AI2100/AI5100: Deep Learning

Zero Reference Low-Light Image Enhancement with Attention

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Introduction

- It is common to have images taken in low-light conditions due to **environmental** conditions or **technical** issue.

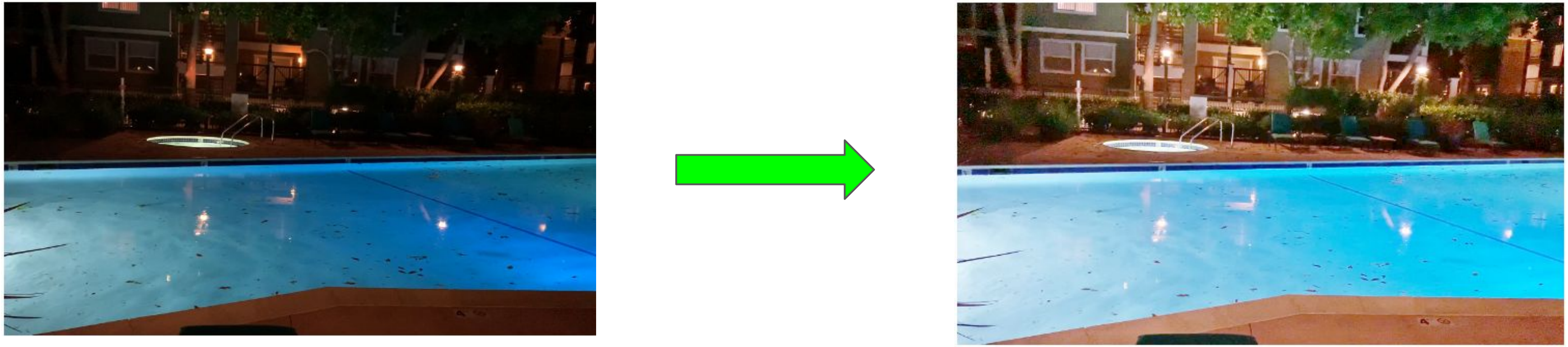
- Good quality images or videos are crucial for **surveillance**, **autonomous driving**, etc.

- Zero-reference deep curve estimation **(Zero-DCE)** is an effective low-light image enhancement technique.

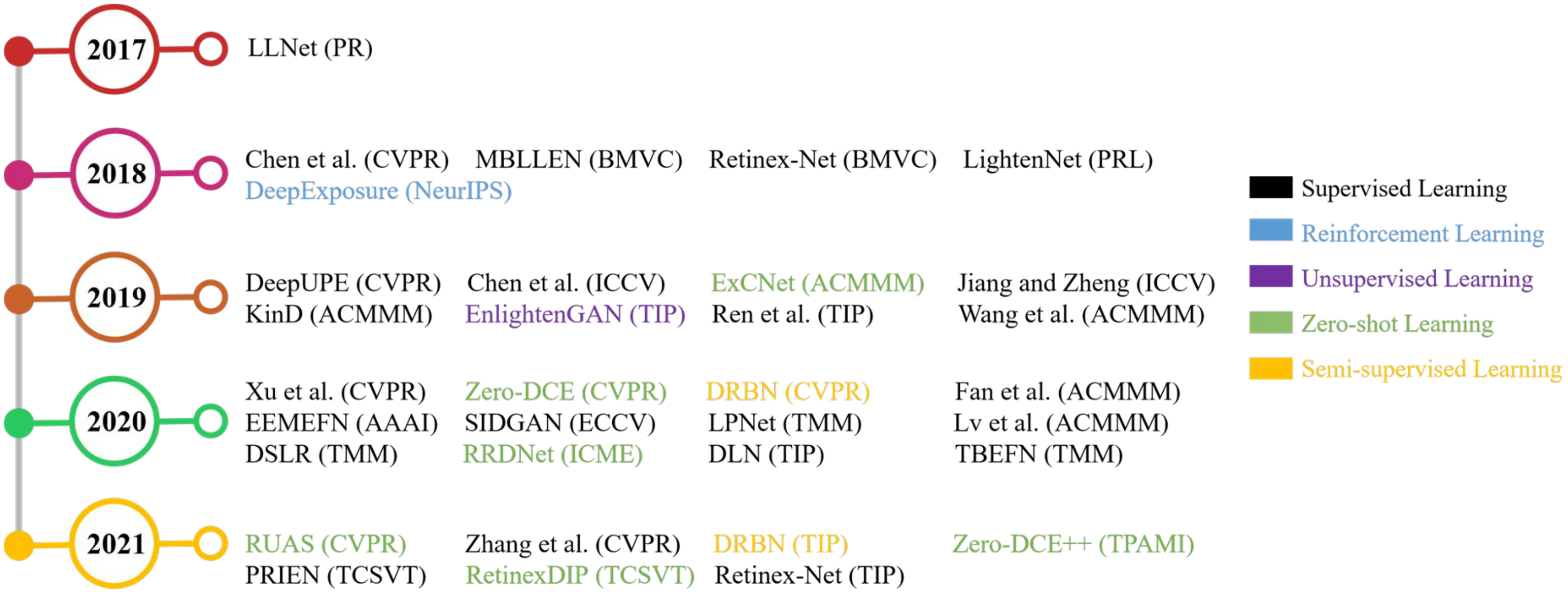
- Zero-DCE++ is an **accelerated** and **lightweight** but equally effective version of original Zero-DCE.

