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A Retinex based GAN Pipeline to Utilize Paired and Unpaired Datasets for Enhancing Low Light Images

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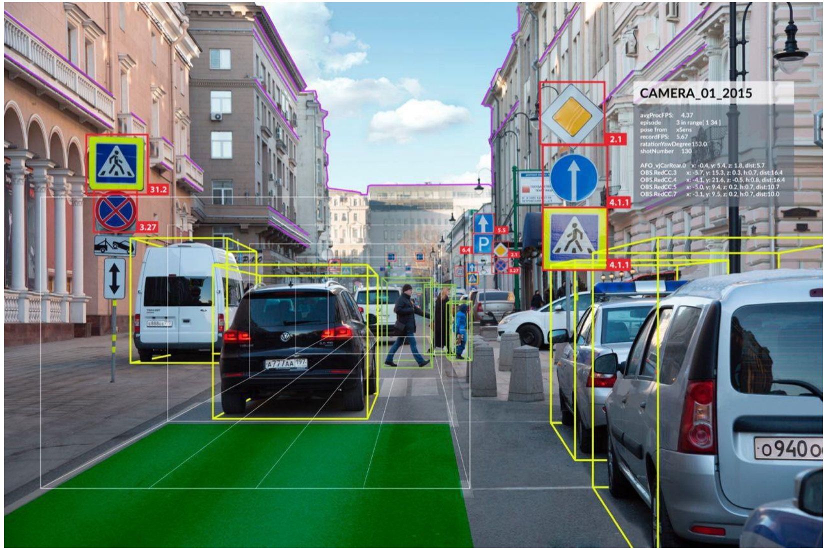
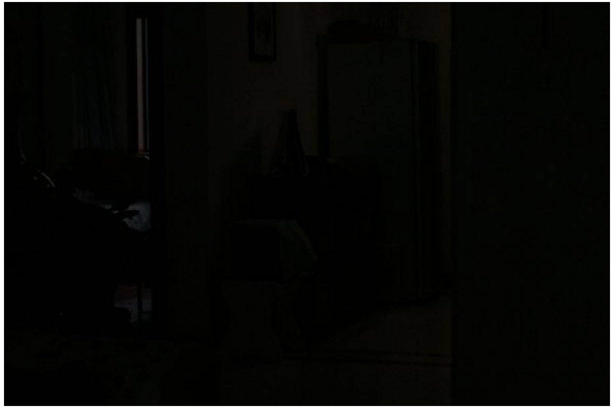
Computer vision

- more than **2000 high quality research papers** are being published on computer vision annually.
    - These papers discuss how to interpret visual input for **object detection, scene interpretation, colour adjustments**, etc.
- There are **many vision based products** based on these researches.



Computer vision: The problem

99% of the existing work in computer vision applies for good lighting conditions which restricts its application.



How??

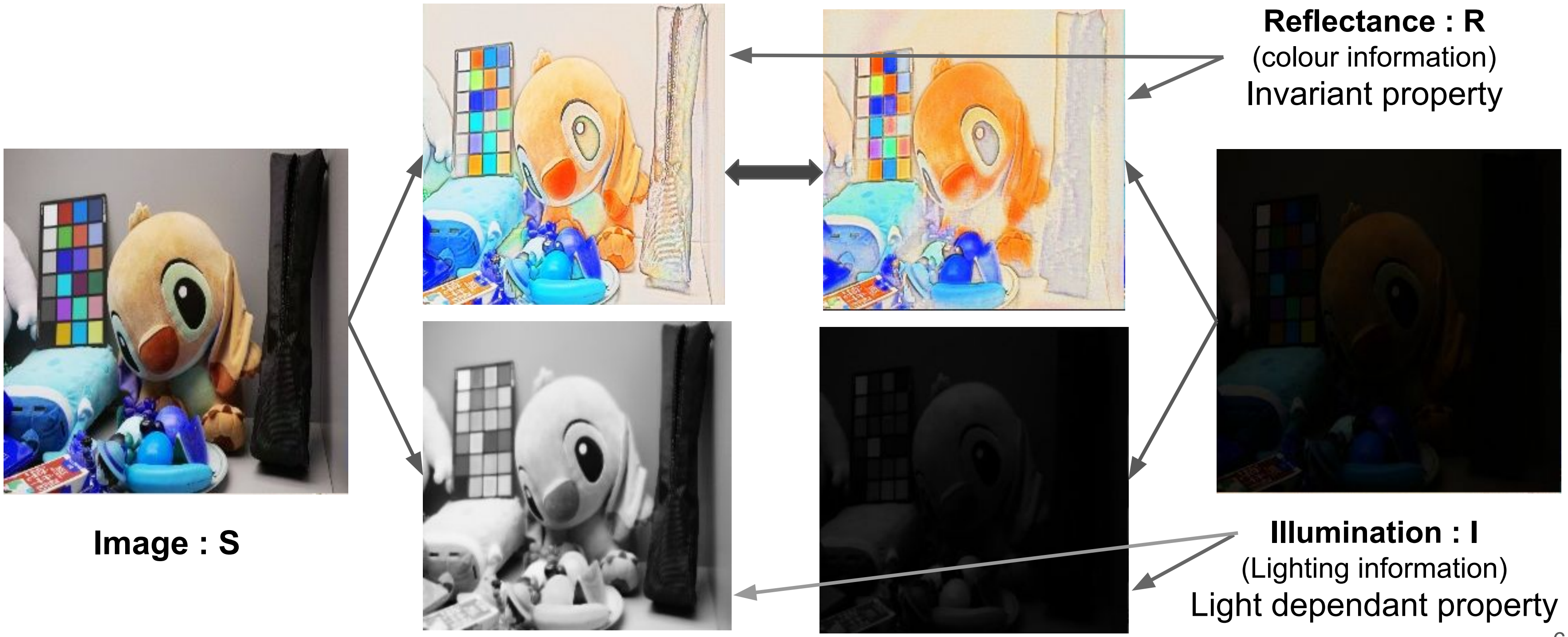
Existing solutions (Non Algorithmic)

- Artificial lighting
  - Consumes energy
  - Disturbs natural ecosystems.
- Sophisticated camera hardware
  - The night mode in cameras is enabled through expensive hardware.
- High-Dynamic-Range (HDR) Imaging
  - Movement of dynamic objects cause “ghosting effect”.

