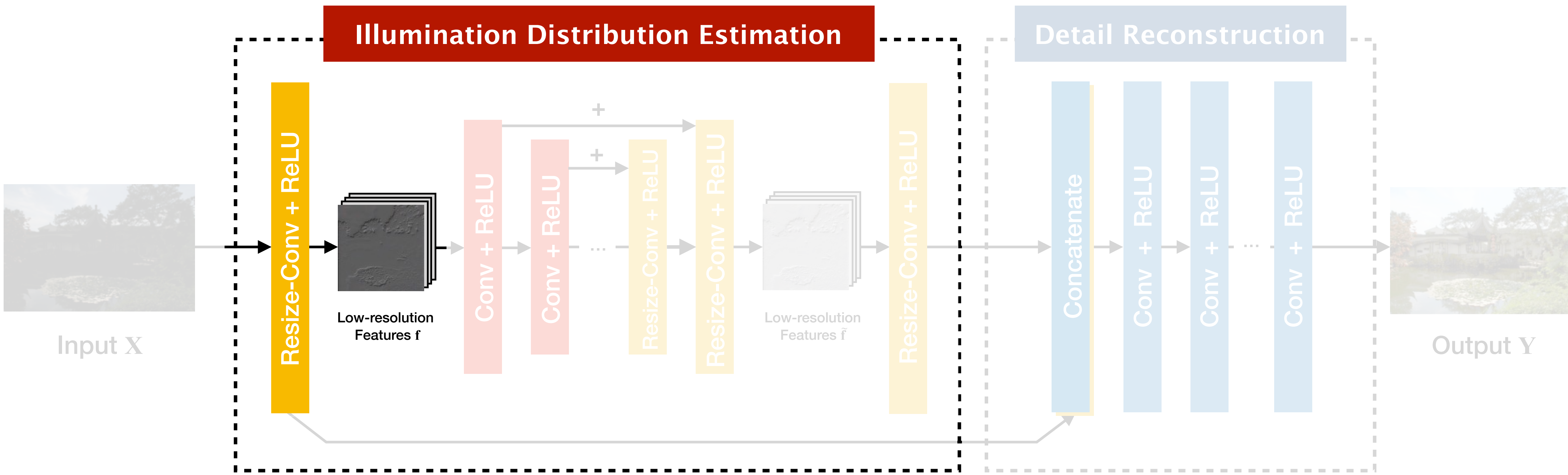
Proposed GLADNet

- **GL**obal illumination-**A**ware and **D**etail-preserving **N**etwork (**GLADNet**)