Introduction(contd.)

- On top of Zero-DCE++, we have used **attention** to improve the quality of enhanced images.



Literature Review



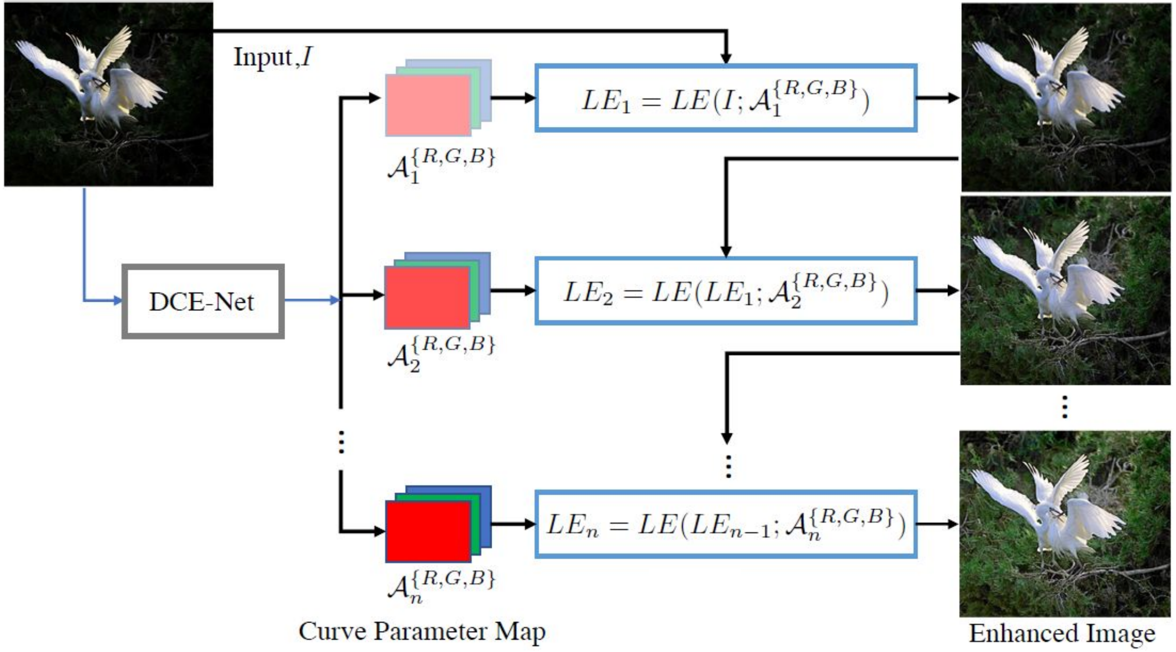
Ref : Li, Chongyi, et al. "Low-light image and video enhancement using deep learning: a survey." IEEE Transactions on Pattern Analysis & Machine Intelligence 01 (2021): 1-1.