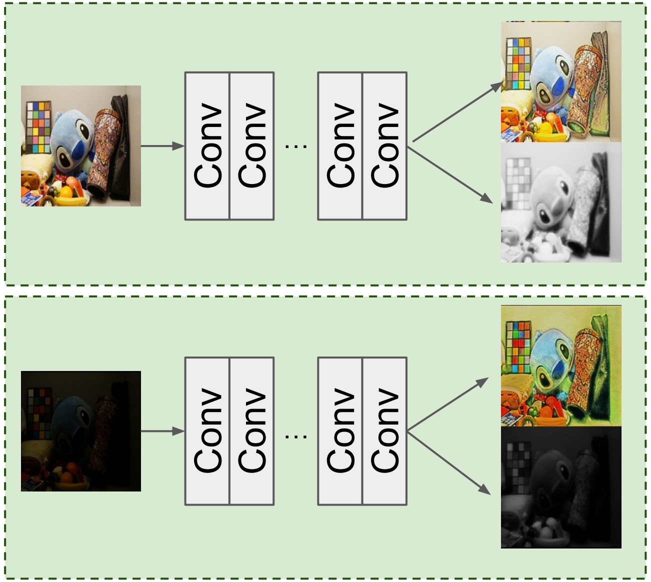
Evolution of low-light enhancement algorithms

- Classical algorithms (*unpaired dataset*)
    - Intensity based (Histogram Equalization) / Gradient based (Grad-Enhance)
- Retinex-theory (*paired/unpaired dataset*)
- Deep Convolutional Neural Network (*paired/unpaired dataset*)
    - LLNet, LLCNN, **RetinexNet**
- Adversarial learning (*paired/unpaired dataset*)
    - Retinex-GAN, **Enlighten-GAN**

Retinex based model



Retinex based decomposition network



$$\mathcal{L} = \lambda_{IR}\mathcal{L}_{IR} + \mathcal{L}_{recon} + \lambda_{IS}\mathcal{L}_{IS}$$

Invariable reflectance Loss

$$\mathcal{L}_{IR} = \|R_{low} - R_{high}\|$$

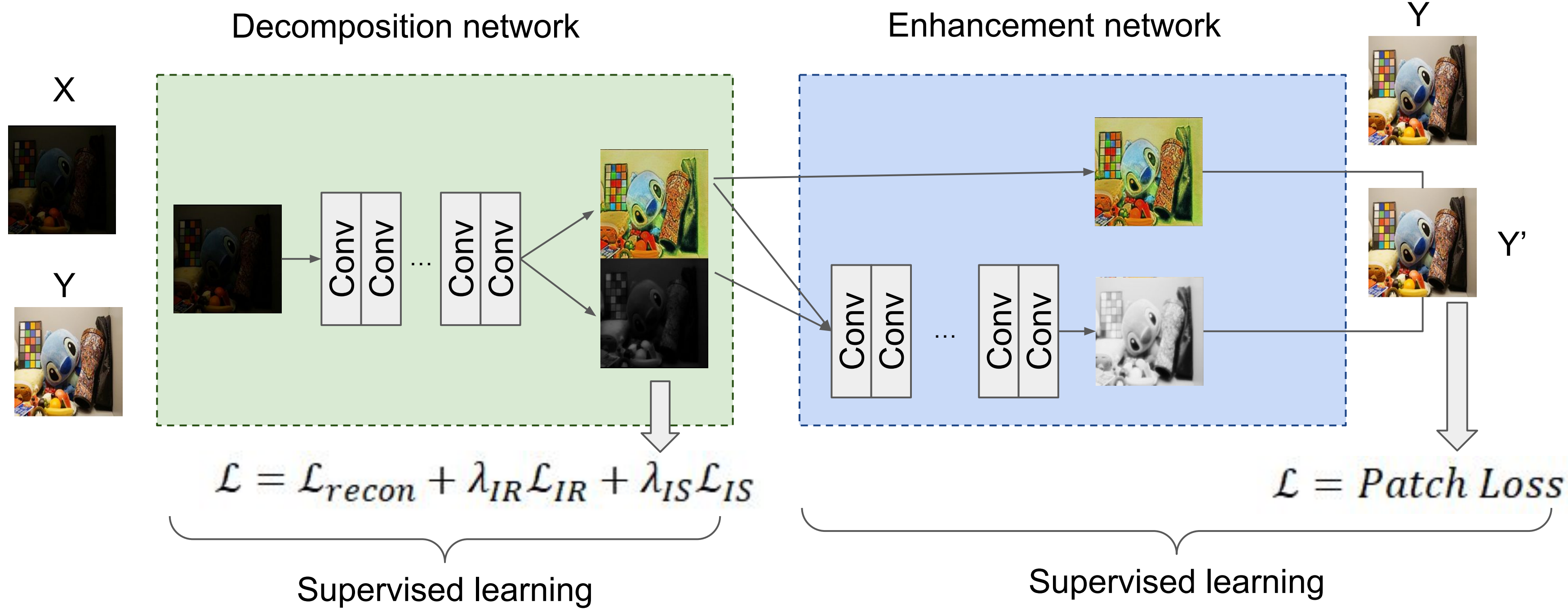
Reconstruction Loss

$$\mathcal{L}_{recon} = \lambda_r \|R_{low} \circ I_{high} - S_{high}\| + \lambda_h \|R_{high} \circ I_{low} - S_{low}\|$$

