CS 512 Computer Vision Project

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Denoising and Deblurring Images using Dual Autoencoders

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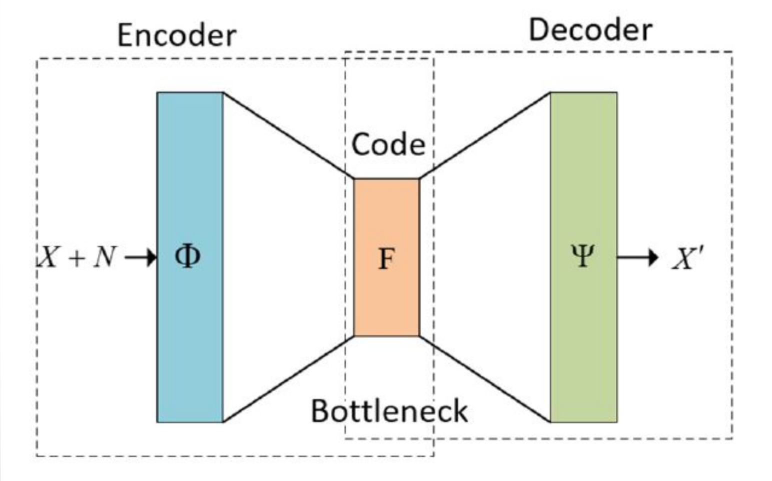
Problem Statement

- Images are highly prone to noise which significantly degrade their quality / obscure important features
- Reduces the accuracy of image-based analysis and decision-making
- Aim is to remove this noise while preserving important features
- It is a challenging task due to the random nature and variability of image noise

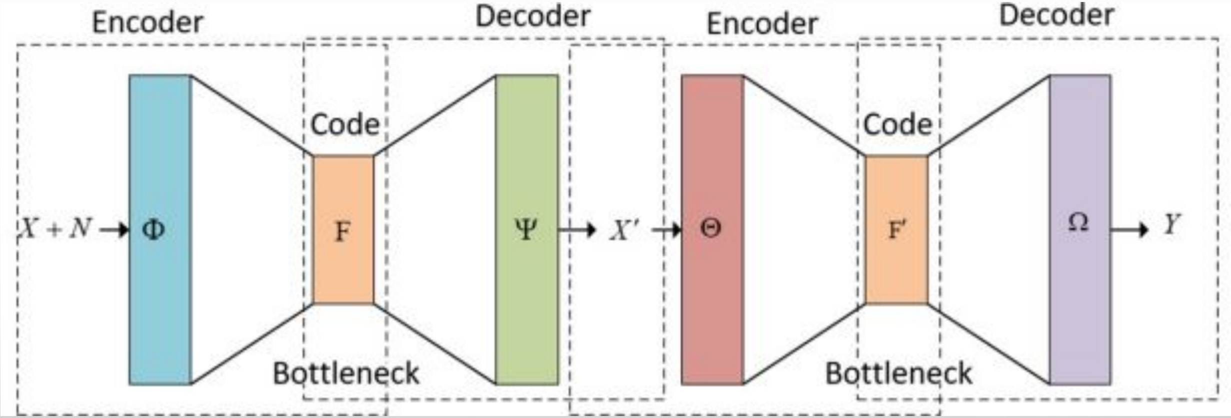
Introduction

Autoencoders - Autoencoders are a kind of neural networks that are utilized to perform image denoising / deblurring and develop efficient coding for unlabeled input data. The bottleneck in a neural network compresses the input data which can be used for reconstruction with a loss of information and encourages the model to prioritize relevant pixel values during reconstruction.