Baseline

- **Zero-DCE**
  - It doesn’t required **paired images** for training.
  - Reformulates the task as an **image-specific curve estimation** problem.
  - Uses carefully curated **non-reference loss** functions.
  - The final loss function combines exposure control loss, spatial consistency loss, illumination smoothness loss, and color constancy loss.
  - It takes a low-light image as input and produces high-order curves as its output.

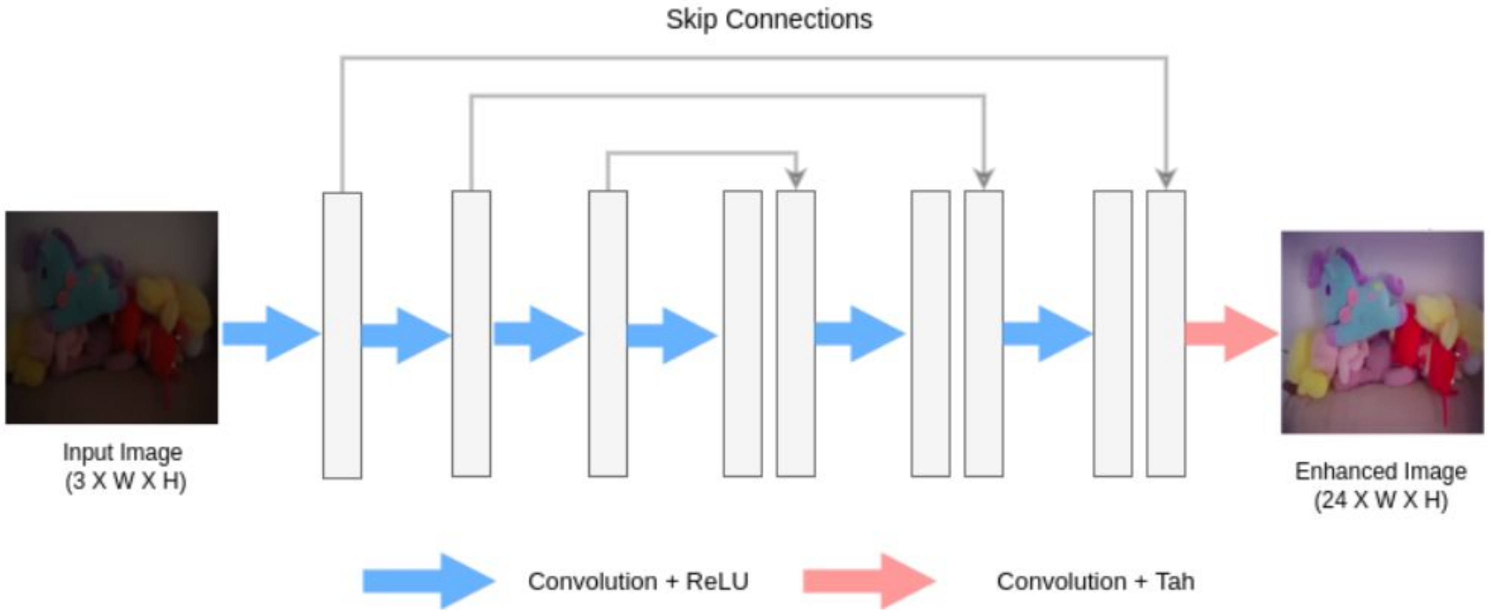
Baseline(contd.)

- **Zero-DCE framework**



Baseline(contd.)