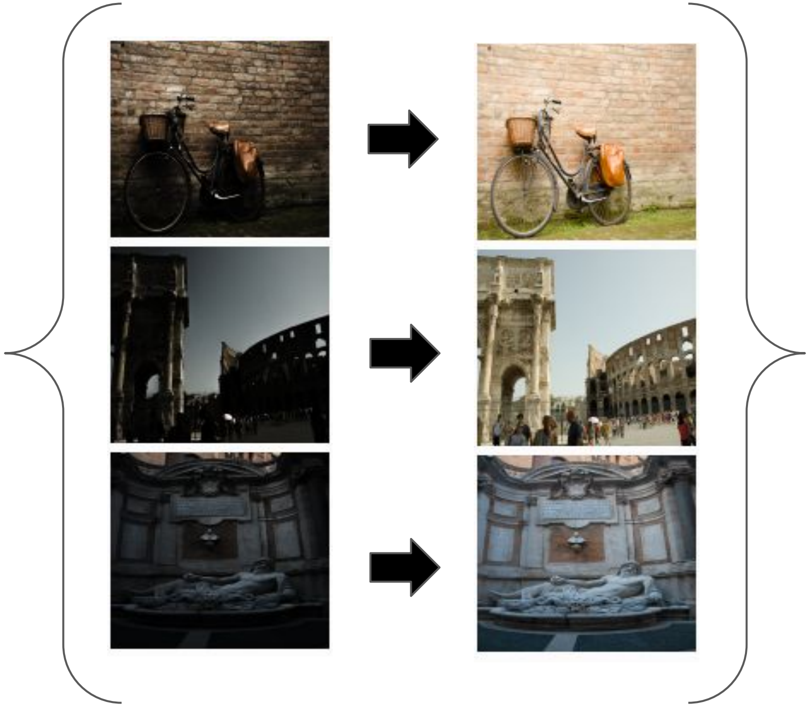
Illumination Smoothness Loss

$$\mathcal{L}_{IS} = \|\nabla I \circ \exp(-\lambda_g \nabla R)\|$$

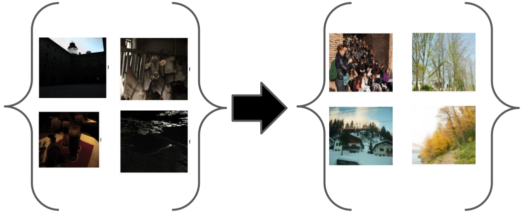
RetinexNet (2018)



Dataset: Types (1/2)

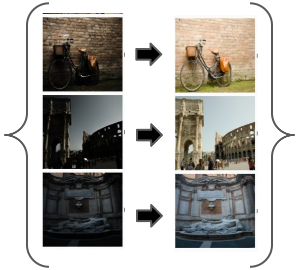


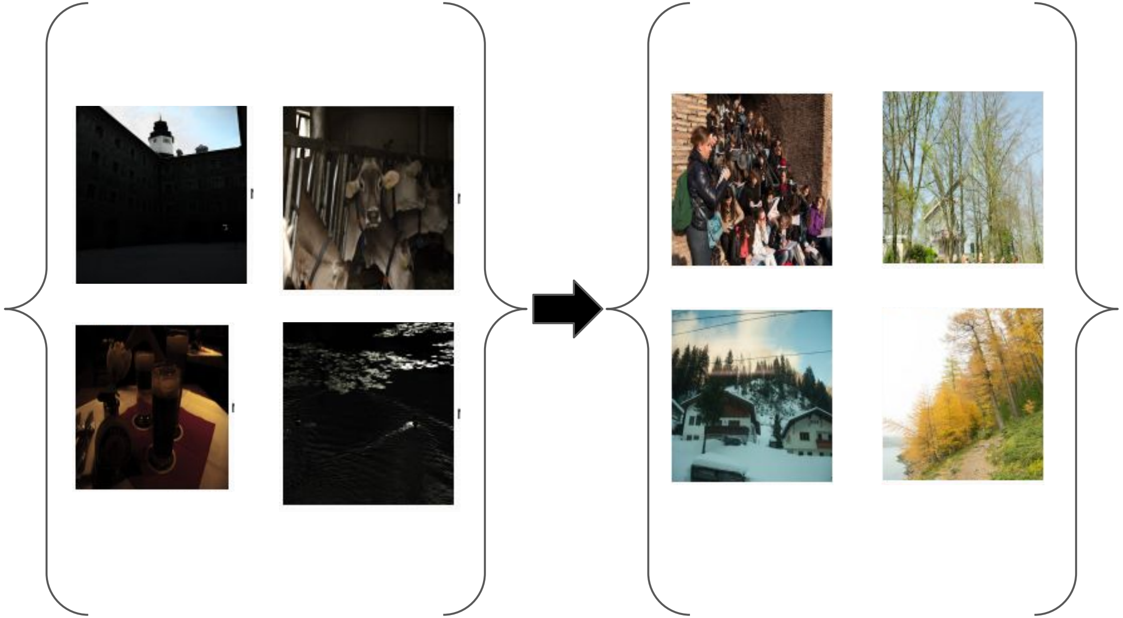
- **Paired dataset**: Every dark image has it's well light counterpart.
  - Difficult to collect.
  - More information.