Dual Autoencoder

- Combination of two sequential autoencoders
- Left autoencoder aims to denoise image
- Right autoencoder aims to reconstruct image
- Drives the image through the bottleneck twice
- Different Encoders and Decoders for left and right autoencoders



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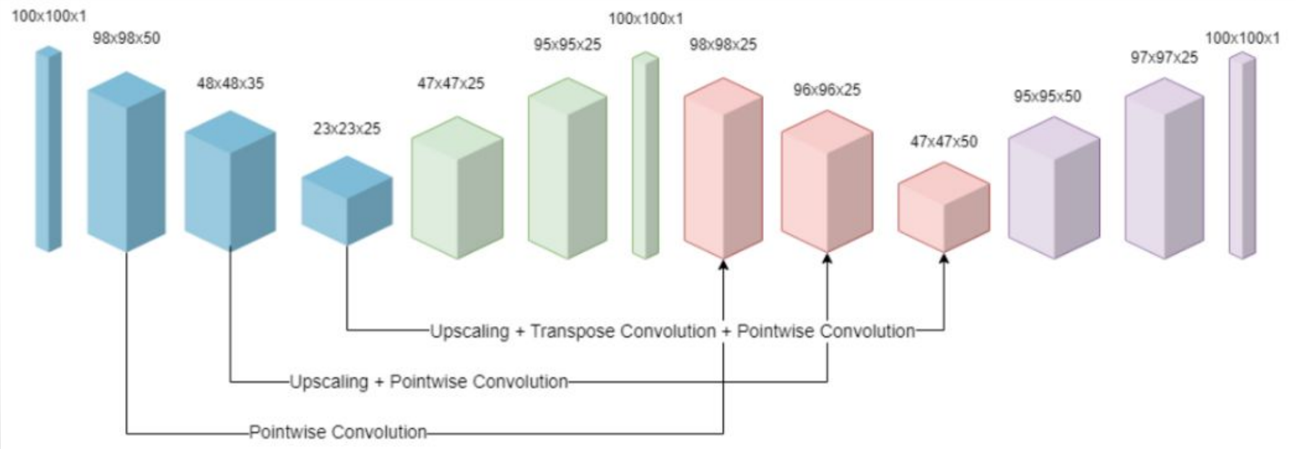
Dual Autoencoder with skip connections

- Skip connection between Encoder of left autoencoder to Encoder of right autoencoder
- Upscaling and Pointwise convolution used to match the target dimensions
- Addition instead of concatenations
- Increases amount of information for reconstruction



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Data Preparation
(IMDB-WIKI Face Dataset)

Gaussian Noise

Impulse Noise (S&P)

Speckle Noise

Poisson Noise

Implementation Details

Models Trained (with and without separable convolutions)

- Single / Ordinary Autoencoder
- Dual Autoencoder
- Dual Autoencoder with skip connections (ours)

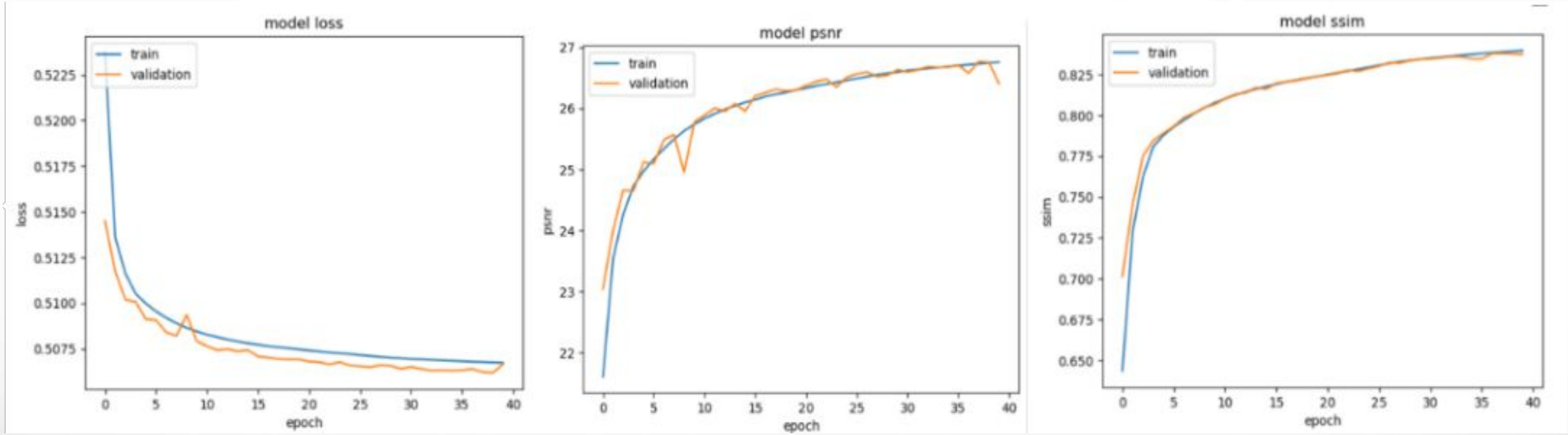
Training and configuration :