- **DCE-Net**



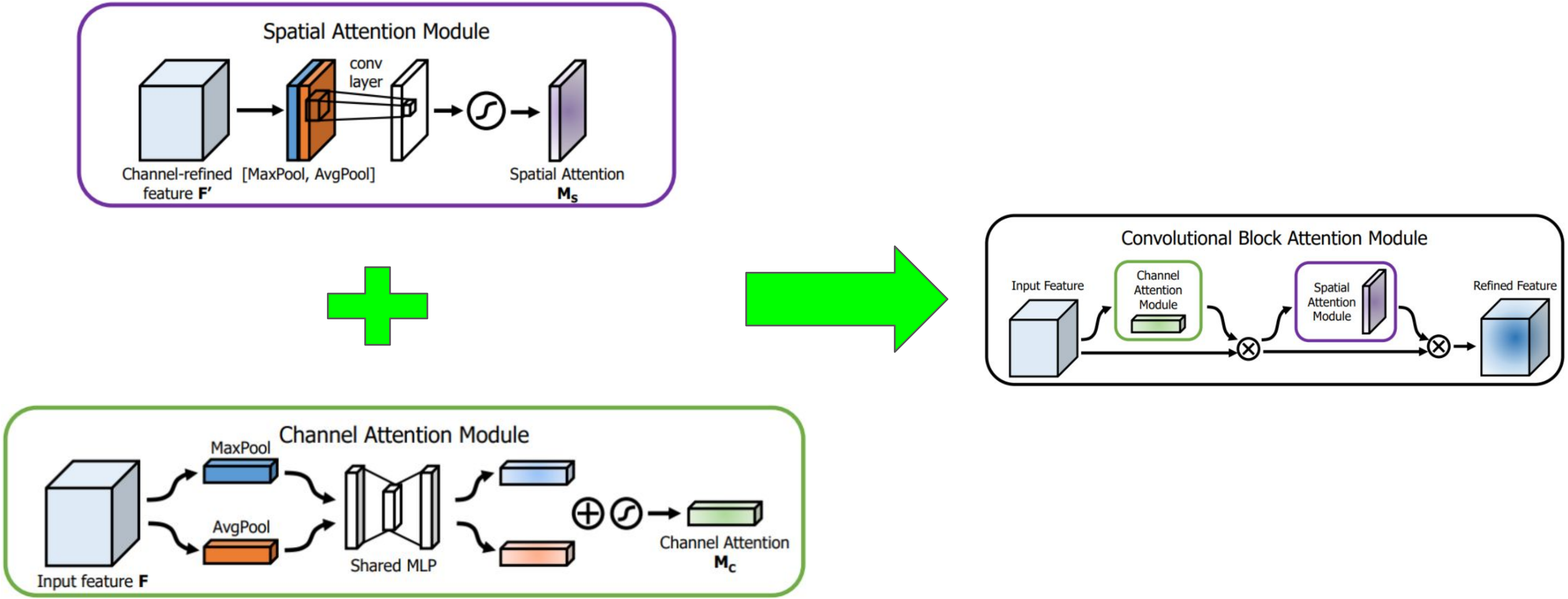
Baseline(contd.)

- **Zero-DCE++**
  - Zero-DCE++ have **8 times less parameters** than original Zero-DCE.
  - Uses more efficient **depthwise** separable convolutions.
  - Estimated curve parameters are **3** (in original Zero-DCE, it was 24).
  - It uses **downsampled** input images and **up samples** after enhancement.