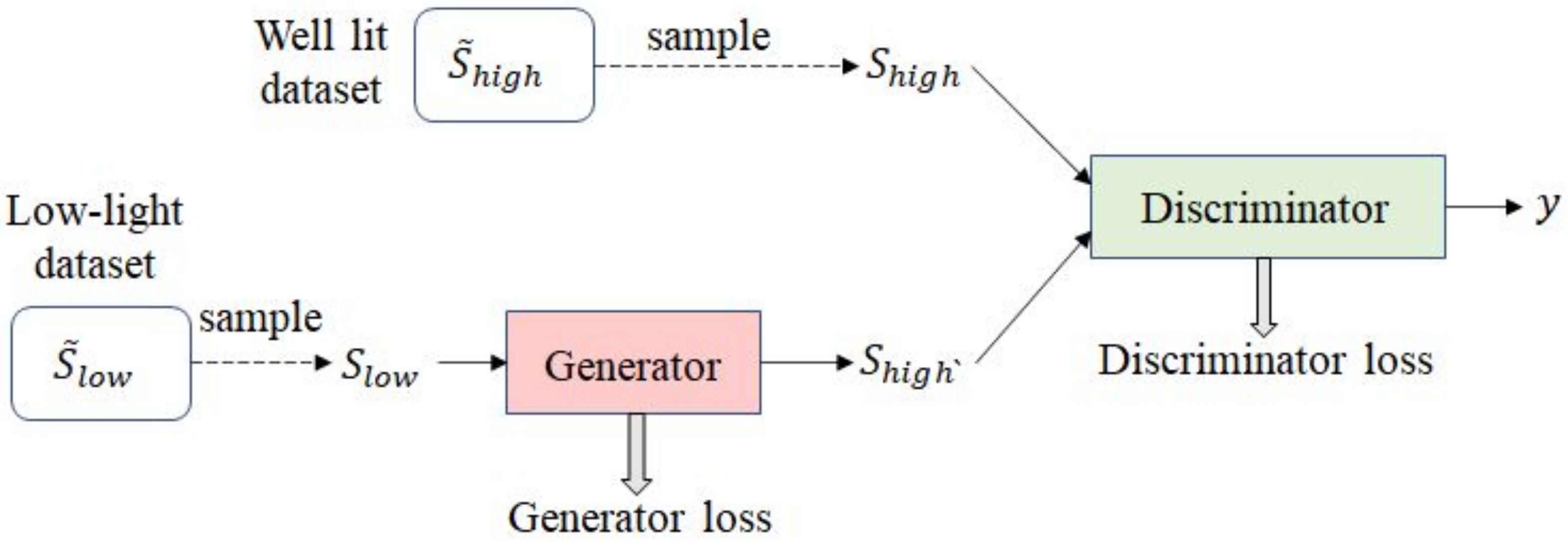
Dataset: Types (2/2)

- **Unpaired dataset**: There are unrelated sets of well lit and dark images.
  - Easy to obtain.