- Epochs : 40
- Input image size = (100, 100, 1)
- Batch Size : 128
- Learning rate : Initially set to 0.001
- Optimizer : Adaptive moment estimation (Adam)
- Loss Function : Binary cross entropy
- Training:144003, Testing: 40001 and Validation: 16000 images
- Activation Functions : ReLU in intermediate layers and Sigmoid in the output layer

Evaluation Metrics :

- SSIM (Structural Similarity Index), PSNR (Peak Signal-To-Noise Ratio)

Training



Single / Ordinary Autoencoder

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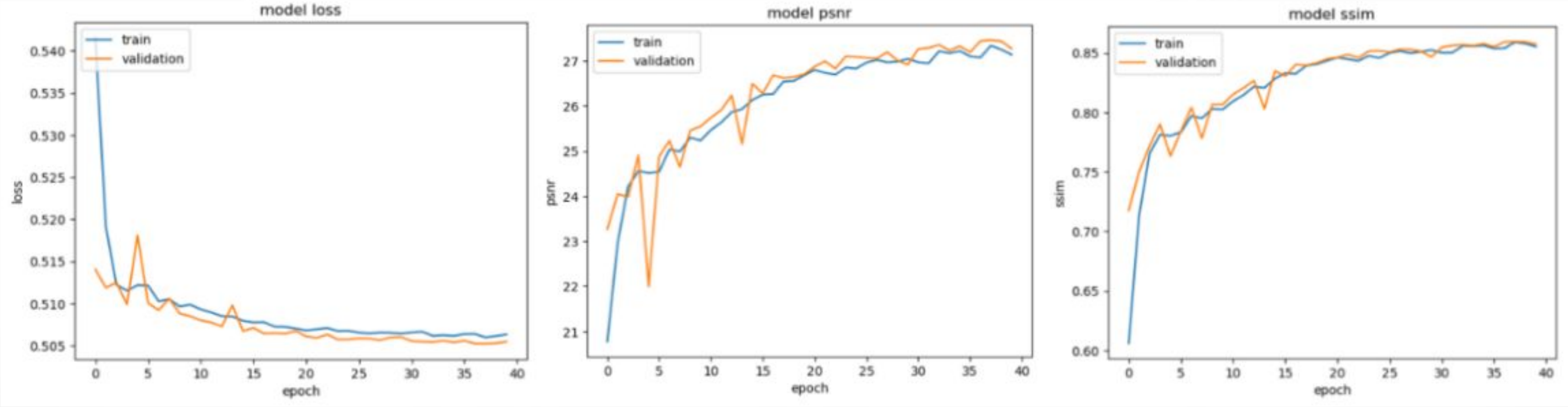
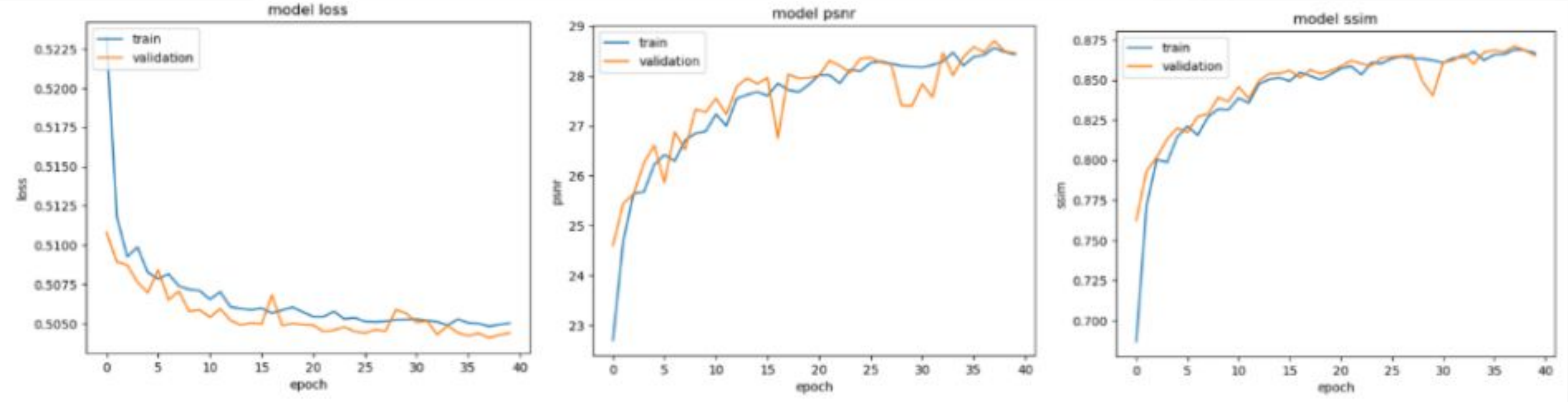
Training