Proposed Approach

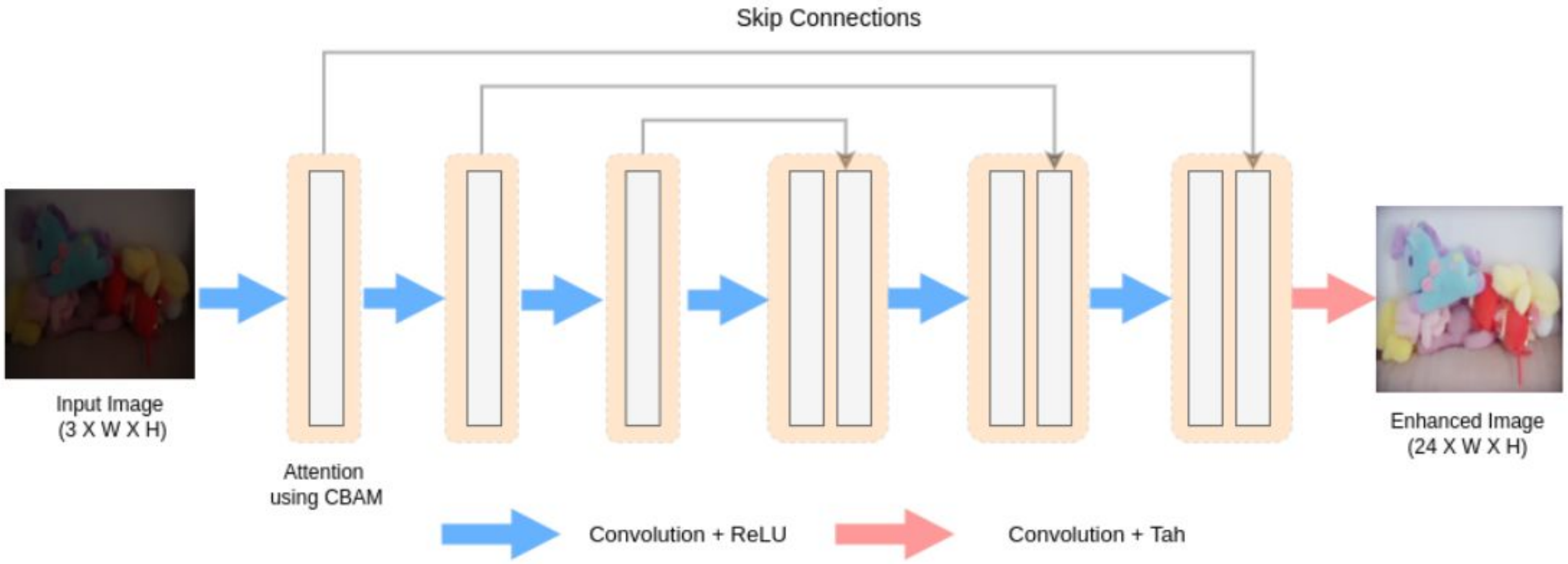
- **Zero-DCE++ with Attention**
  - Attention has brought significant advancement in **NLP** domain in past 5-7 years.
  - In **Computer Vision** also people have tried to use different type of attentions(special, temporal, self etc.)[SAGAN,SCA-CNN].
  - Convolutional Block Attention Module(**CBAM**)[5] combines channel and special attention together.
  - We have applied CBAM module over each convolution layer of DCE-Net.

Proposed Approach(contd.)



Proposed Approach(contd.)

- **Zero-DCE++ with CBAM**



Results & Analysis

- **Quantitative Analysis**

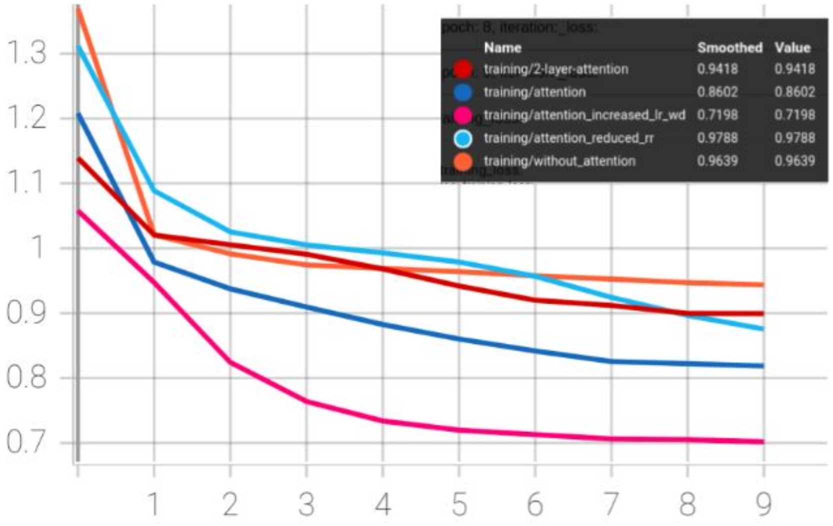
Model	PSNR↑	SSIM↑	MAE↓
Zero-DCE++ (baseline)	11.52	0.062	66.19
CBAM in first 6 layers (A)	13.22	0.062	55.19
CBAM(A) with bias and no batch_norm (B)	11.98	0.062	63.19
CBAM(B) with 4 pooling types	**13.45**	0.062	**42.88**
CBAM in all 7 layers with bias and no batch_norm (C)	9.10	0.062	87.39
CBAM(C) with reduced reduction_rate (D)	8.66	0.062	92.02
CBAM(D) with wd=0.001 and lr=0.001	6.04	0.055	122.54
CBAM(D) in first 4 layers	10.38	0.055	75.42