GAN & DCGAN*

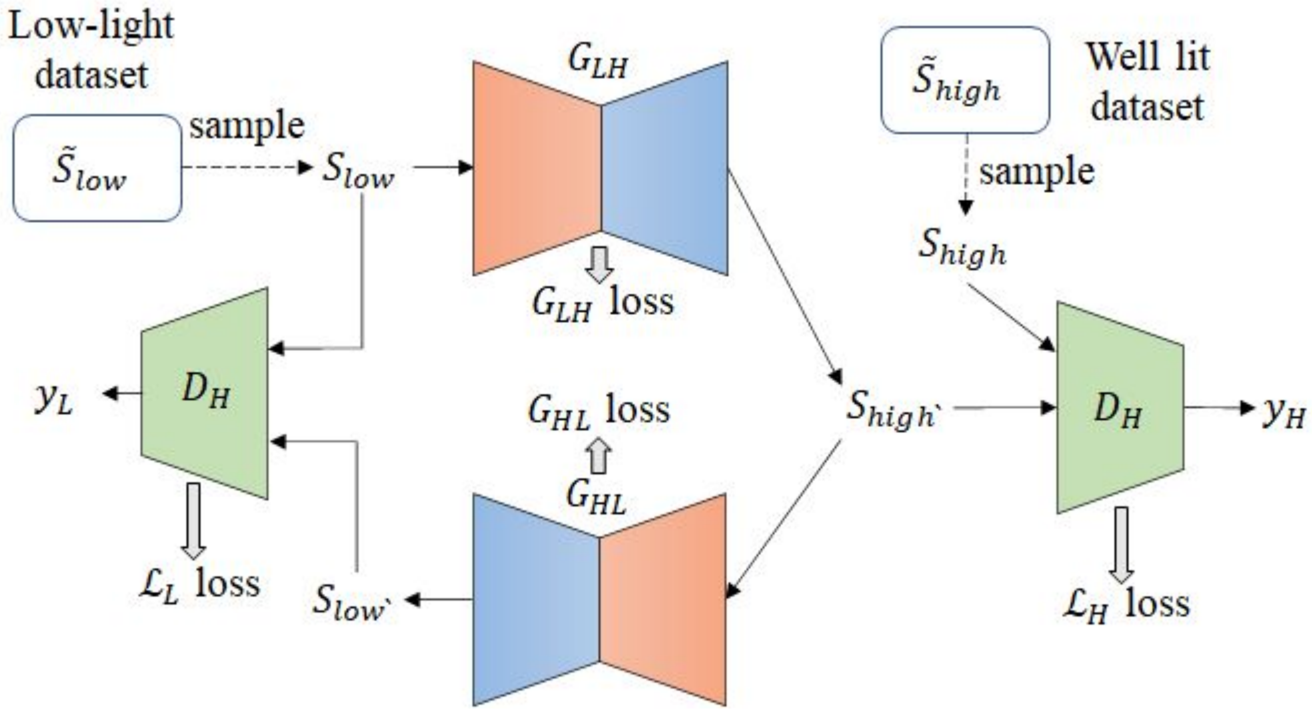


*Deep Convolutional Generative Adversarial Network

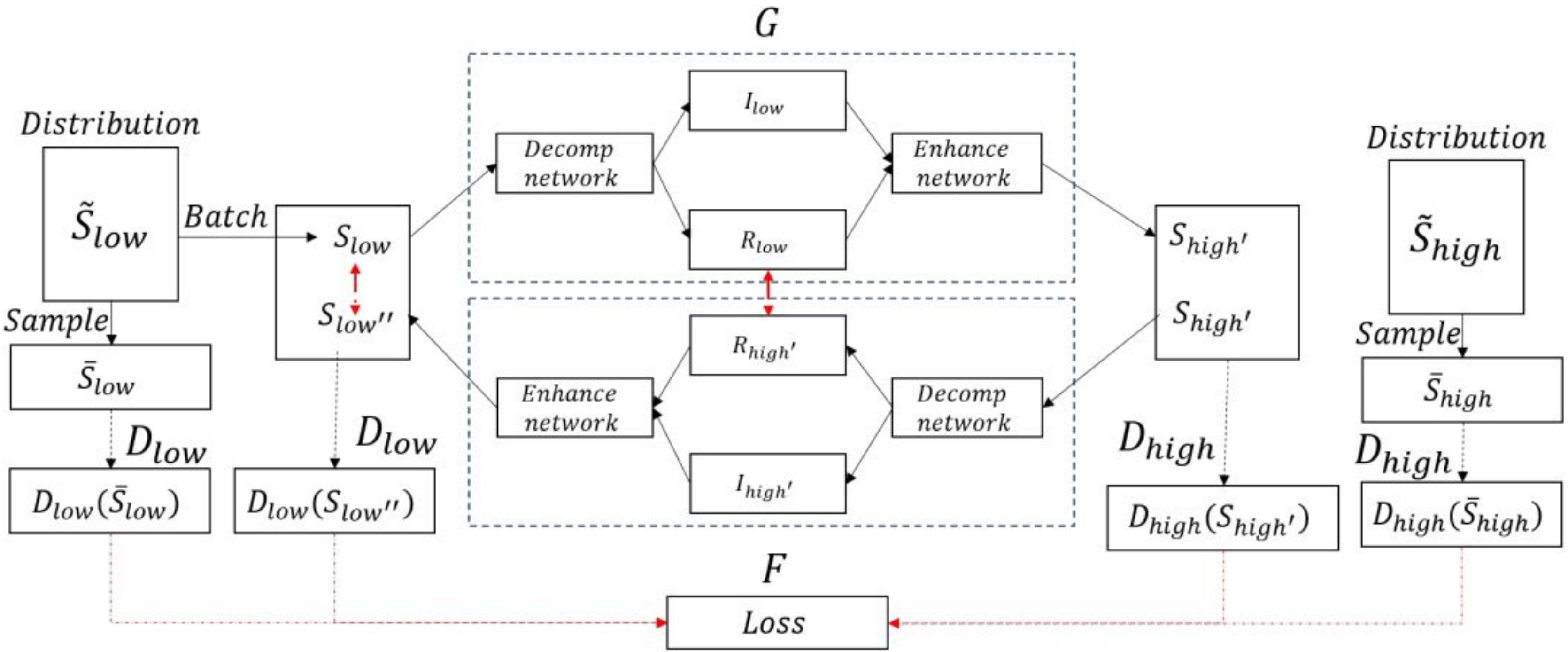
Proposed method: Steps

1. Identification of **illumination level**.
2. Extracting **color information** even in the poorly-light condition.
3. **Increase image illumination** while **preserving and enhancing the color** information.
4. **Handle the noise** and deformations introduced to the image during the enhancement process.