Proposed GLADNet

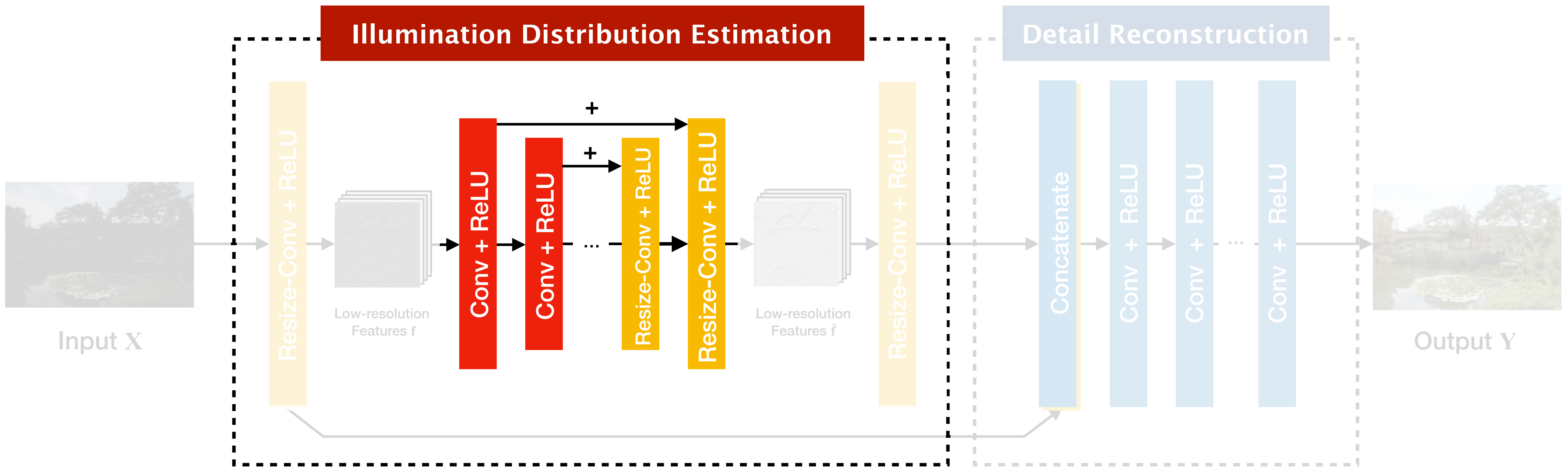
- Global Illumination estimation



1. scaling the input image to
   a certain resolution

Proposed GLADNet

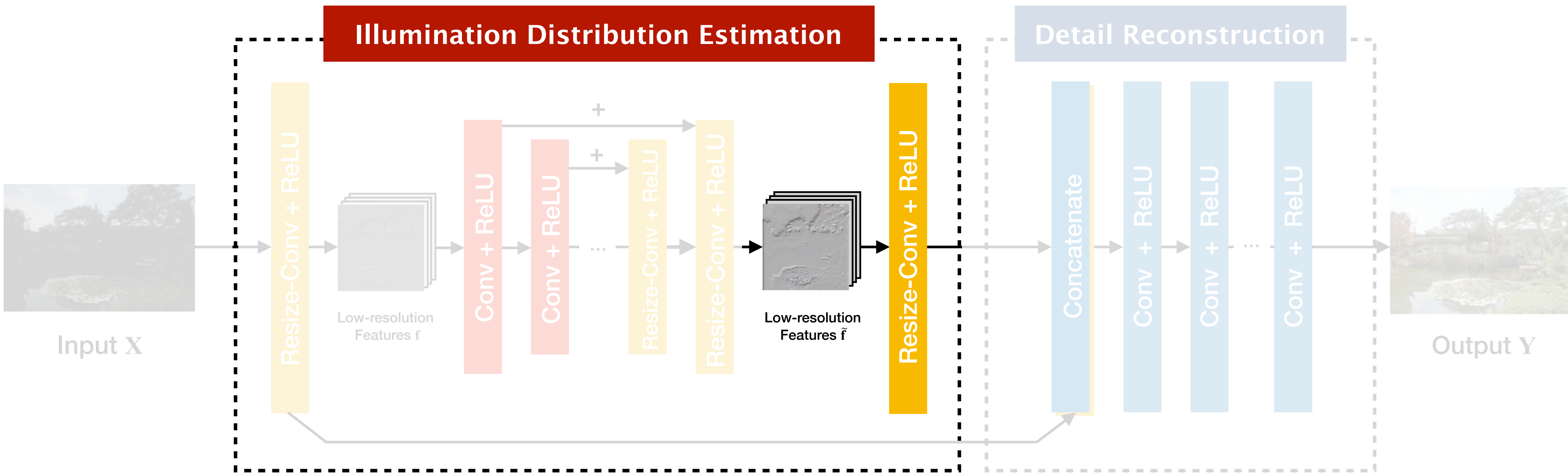
- Global Illumination estimation



2. passing through an encoder-decoder
network for global illumination prediction

Proposed GLADNet

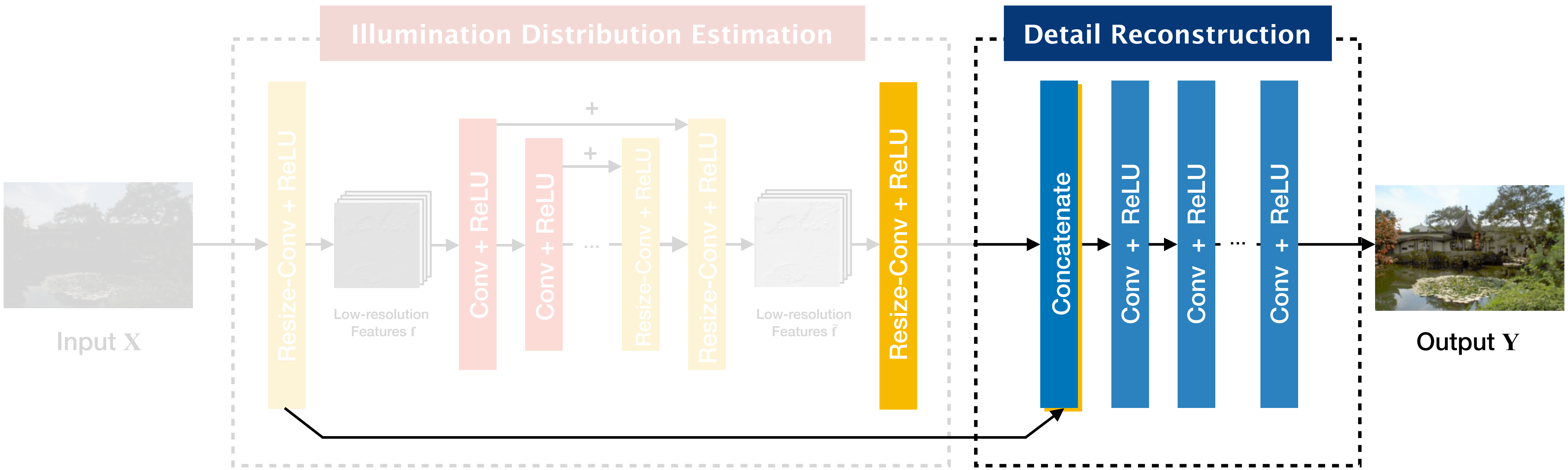
- Global Illumination estimation



3. rescaling back to the original resolution

Proposed GLADNet

- Details reconstruction



Proposed GLADNet

- Loss Function
  - Minimizing the loss between the restored image $F(X_i,\Theta)$ and the corresponding ground-truth image Y_i.

$$Loss(X,Y) = \frac{1}{N}\sum_{i=1}^{N} \|F(X_i,\Theta) - Y_i\|_1,$$

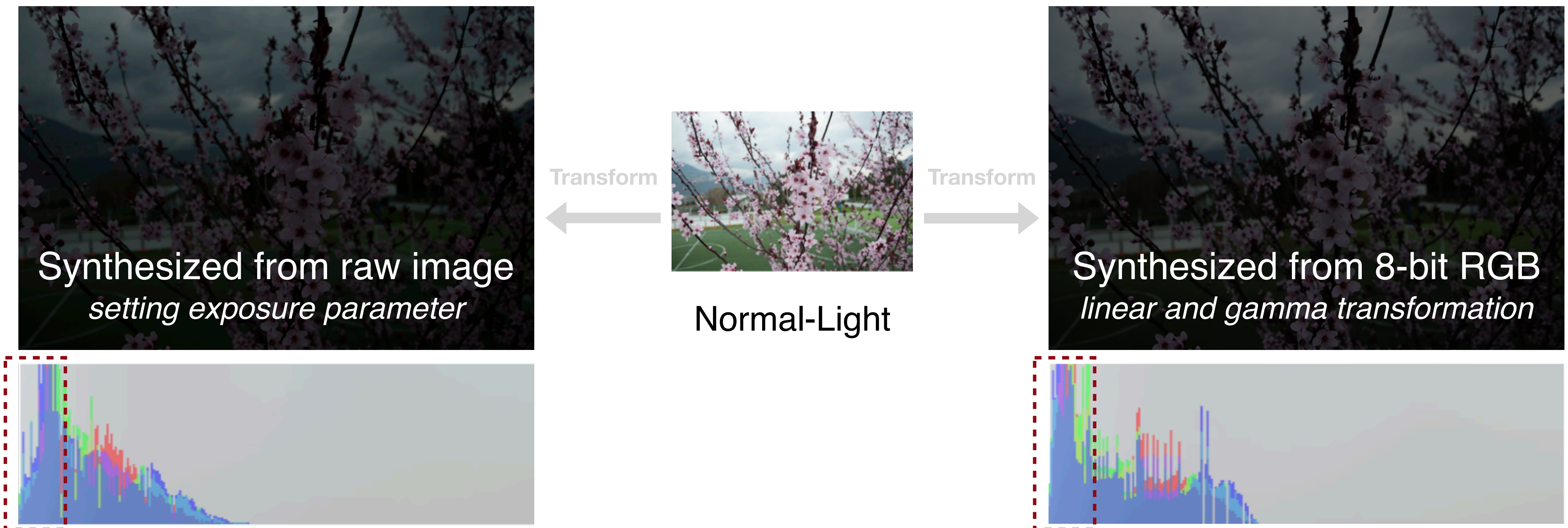
where N is the number of all training samples and $\|\cdot\|_1$ is L1 norm.

