



# Low-light Image Enhancer

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# Problem and Motivation

- Low-light image enhancement has wide applications in our daily life and in different scientific research fields such as night surveillance, automated driving, etc. This technique can improve the usefulness of an image to satisfy human viewing and with more application applied machine/deep learning methods for improvement, we'd like to research how to use deep learning to enhance low-light images.
- Problem: Low-light images typically suffer from low visibility and high noise
  - Low visibility shows that the image has small pixel values due to few amount of photon
  - High noise would dominate and disrupt the image content, so the overall signal-to-noise ratio is low
- Dataset: Total 485 low-light and high-light paired training images and 15 testing images originally used for Retinex-Net

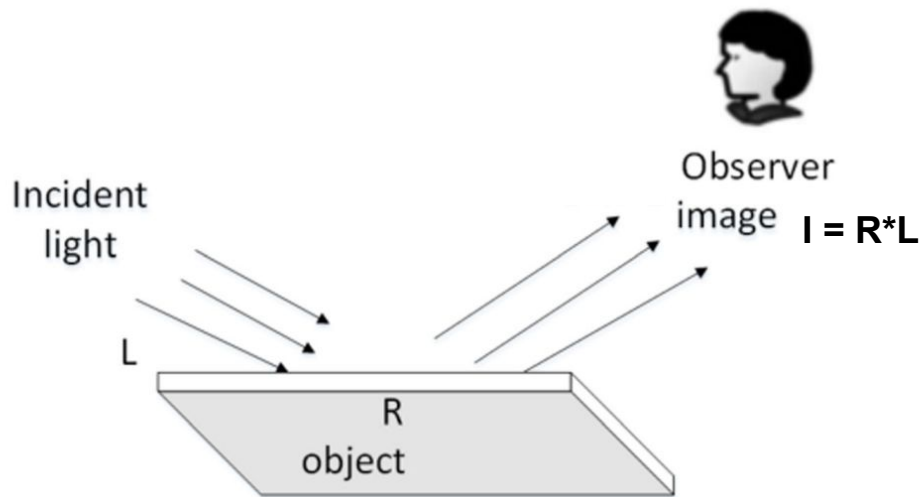
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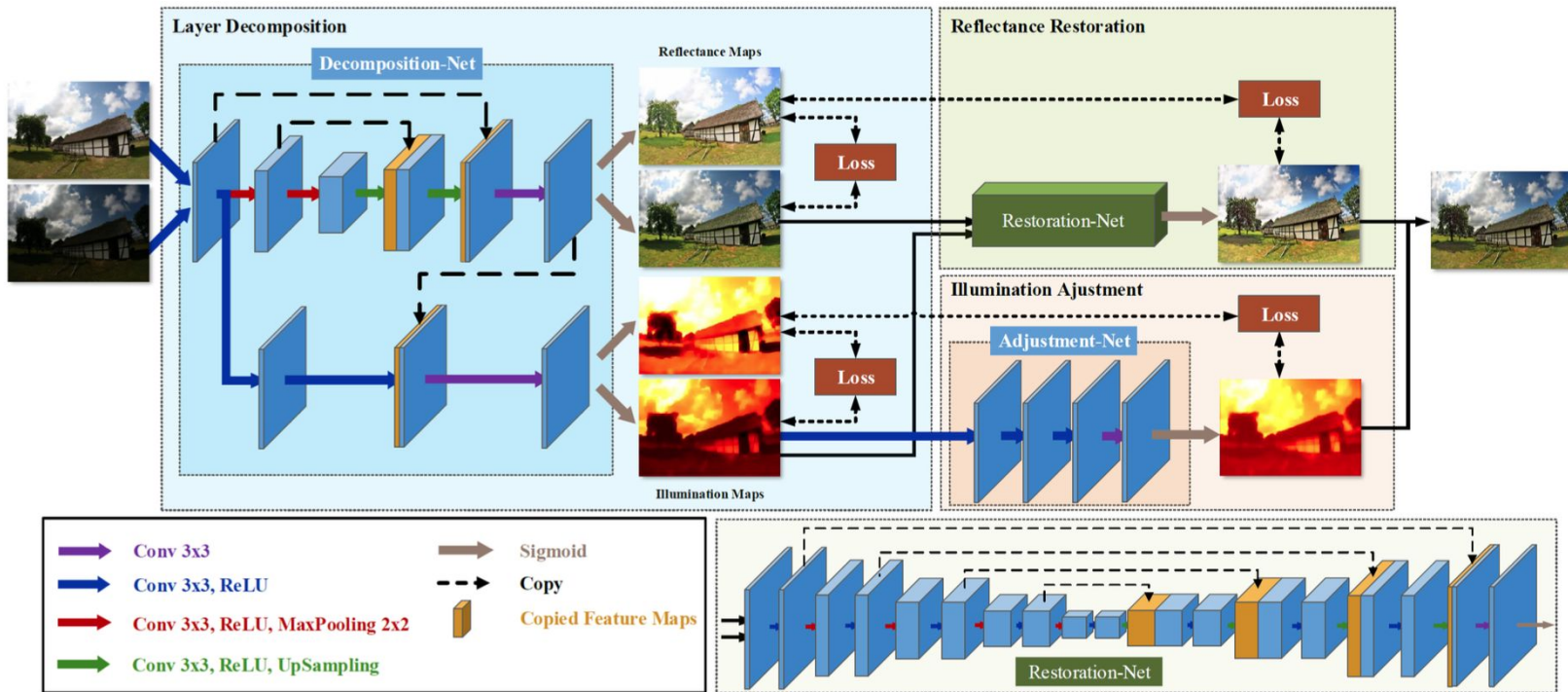