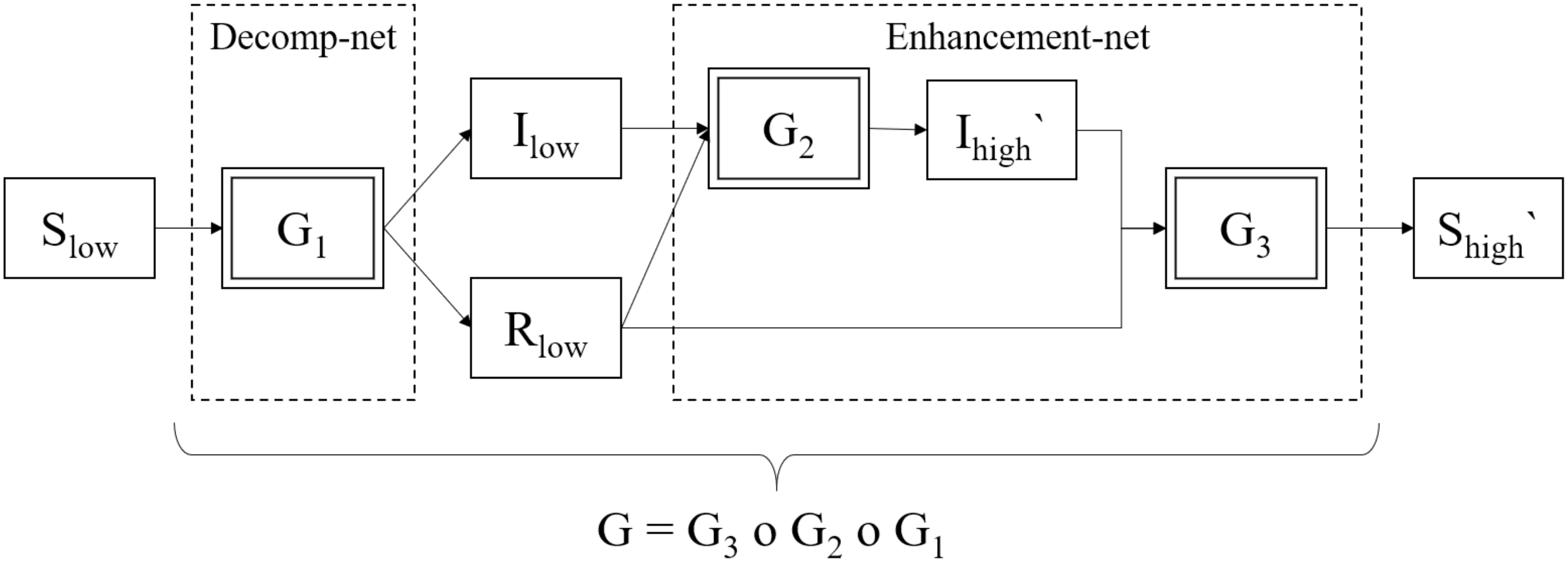
CycleGAN


Low-light dataset
$\tilde{S}_{low}$
sample
S_{low}
G_{LH}
G_{LH} loss
Well lit dataset
$\tilde{S}_{high}$
sample
S_{high}
y_L
D_H
G_{HL} loss
G_{HL}
$S_{high`}$
D_H
y_H
$\mathcal{L}_L$ loss
$S_{low`}$
$\mathcal{L}_H$ loss

