Alma Mater Studiorum University of Bologna

Artificial Intelligence - Deep Learning

Deep Deblurring project

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Introduction

Problem

Remove blurring artifact from images

- CIFAR10[1]
- REDS[2]

Introduction

Hardware

- CPU: i7-8750H@2.20GHz
- GPU: Nvidia GTX 1060 (6 GB)

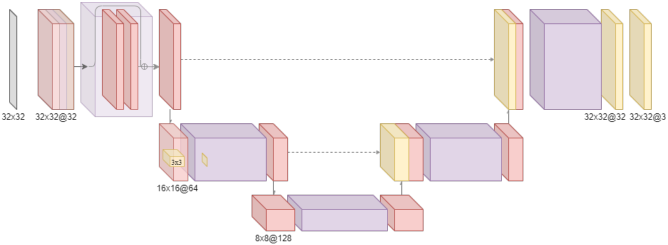
Autoencoders

Networks implemented:

- ResUNet
- EDDenseNet
- CAESSC
- SRNDeblur

Autoencoders - ResUNet[3][4]

Architecture



- The backbone is a UNet architecture
- Use of ResBlock at each level improves the flow of the information
- Conv $\rightarrow$ BN $\rightarrow$ $ReLU$
- Conv2DTranspose at the end for learning additional information

Autoencoders - ResUNet[3][4]

Results

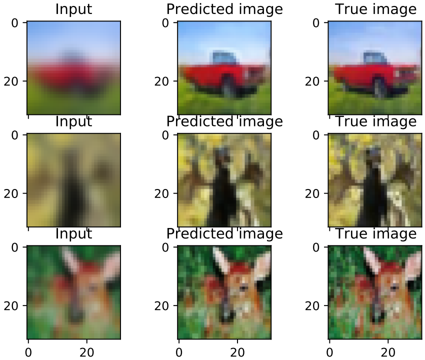


Figure: ResUNet1 - Run test for ResUNet1

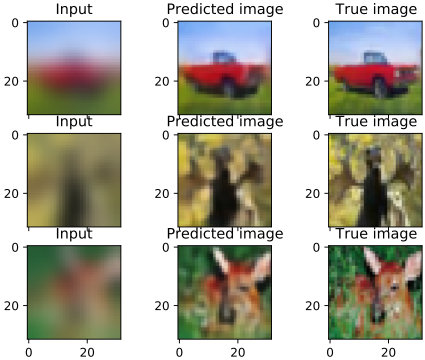
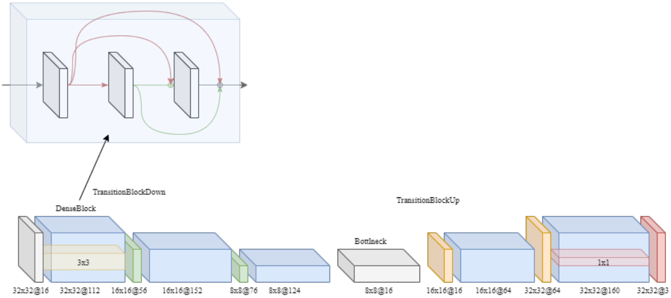


Figure: ResUNet3 - Run test for ResUNet3

number of ResBlock	MSE	PSNR	SSIM
1	0.0018	28.49	0.930
3	0.0016	29.03	0.935

Autoencoders - EDDenseNet[5]

Architecture



- Growth rate: 16
- Encoder: [6,6,3]
- Decoder: [3,6]
- Use of DenseBlock
- Conv $\rightarrow$ *BN* $\rightarrow$ *ReLU*
- Conv2DTranspose at the end

Autoencoders - EDDenseNet[5]

Results

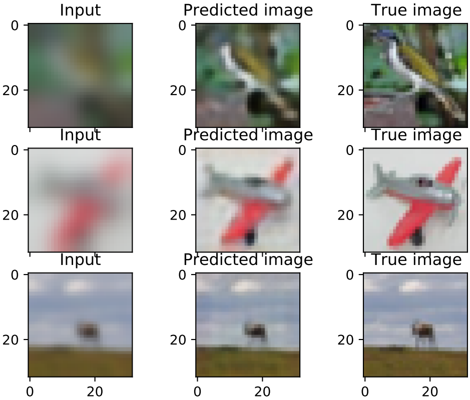
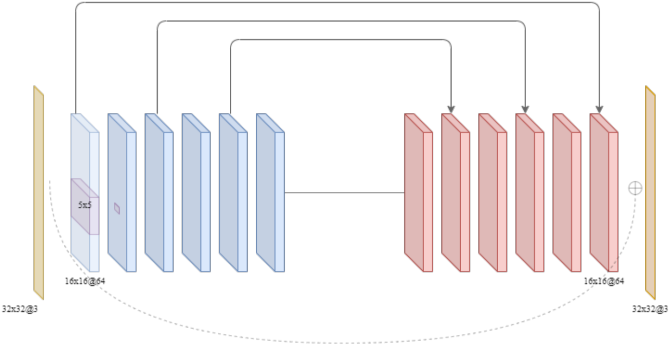