  - The red, the green and the blue channel have their own weights in the loss function: (0.29891, 0.58661, 0.11448)

Contents

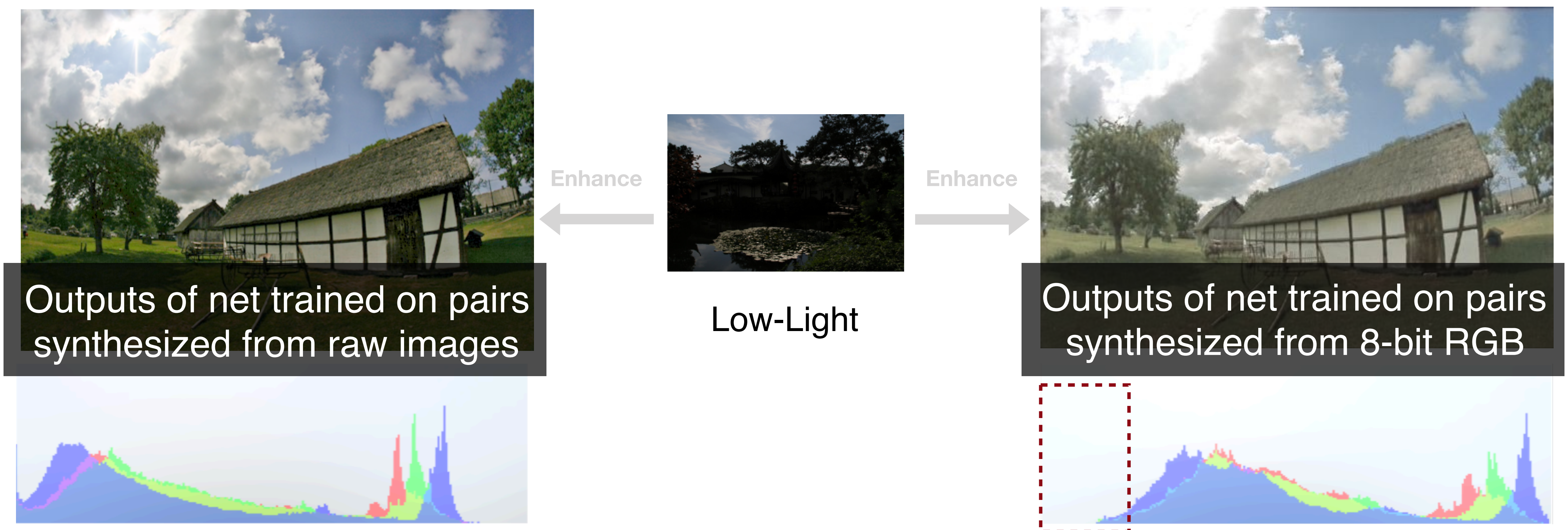
Training Dataset Generation

- Instead of synthesizing pairs from 8-bit RGB images, we synthesize pairs from raw images.



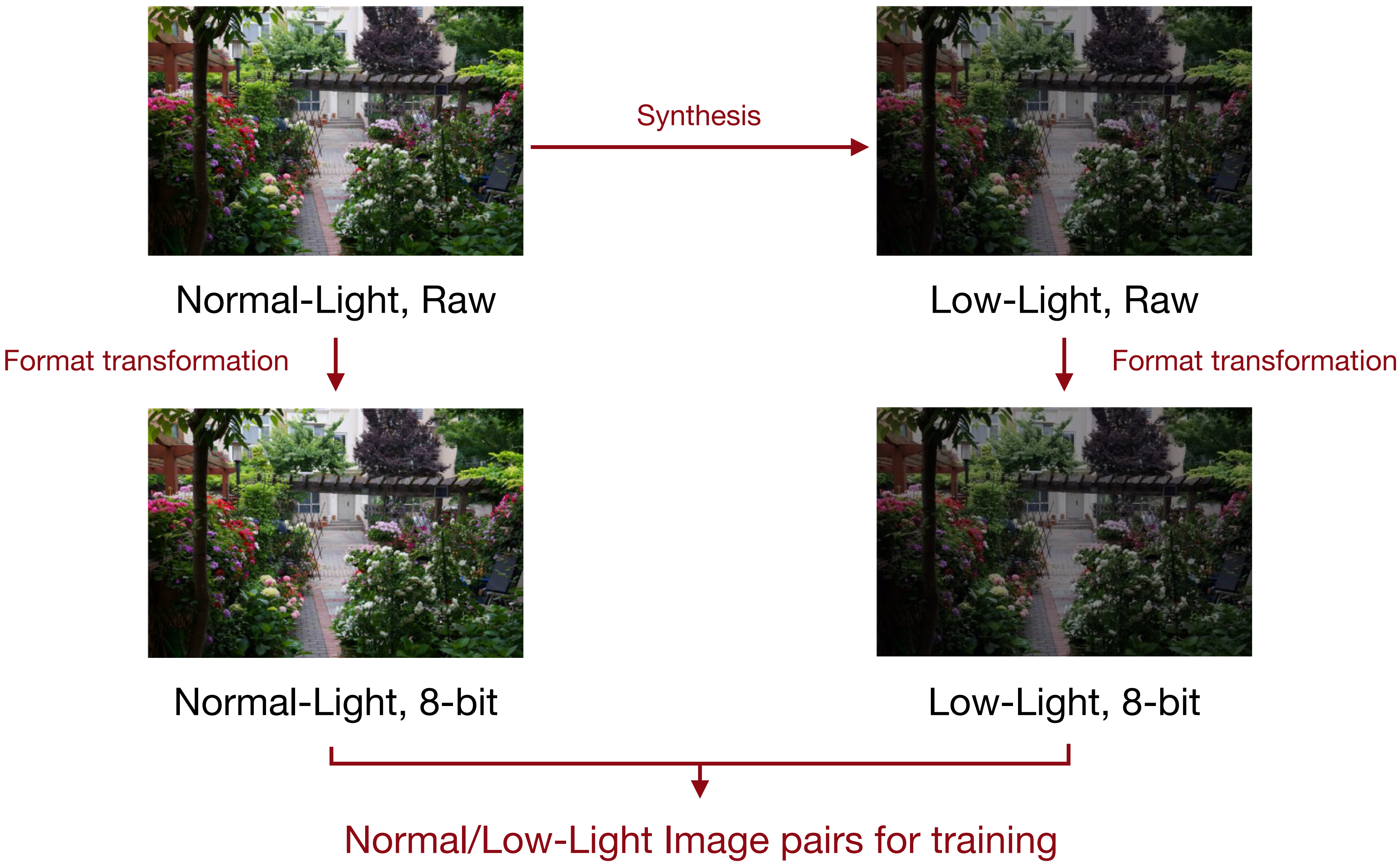
Training Dataset Generation

- Instead of synthesizing pairs on 8-bit RGB images, we synthesize pairs on raw images.



Need to set the black point to correct this

Training Dataset Generation



Training Dataset Generation

- Synthesize low-light raw images by using Adobe Lightroom and setting
  - Exposure parameter E to [–5, 0]
  - Contrast parameter C to [–100, 0]

Some Tricks to Improve the Dataset

- To keep the black and the white regions the same before and after the enhancement
    - add black-to-black and white-to-white training pairs.
- To prevent color-bias
    - add gray-scale image pairs which are converted from color image pairs.