- **Image quality assessment matrices**
  - PSNR, SSIM, and MAE metrics are used to quantitatively compare the performance of different methods.

Results & Analysis(contd.)

- **Quantitative Analysis(contd.)**

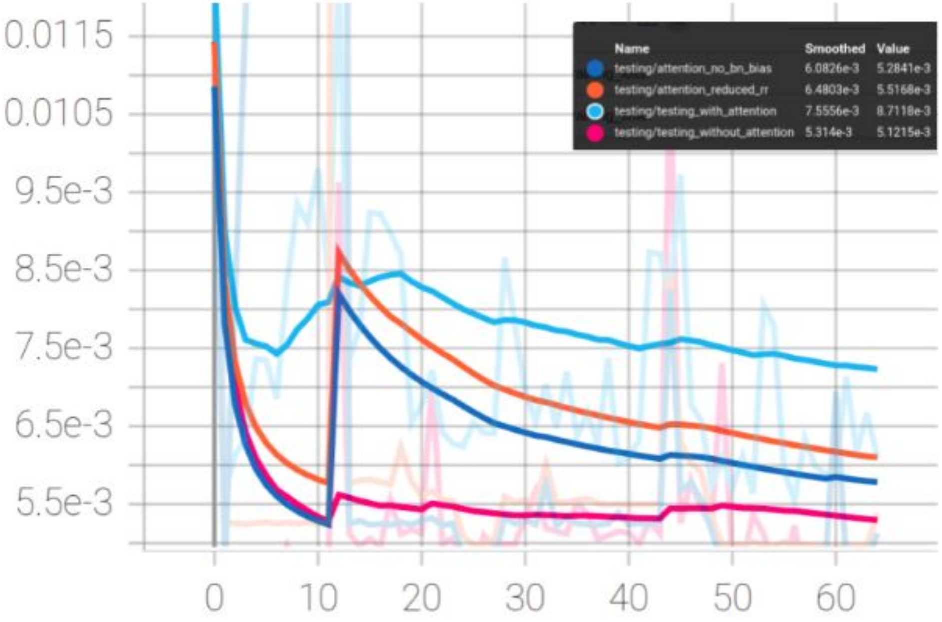
- **Training loss comparison**
  - We can see with addition of attention, **decrease in loss in more** which suggests better learning.



Results & Analysis(contd.)

- **Quantitative Analysis(contd.)**

- **Testing time comparison**
  - As addition of CBAM, introduces **more parameters**, inference time increases.