Figure: EDDenseNet - Run test for EDDenseNet

kernel type	MSE	PSNR	SSIM
gaussian	0.0021	27.62	0.90

Autoencoders - CAESSC[6]

Architecture



- Simple structure
- Use of symmetric skip connections between with a fixed interval
- Use of highway skip connection improve the outcome

Autoencoders - CAESSC[6]

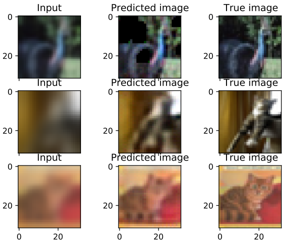


Figure: Run test for CAESSC_d22_f128_half_no_sigmoid

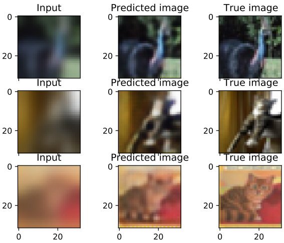


Figure: Run test for CAESSC_d22_f128_half

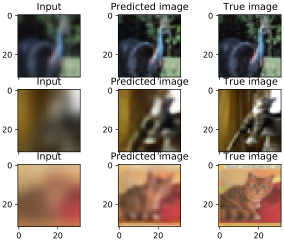
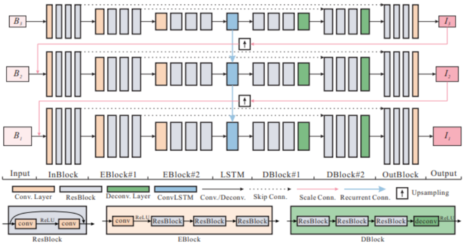


Figure: Run test for CAESSC_d30_f64

Autoencoders - SRNDeblur[7]

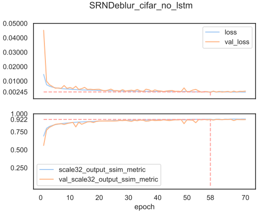
Architecture

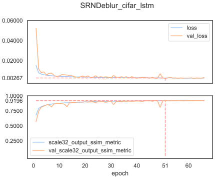


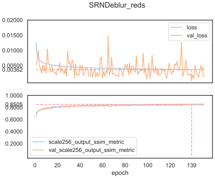
- FCNN
- Use of Blocks
- Encoder-Decoder architecture
- ResBlocks and skip connections
- Multi-Scale network
- Recurrent layer

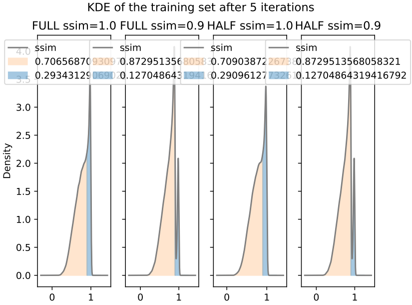
Autoencoders - SRNDeblur[7]

Training









Autoencoders - SRNDeblur[7]

Results

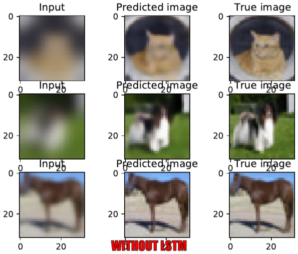


Figure: Test image generated by SRNDeblur_cifar network

- Run test for SRNDeblur_cifar_no_ltsm
- Run test for SRNDeblur_cifar_lstm

CIFAR10 network	MSE	PSNR	SSIM
Without LSTM	0.00175	29.23	0.9225
With LSTM	0.00174	29.38	0.9188

Autoencoders - SRNDeblur[7]

Results

Figure: High resolution test image generated by SRNDeblur_reds network.

- Run test for SRNDeblur_reds with high resolution images

	SRNDeblur_reds			SRN-DeblurNet	
dataset	MSE	PSNR	SSIM	PSNR	SSIM
REDS	0.002	27.23	0.8105	-	-
GOPro	-	-	-	30.26	0.9342

Autoencoders - SRNDeblur[7]

Results

Figure: Low resolution test image generated by SRNDeblur_reds network.

Run test for SRNDeblur_reds with low resolution images

Bibliography

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