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Results - Evaluation

- **MSRCR**[1] Multi-Scale Retinex with Color Restoration [Jobson 1997]
- **DeHZ**[4] de-hazing based method [Dong 2011]
- **SRIE**[3] Simultaneous Reflection and Illumination Estimation [Fu 2016]
- **LIME**[2] Illumination Estimation based method [Guo 2017]

Results - Evaluation

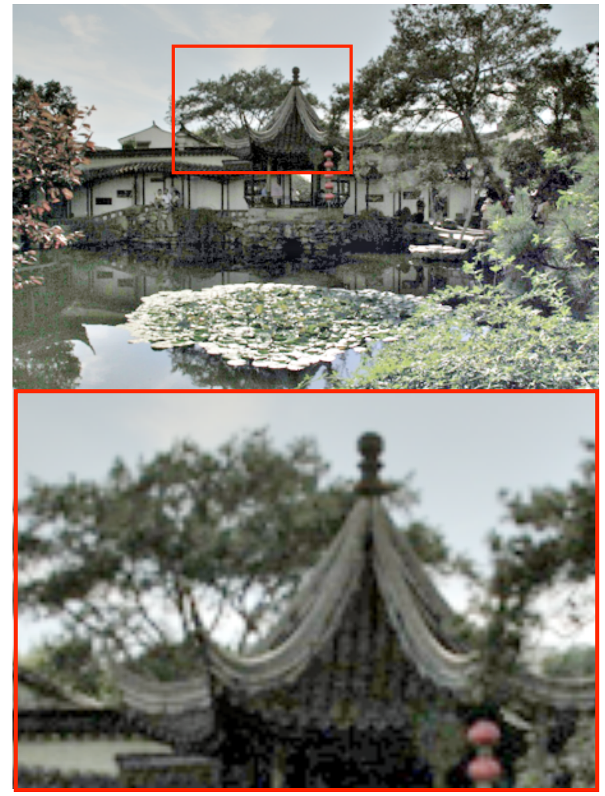
- **LIME[2] dataset** 10 low-light images
- **MEF[7] dataset** 17 image sequences with multiple exposure levels
- **DICM[6] dataset** 69 captured images with commercial digital cameras

Results - Performance

- Naturalness Image Quality Evaluator (NIQE)[5]

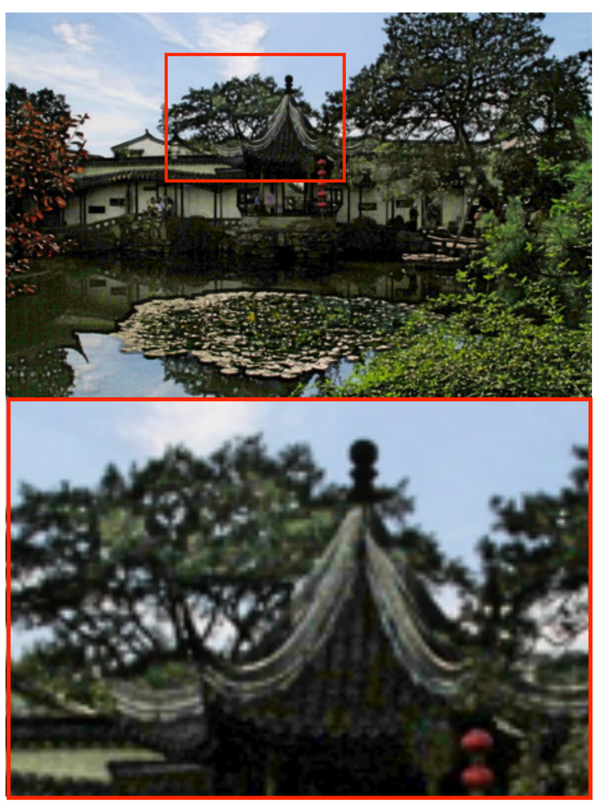
Dataset	DICM	NPE	MEF	Average
MSRCR	3.117	3.369	4.362	3.586
LIME	3.243	3.649	4.745	3.885
DeHZ	3.608	4.258	5.071	4.338
SRIE	2.975	**3.127**	4.042	3.381
GLADNet	**2.761**	3.278	**3.468**	**3.184**