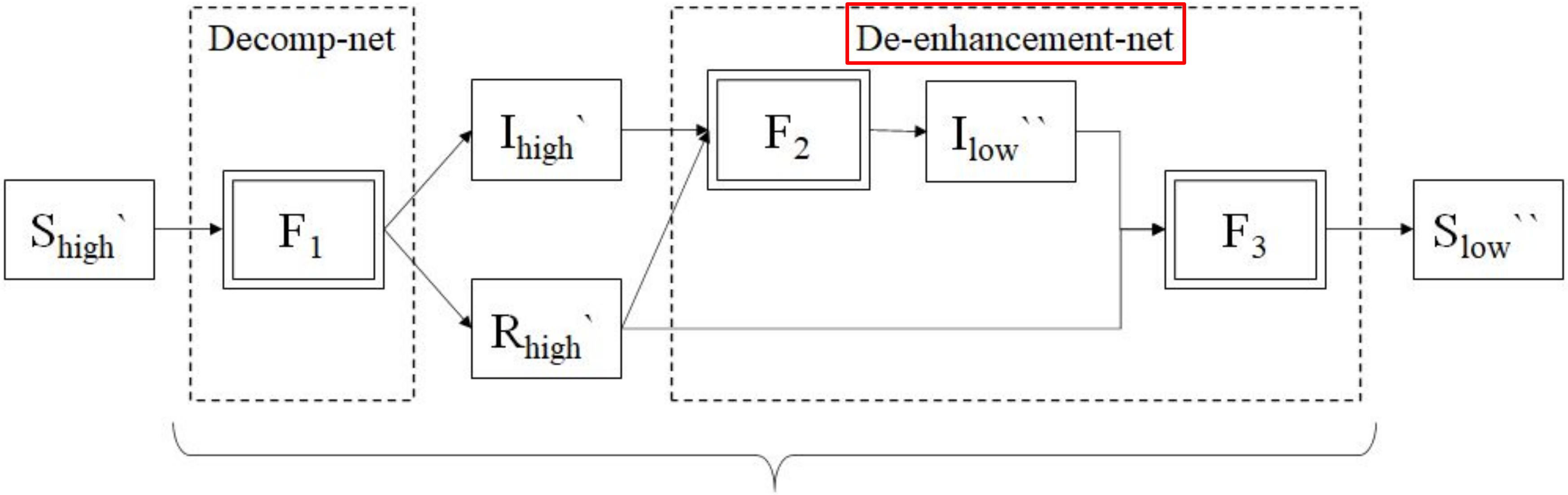
Proposed model: Architecture



Component analysis: Forward generation

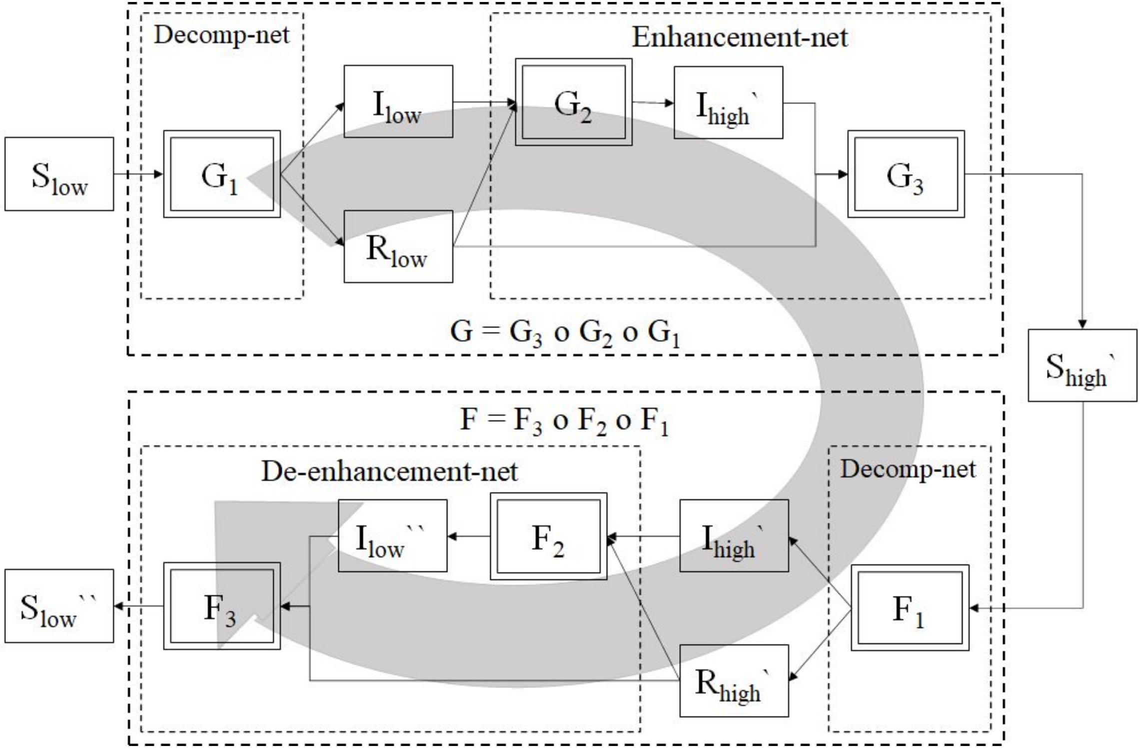


Component analysis: Reverse generation

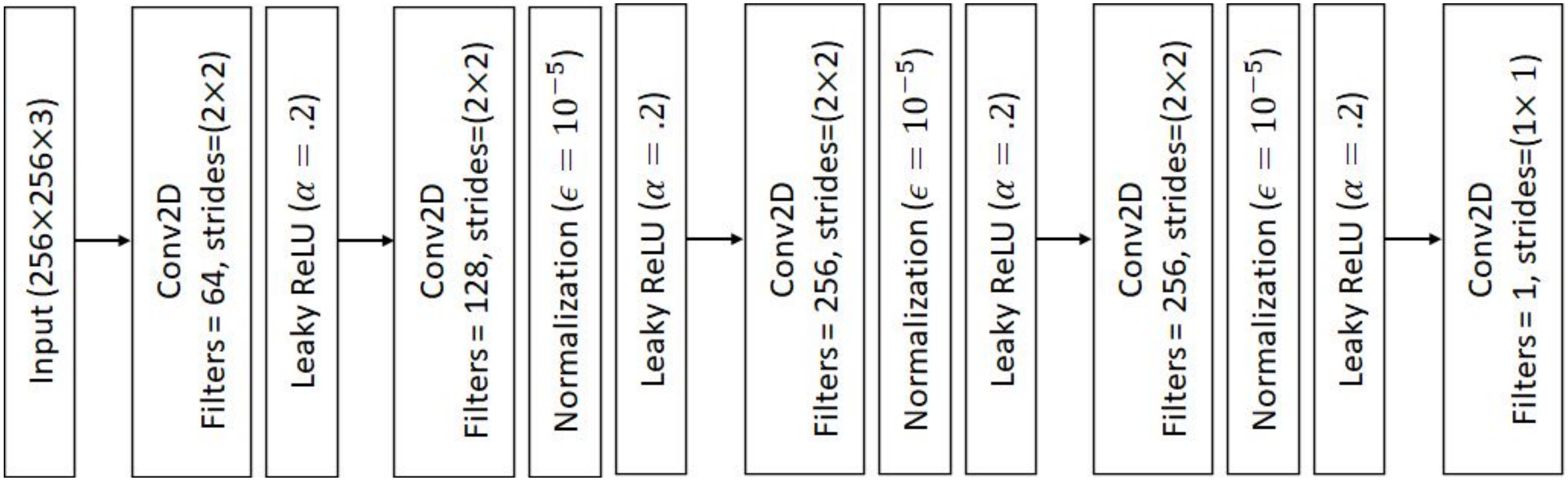


$$F = F_3 \circ F_2 \circ F_1$$

Component analysis: GAN cycle



Component analysis: Discriminator



Component analysis: Loss function

$$\mathcal{L}_{cyc_s} = \mathbb{E}_{S_{low}\ p(S_{low})}\left[\left\|F(G(S_{low})) - S_{low}\right\|_1\right] + \mathbb{E}_{S_{high}\ p(S_{high})}\left[\left\|G\left(F(S_{high})\right) - S_{high}\right\|_1\right]$$

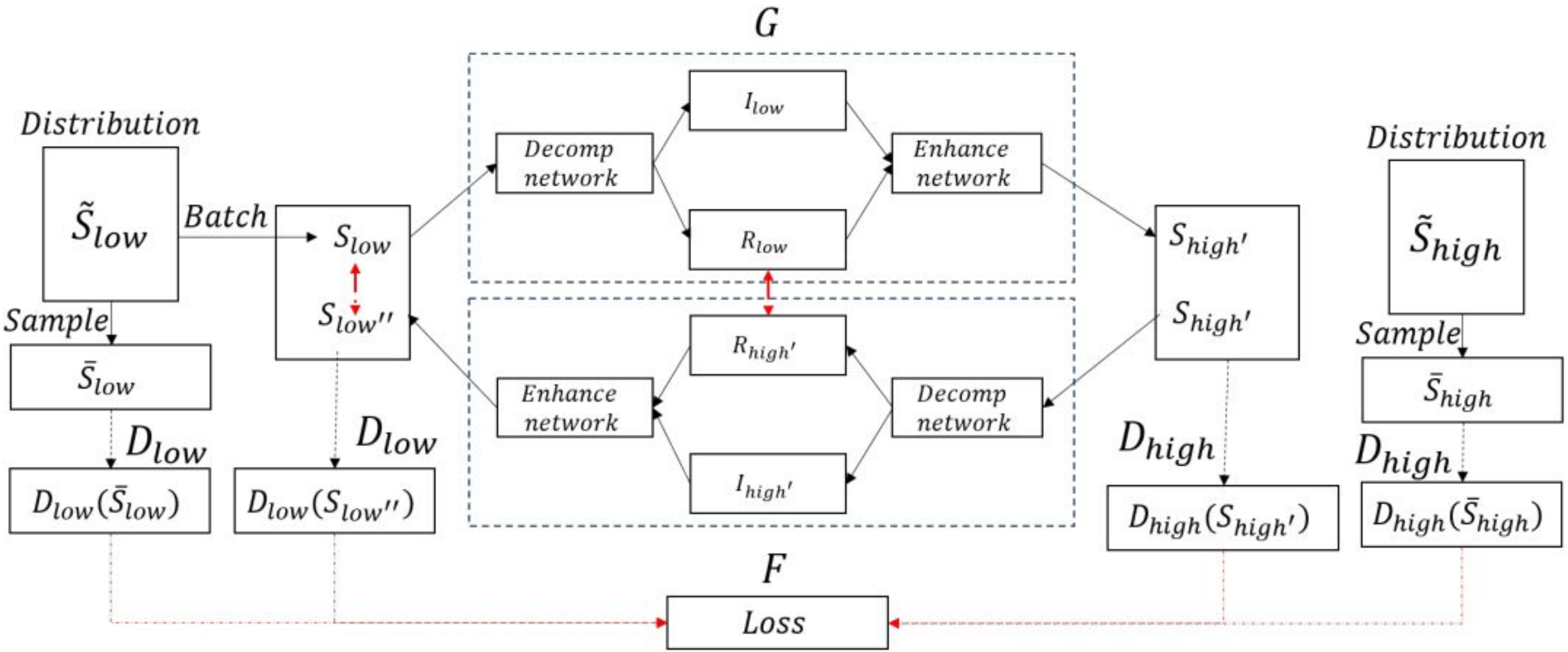
$$\mathcal{L}_{cyc_R} = \left\|R_{low} - R_{high}`\right\|_2 + \left\|R_{high} - R_{low}`\right\|_2$$