# Approach Background: Retinex Theory

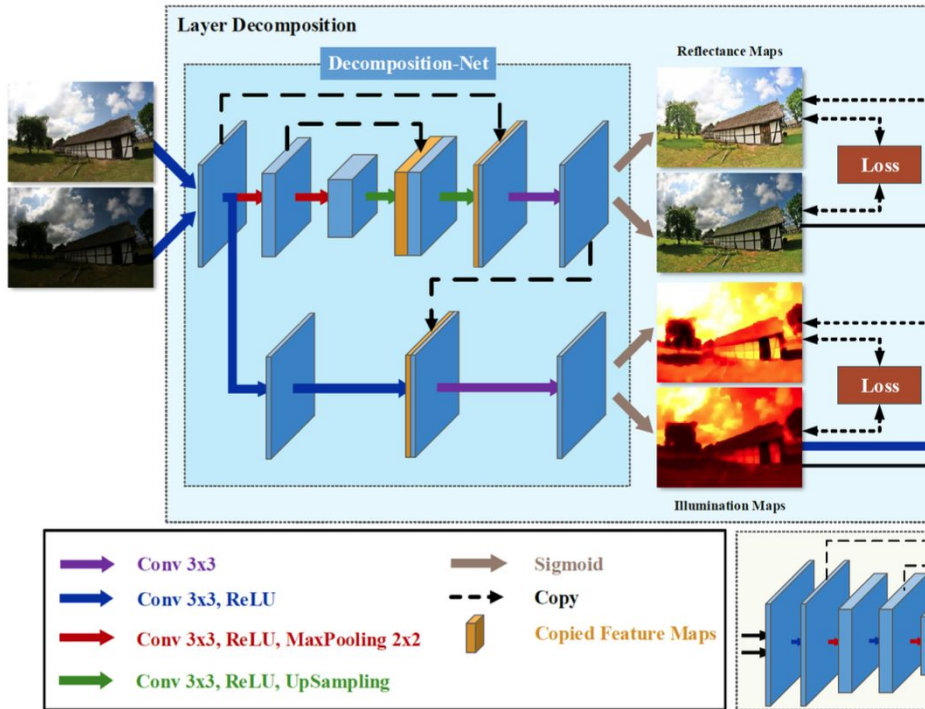
- Image (I) is composition of **illumination map (L)** and **reflectance map (R)**



# Approach: Network Architecture



# Approach: Layer Decomposition Net



$$\mathcal{L}_{rec}^{LD} := \|\mathbf{I}_l - \mathbf{R}_l \circ \mathbf{L}_l\|_1 + \|\mathbf{I}_h - \mathbf{R}_h \circ \mathbf{L}_h\|_1$$