Input



MSRCR

LIME



DeHZ

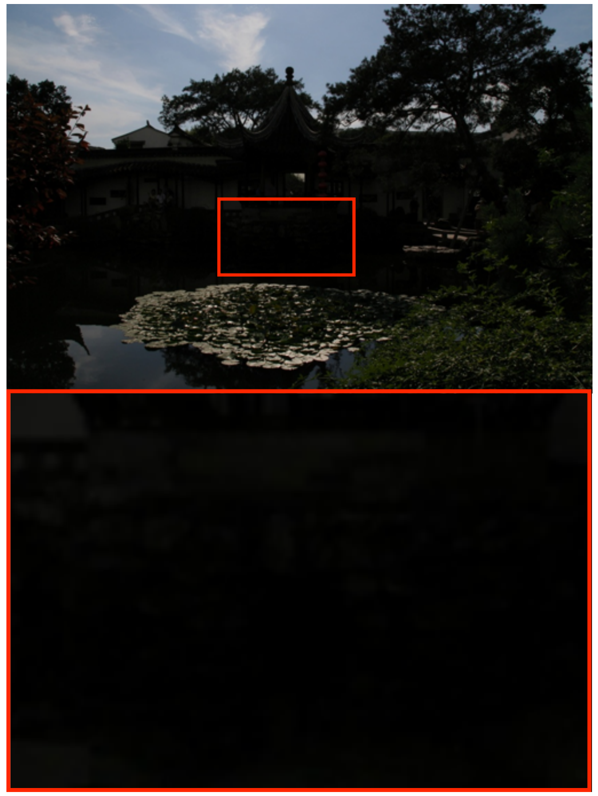
SRIE

GLADNet

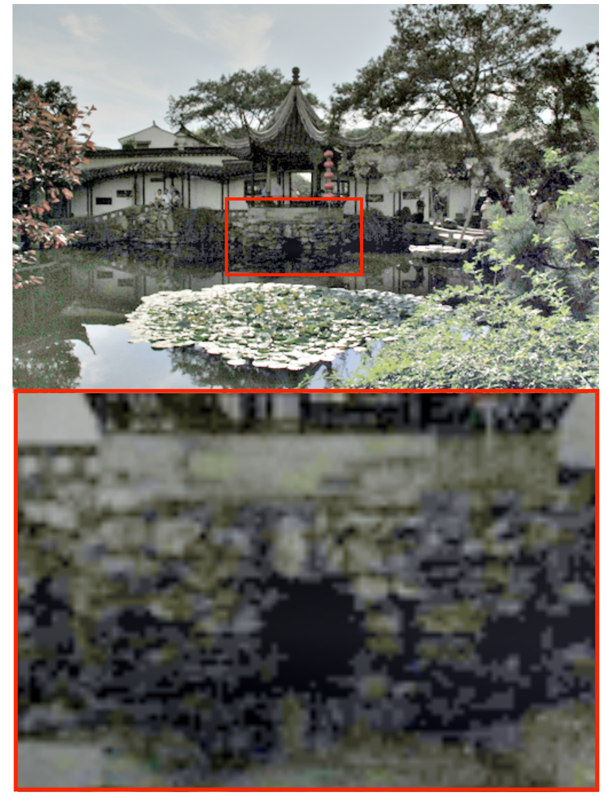
Low-Light
Input

After

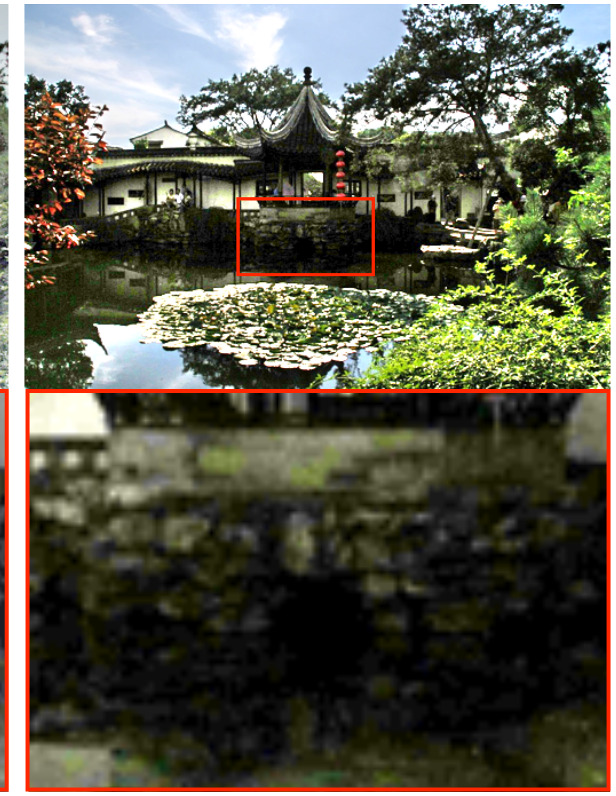
GLADNet



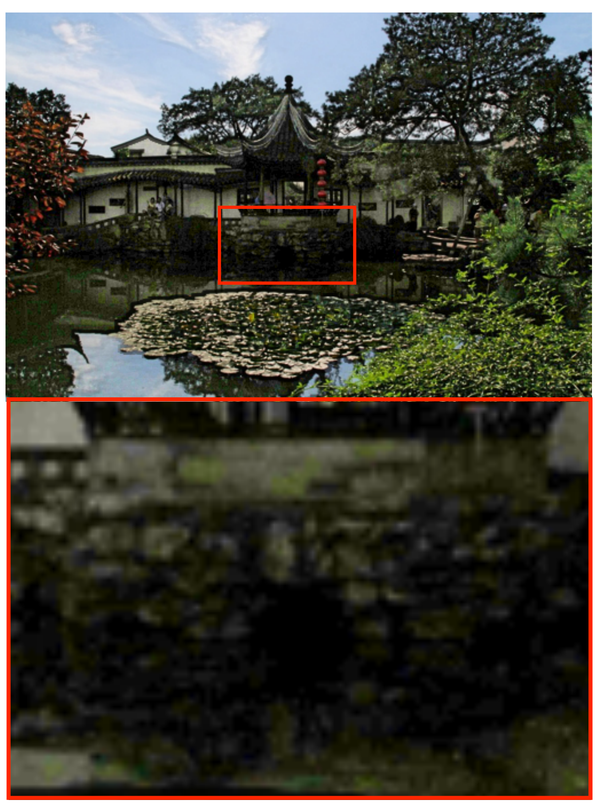
Input



MSRCR

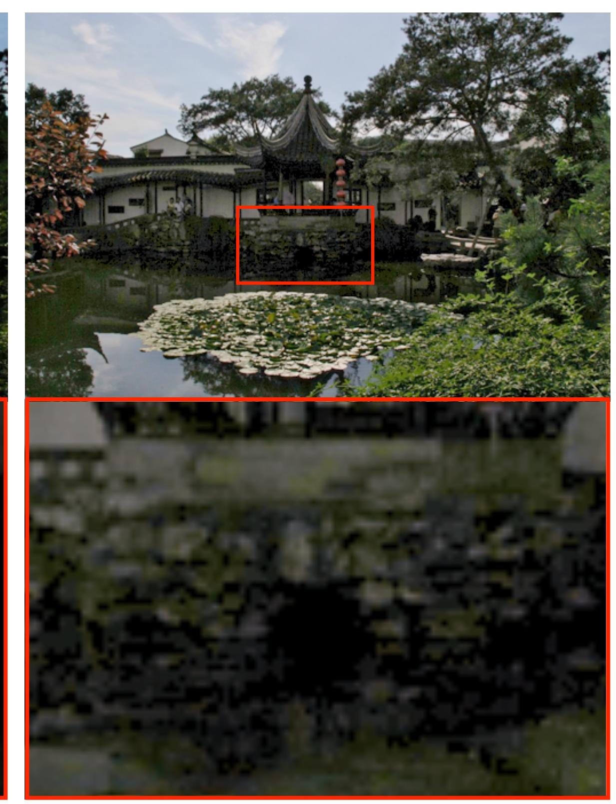