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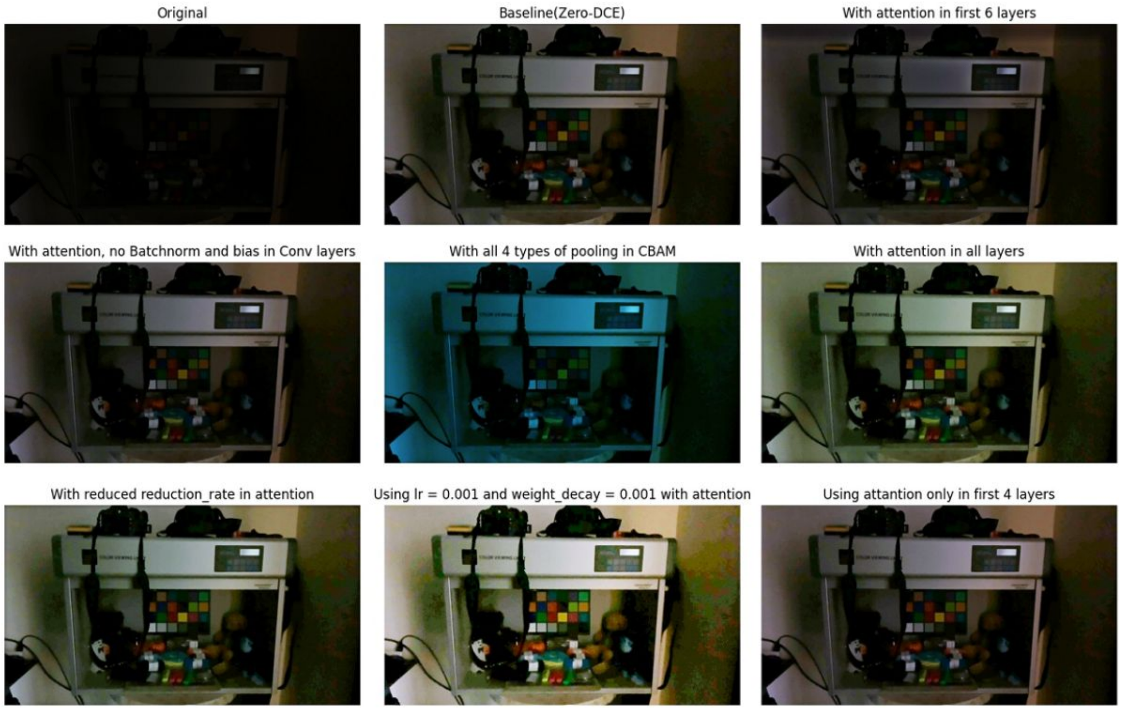
Results & Analysis(contd.)

- **Qualitative Analysis**



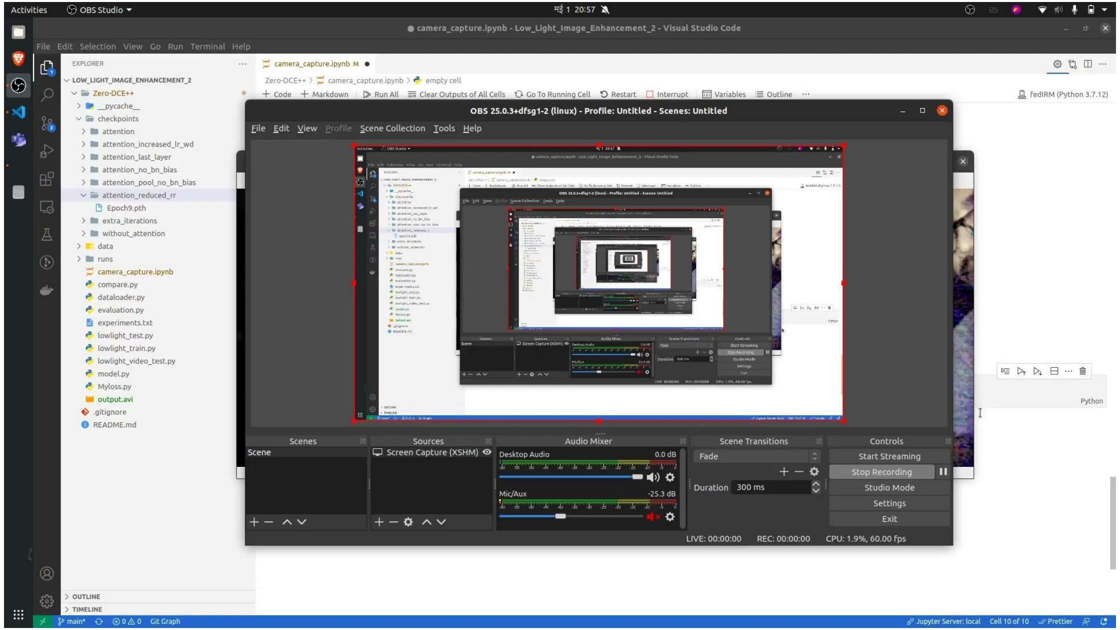
Results & Analysis(contd.)