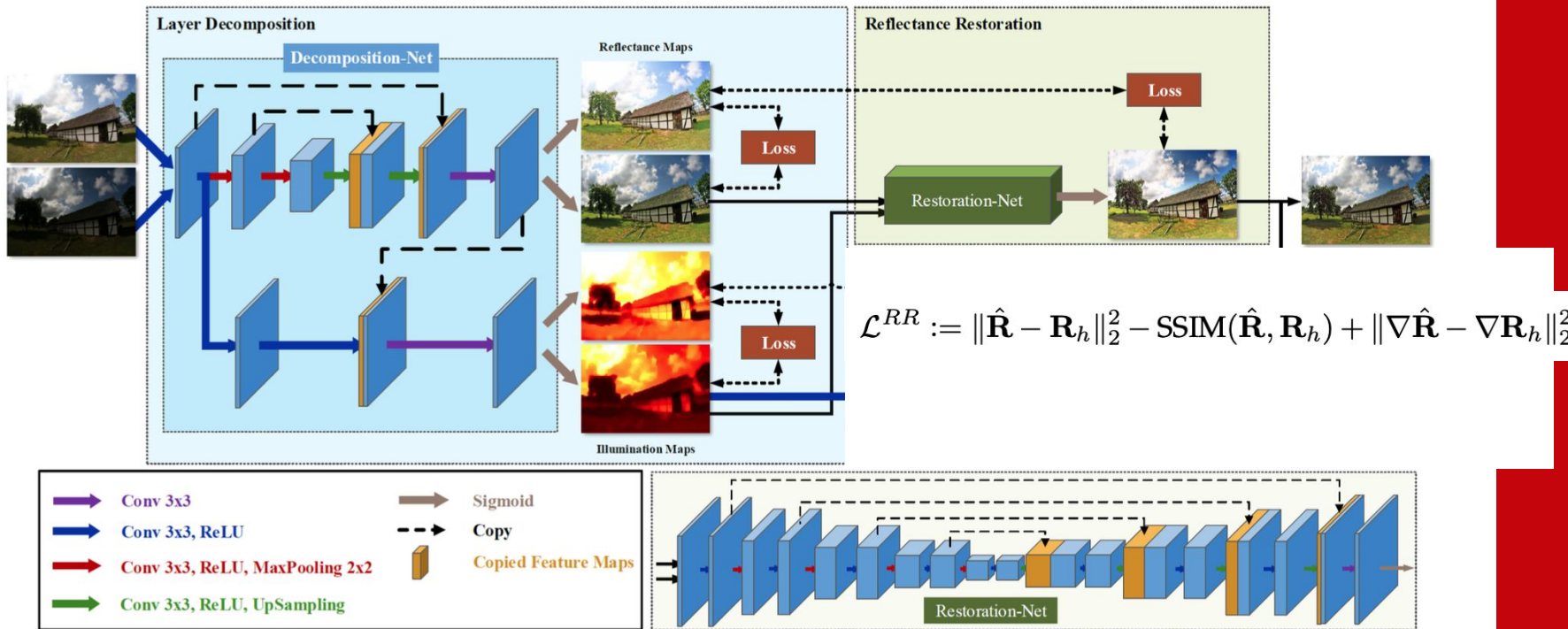
$$\mathcal{L}_{rs}^{LD} := \|\mathbf{R}_l - \mathbf{R}_h\|_2^2$$