$$\mathcal{L}_{cyc} = \mathcal{L}_{cyc_s} + \mathcal{L}_{cyc_R}$$

$$\mathcal{L}_{gen} = \mathcal{L}_{cyc} + H\left(1, D_{high}(G(S_{low}))\right) + H\left(1, D_{low}\left(F(S_{high})\right)\right)$$

$$\mathcal{L}_{disc} = H\left(1, D_{high}(G(S_{low}))\right) + H\left(0, D_{high}(S_{high})\right) + H\left(1, D_{low}\left(F(S_{high})\right)\right) + H(0, D_{low}(S_{low}))$$

Proposed model: Architecture



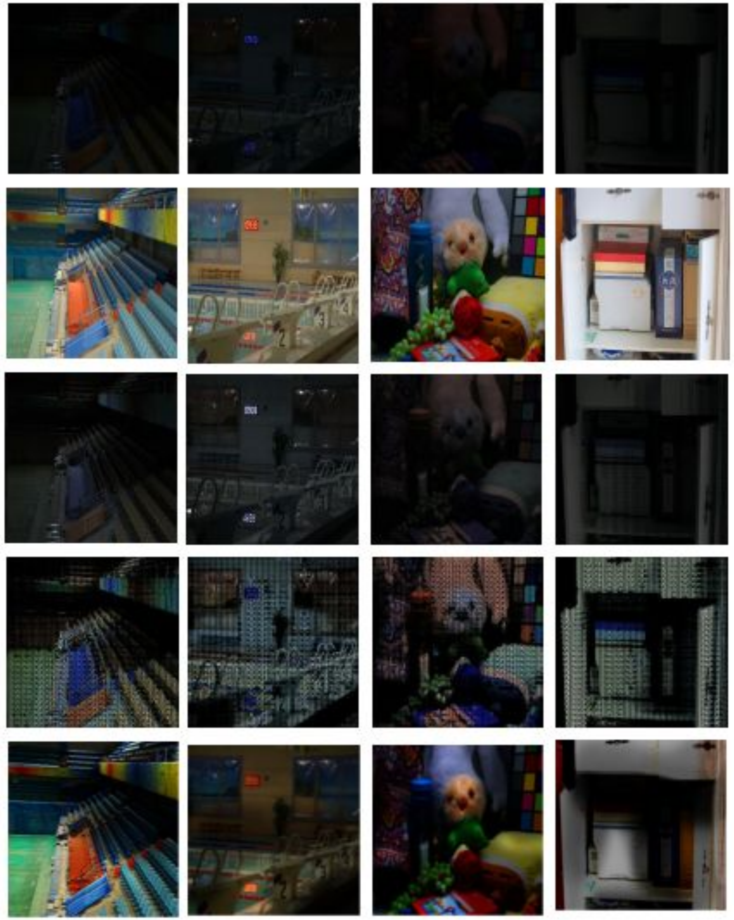
Low lit image (S_{low})

Corresponding well lit image (S_{high})

Enhancing low light images using a **generic GAN**

Enhancing low light images using a **generic CycleGAN**

Proposed model



Conclusion

- The proposed model combines existing ideas from Retinex theory, CNN, and CycleGAN.
- Using both paired (synthetic + non-synthetic) and unpaired (non-synthetic) images, the model provides better performance in comparison.
- The ablation study presents the importance of each component in the pipeline.
- Certain images show issues with respect to smoothness similar to other related works. This must be analyzed for further improvements.
- The segments of the NN pipeline makes use of the paired and unpaired datasets separately in the proposed architecture. Future work will explore the possibility for both CNN and GAN to take use of both datasets each.

Thank you!

Summary

- Image enhancement algorithms are important for 2 reasons:
  - **Enhancement** (Improving image aesthetics)
  - **Interpretation** (Application of computer vision algorithms)
- **Prior works** for low-light image enhancement have been dependant on **either paired or unpaired dataset**.
- This work **proposes a CNN and GAN based model** inspired by the retinex theory which **utilizes both paired and unpaired datasets**.
- The proposed model provides **better results** compared to similar models dependant on single type of dataset.
- Futureworks focus on enhancement on a **continuous illumination space** and **extend to other application** such as object recognition.