- **Qualitative Analysis(contd)**

Original | Baseline (Zero-DCE++) | Attention with reduced reduction_rate | Attention with lr=0.001 and wd=0.001

Results & Analysis(contd.)

- **Qualitative Analysis(contd.)**



Ablation Study

- **Effect of different number of attention layers**

Using attention only in first 4 layers

With attention in all layers

Ablation Study(contd.)

- **Effect of applying Batch norm and bias in CBAM**

Ablation Study(contd.)

- **Effect of reduction rate of CBAM**

Ablation Study(contd.)

- **Effect of different types of pooling in CBAM**

Drawbacks

- **Increase in training time**
  - We have observed a **6 times** increase in training time wrt baseline when we added CBAM on it.
  - With **batch norm**, the increase in training time is negligible but it also affects the output quality.
  - We haven't observed much difference in **inference** time wrt baseline.

- **Discrepancies between qualitative and quantitative results**
  - More the **PSNR** and **SSIM** is better the output image and similarly less the **MAE** is better for output.
  - We don't think these matrices correctly asses the enhancement.
  - our best model has **lower PSNR**(8.66 vs 11.52) and **higher MAE**(92.03 vs 66.19) than Zero-DCE++ but the output images look better to the human eye.

Drawbacks(contd.)

- **Saturation in enhanced images**
  - We have observed that at times, our model **reduces the natural colors** or saturates the enhanced image.
  - This is particularly visible for images having **light texture**.


Conclusion

- In this work, we have considered **Zero-DCE++** as baseline and applied **CBAM** on top of that.
- Results show that the attention module **improves** the quality of enhanced images.
- We have done detailed **ablation study** and decided the hyper-parameters accordingly.
- We have tested the application of our model for **video** and **real-time video** enhancement.
- Improvements are still required in terms of visual quality, **noise correction**, inference time, **training time**, etc.

Individual Contributions

Activity	Tamal Mondal	Kamal Shrestha	Aman Aggarwal	Praveen Vishwakarma	Jayamohan. C.B
Problem Identification	✓	✓	✓	✓	✓
Literature Review	✓	✓	✓	✓	✓
Proposed Approach:					
Implementation of Attention mechanism	✓	✓			
Video Enhancement	✓				
Real Time Video Enhancement					✓
Fine Tuning hyper parameters:					
Effect of multiple attention layers	✓	✓			
Effect of Pooling	✓		✓		
Effect of Batch norm and bias		✓		✓	
Effect of learning rate and Weight Decay	✓				✓
Tensorboard Evaluations and ML-Flow check-points		✓			
Model Testing		✓	✓	✓	
Configuration Management	✓	✓			
Documentation	✓	✓	✓	✓	✓

References

[1] Partha Pratim Banik, Rappy Saha, and Ki-Doo Kim. Contrast enhancement of low-light image using histogram equalization and illumination adjustment. In 2018 International Conference on Electronics, Information, and Communication (ICEIC), pages 1–4, 2018. 2

[2] Zilong Chen, Yaling Liang, and Minghui Du. Attention based broadly self-guided network for low light image enhancement, 2021. 3

[3] Chi-Mao Fan, Tsung-Jung Liu, and Kuan-Hsien Liu. Half wavelet attention on m-net+ for low-light image enhancement, 2022. 3

[4]Chunle Guo, Chongyi Li, Jichang Guo, Chen Change Loy,Junhui Hou, Sam Kwong, and Runmin Cong. Zero-reference deep curve estimation for low-light image enhancement. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020. 1

[5] Xiaojie Guo, Yu Li, and Haibin Ling. Lime: Low-light image enhancement via illumination map estimation. IEEE Transactions on Image Processing, 26(2):982–993, 2017. 3

Thank You!

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