$$\mathcal{L}_{mc}^{LD} := \|\mathbf{M} \circ \exp(-c \cdot \mathbf{M})\|_1$$

$$\mathbf{M} := |\nabla \mathbf{L}_l| + |\nabla \mathbf{L}_h|$$

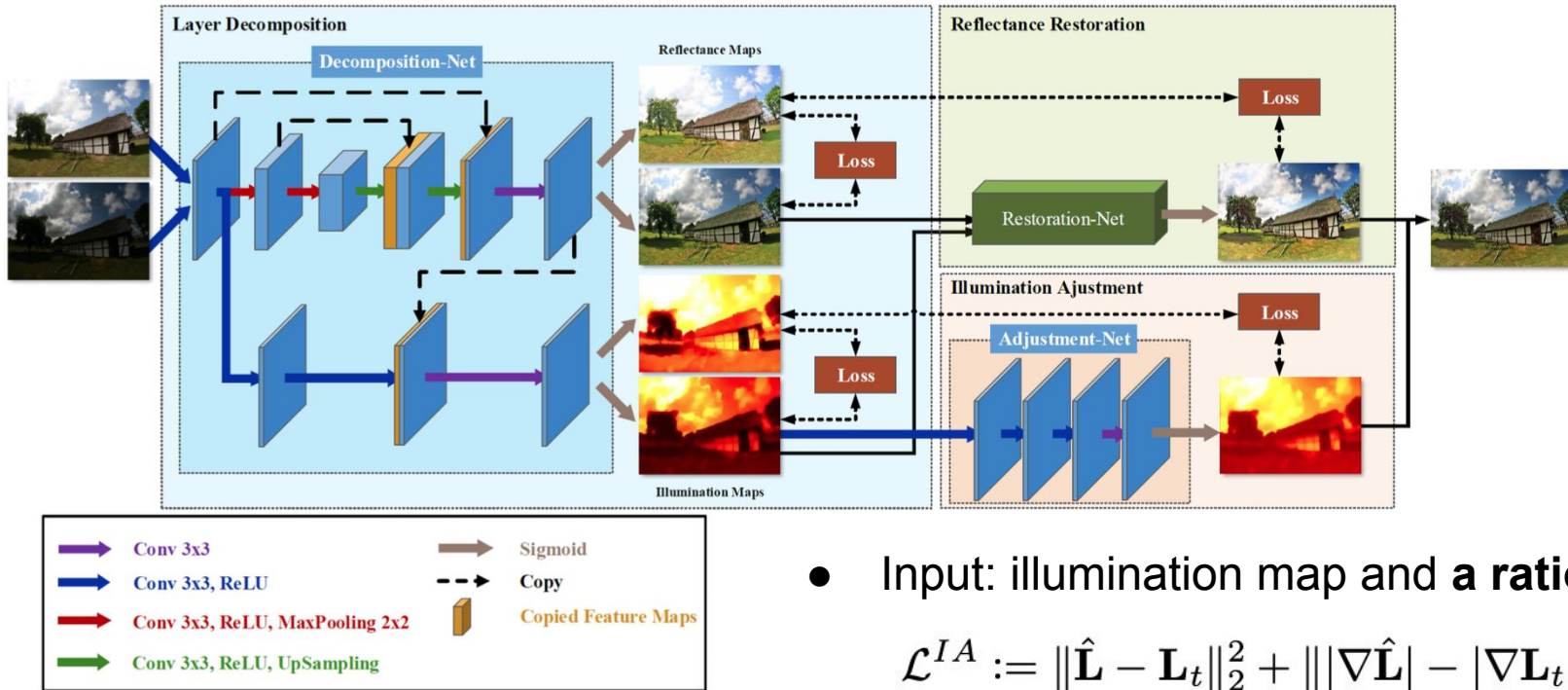
$$\mathcal{L}_{is}^{LD} := \left\| \frac{\nabla \mathbf{L}_l}{\max(|\nabla \mathbf{I}_l|, \epsilon)} \right\|_1 + \left\| \frac{\nabla \mathbf{L}_h}{\max(|\nabla \mathbf{I}_h|, \epsilon)} \right\|_1$$