LIME



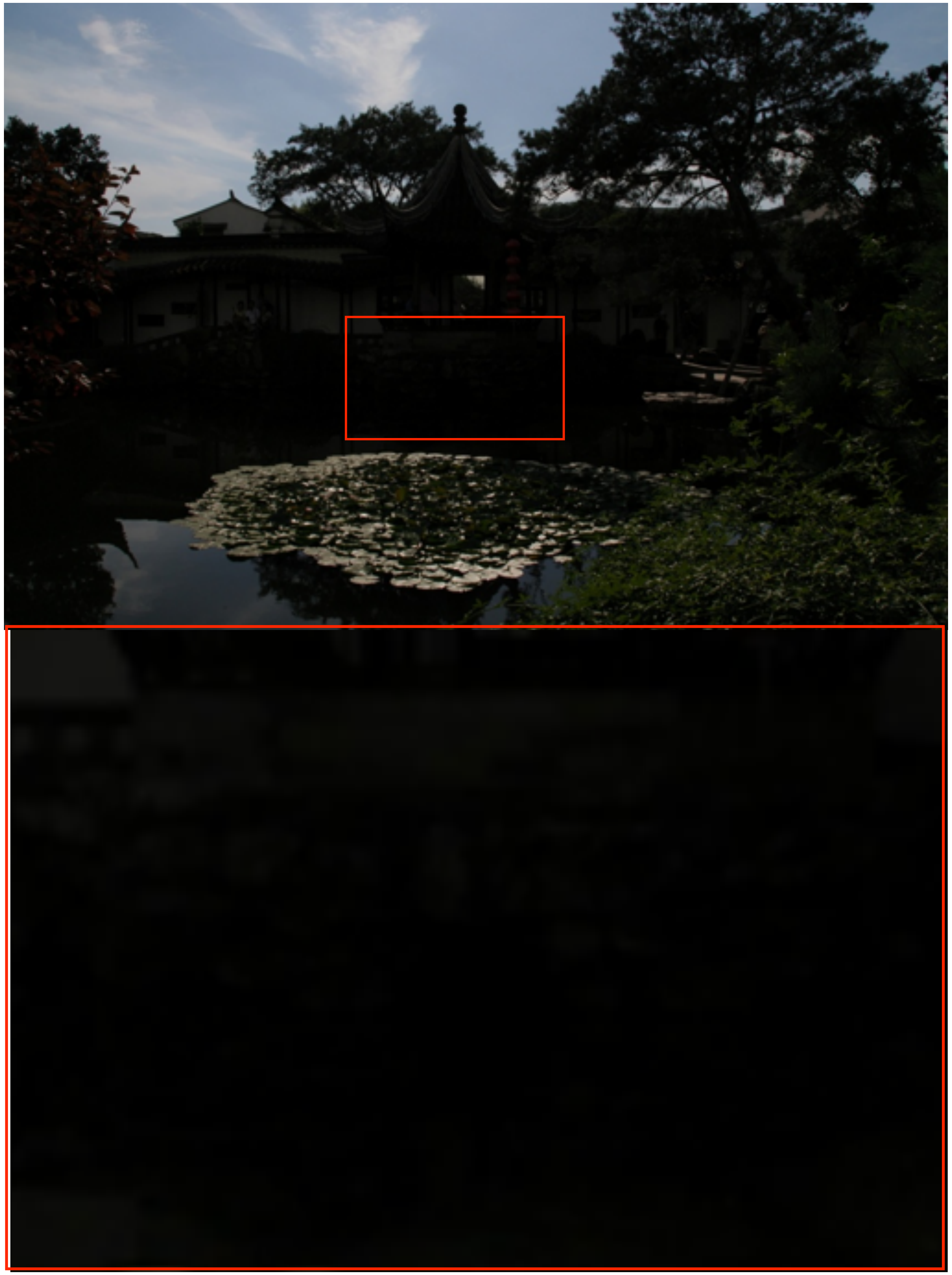
DeHZ

SRIE



GLADNet

Low-Light Input

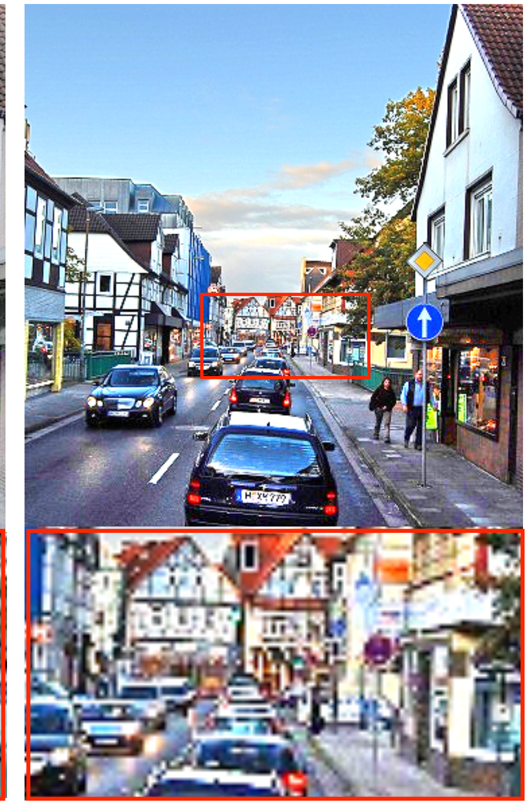


After

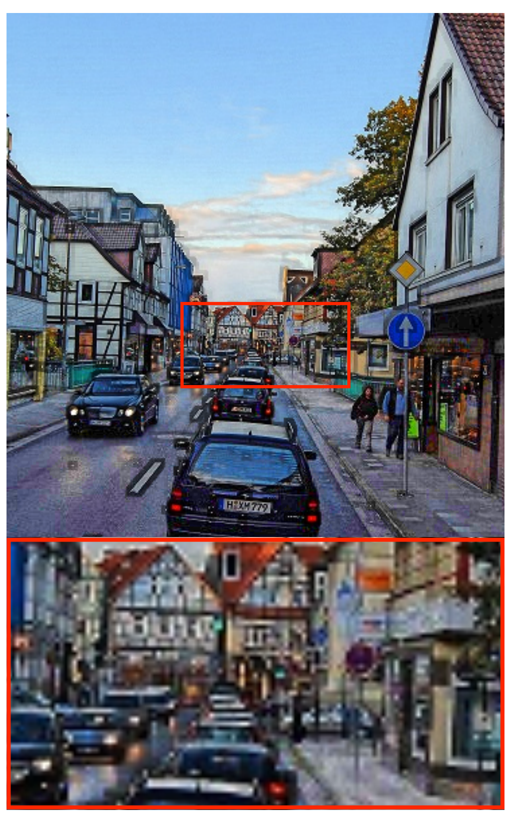
GLADNet

Input

MSRCR



LIME

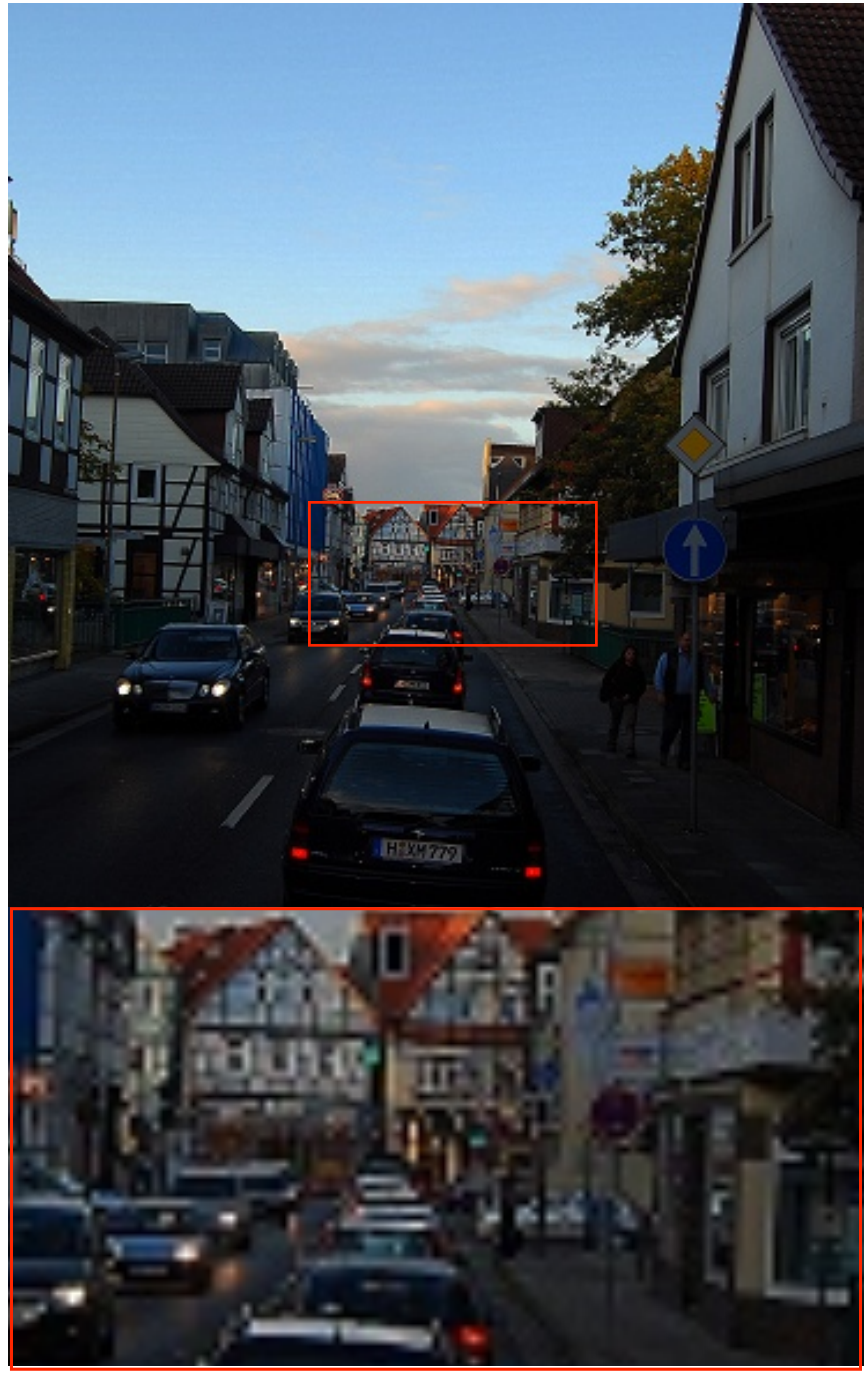


DeHZ

SRIE

GLADNet

Low-Light