# Approach: Reflectance Restoration Net



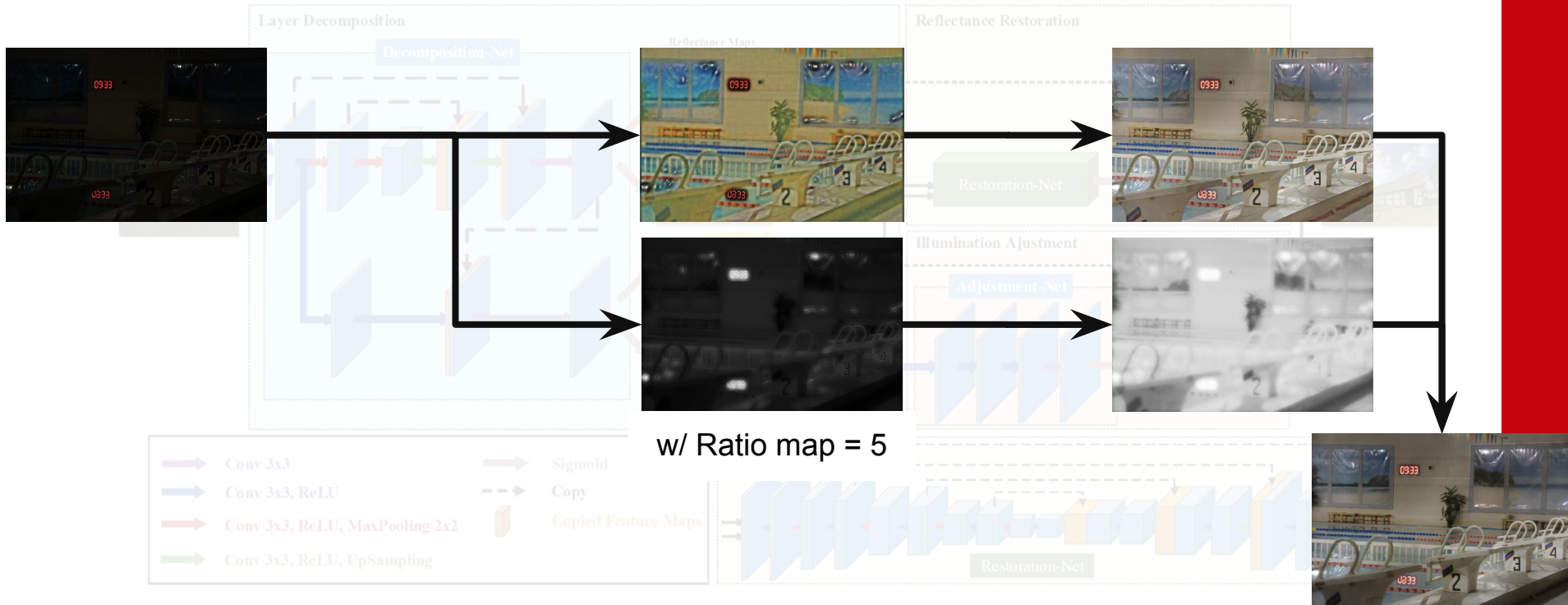


# Approach: Illumination Adjustment Net





# Inference Flow w/ Real Data



# Evaluation: Result of Different Ratio

Input

Ratio = 2

Ratio = 3

Ratio = 4

Ratio = 5



# Evaluation: Quantitative Results

- PSNR and SSIM with high light image as target

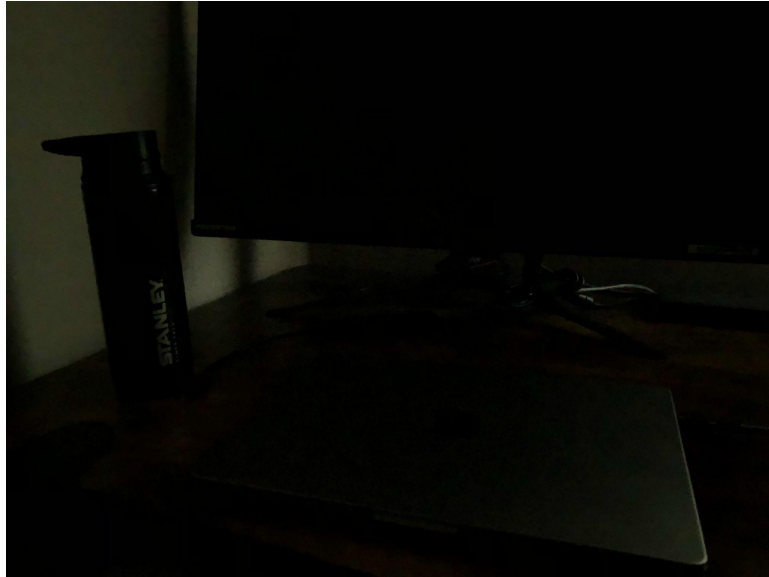
	PSNR	SSIM
w/o enhancement	7.77	0.1952
w/ enhancement	18.50	0.8016

# Evaluation: Artifacts



# Evaluation: Same Model on Our Photo

- Image captured by Iphone X





# Discussion and Future Work

- The evaluation showed that a higher ratio might get better low-light enhancement and with enhancement implementation, we could get higher PSNR and SSIM which represented better performance.
- Strength
  - a. Enhance low-light image under different light/exposure conditions
  - b. Clearly remove degradations
  - c. Adjustable ratio
  - d. Trainable without ground truth of illumination and reflectance layer
- Weakness
  - a. Different model camera will need collect new dataset and re-train the model
  - b. Results contained artifacts, like color inconsistency and halos
- Our project successfully achieved the goal to enhance low-light image, but our training data couldn't apply for every device. For future work, it might be a good topic to research how to make adjustments to let the method could apply to all types of devices and the improvement of artifacts.





**Thanks!**