Input



After
GLADNet

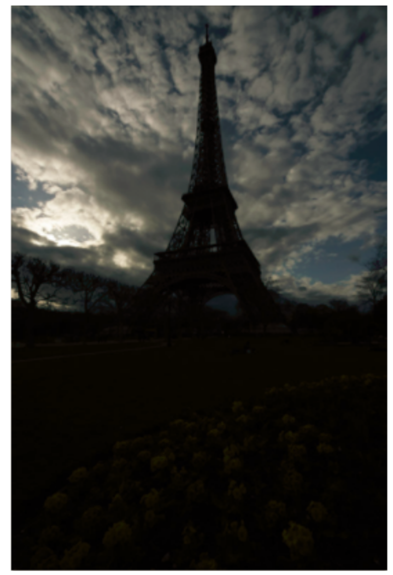
The result in the paper

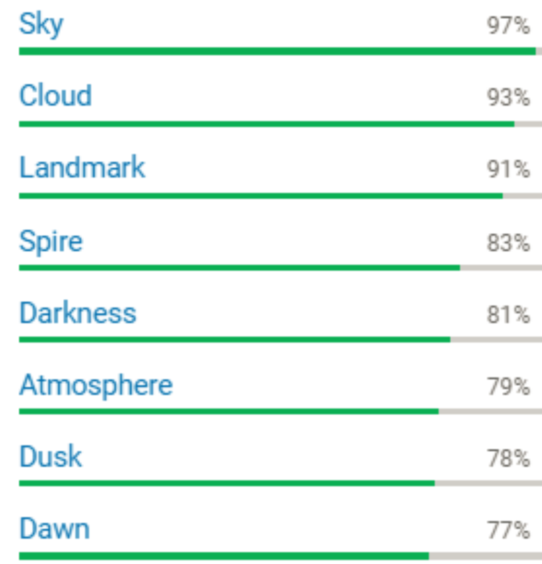
New result

by randomly reducing the saturation when generating training dataset

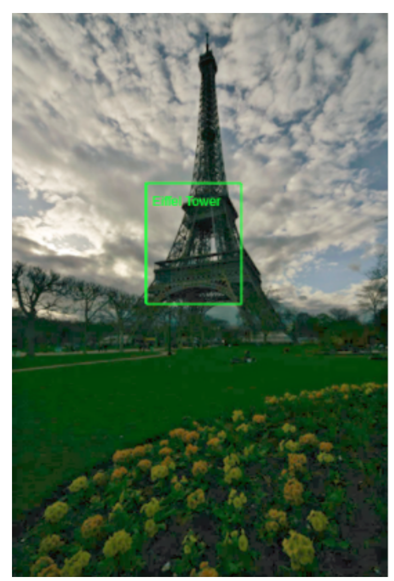
Results - Benefit Visual Recognition Models

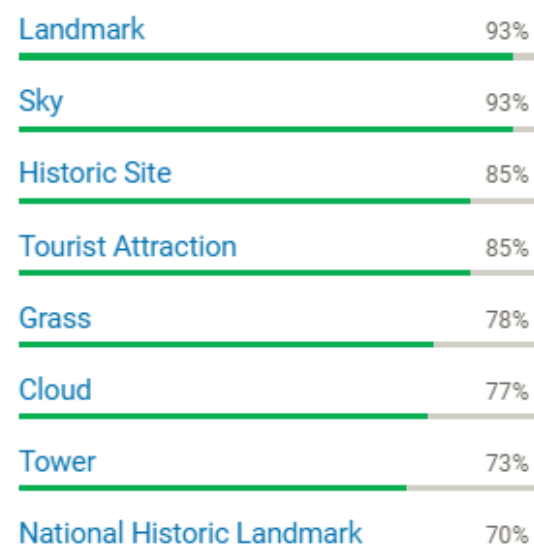
Low-Light Image





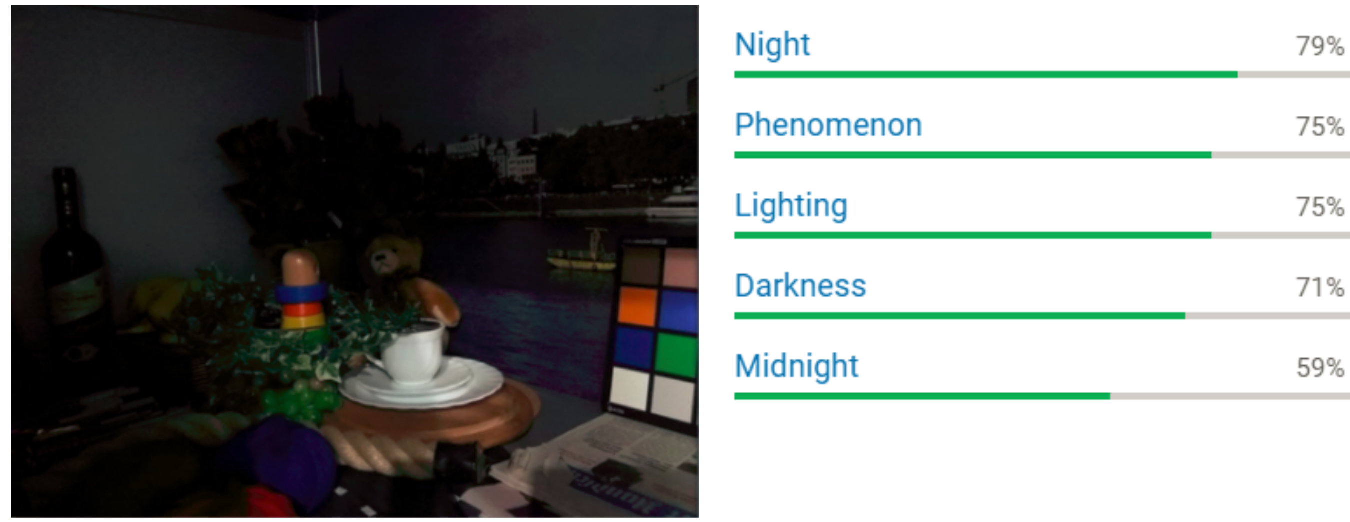
After GLADNet



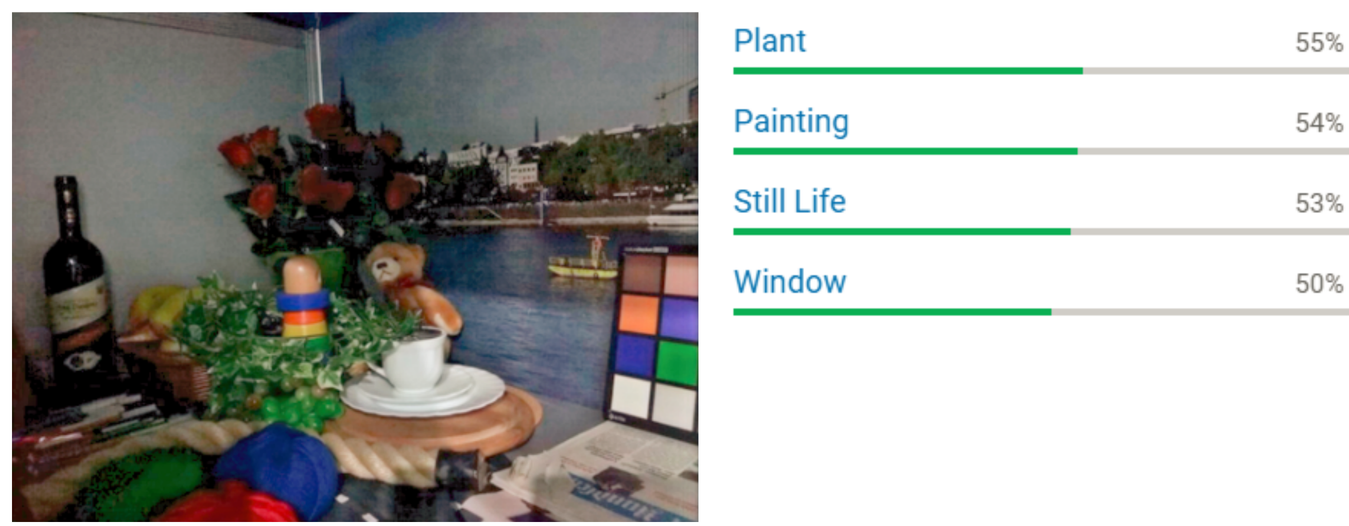


Results - Benefit Visual Recognition Models

Low-Light Image



After GLADNet



Reference

[1] Z. Jobson, Daniel Jand Rahman and G. A. Woodell, “A multiscale retinex for bridging the gap between color images and the human observation of scenes,” IEEE Transactions on Image Processing, vol. 6, no. 7, pp. 965–76, 1997.

[2] X. Guo, Y. Li, and H. Ling, “Lime: Low-light image enhancement via illumination map estimation,” IEEE Transactions on Image Processing, vol. 26, no. 2, pp. 982–993, 2017.

[3] X. Fu, D. Zeng, Y. Huang, X. P. Zhang, and X. Ding, “A weighted variational model for simultaneous reflectance and illumination estimation,” Computer Vision and Pattern Recognition, pp. 2782–2790, 2016.

[4] X. Dong, Y. Pang, and J. Wen, “Fast efficient algorithm for enhancement of low lighting video,” IEEE International Conference on Multimedia and Expo, pp. 1–6, 2011.

[5] A. Mittal, R. Soundararajan, and A. C. Bovik, “Making a ‘completely blind’ image quality analyzer,” IEEE Signal Processing Letters, vol. 20, no. 3, pp. 209–212, 2013.

[6] C. Lee, C. Lee, and C. S. Kim, “Contrast enhancement based on layered difference representation,” IEEE International Conference on Image Processing, pp. 965–968, 2013.

[7] K. Ma, K. Zeng, and Z. Wang, “Perceptual quality assessment for multi-exposure image fusion,” IEEE Transactions on Image Processing, vol. 24, no. 11, p. 3345, 2015.

[8] Kin Gwn Lore, Adedotun Akintayo, and Soumik Sarkar, “Llnet: A deep autoencoder approach to natural low-light image enhancement,” Pattern Recognition, vol. 61, pp. 650–662, 2016.

Thank you