Dual Autoencoder

Training

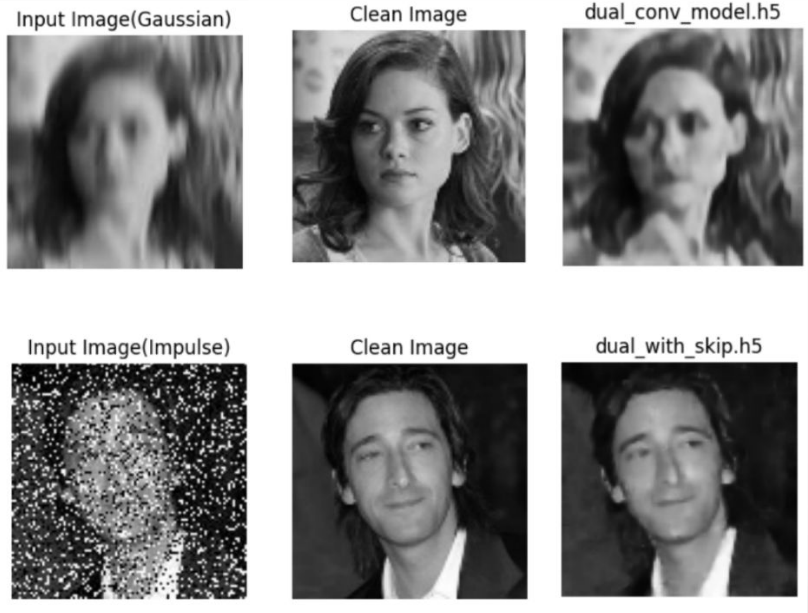


Dual Autoencoder with skip connections

Evaluation and Results

Model Name	Noise Type	PSNR	SSIM	Trainable Parameters
Single Autoencoder	Gaussian	24.30	0.76	36,386
	Impulse	25.99	0.82	
	Speckle	27.19	0.86	
	Poisson	28.14	0.89	
Single Autoencoder (Separable Convolutions)	Gaussian	24.18	0.75	15,760
	Impulse	22.12	0.62	
	Speckle	26.78	0.83	
	Poisson	27.51	0.87	
Dual Autoencoder	**Gaussian**	25.01	0.78	87,812
	Impulse	26.88	0.85	
	Speckle	28.11	0.88	
	Poisson	29.08	0.90	
Dual Autoencoder (Separable Convolutions)	Gaussian	24.65	0.76	52,445
	Impulse	22.79	0.67	
	Speckle	27.26	0.86	
	Poisson	27.91	0.88	
Dual Autoencoder with skip Connections	Gaussian	24.92	0.76	91,488
	Impulse	28.59	0.88	
	Speckle	29.52	0.89	
	Poisson	30.83	0.91	
Dual Autoencoder with skip Connections (Separable Convolutions)	Gaussian	24.37	0.75	56,231
	Impulse	24.27	0.73	
	Speckle	27.95	0.87	
	Poisson	28.84	0.89	

Evaluation and Results



References

- Dual Autoencoder Network with Separable Convolutional Layers for Denoising and Deblurring Images by Elena Solovyeva and Ali Abdullah published on 13th September 2022 by MDPI
  https://www.mdpi.com/2313-433X/8/9/250

- Deep Residual Learning for Image Recognition by Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun and Microsoft Research
  https://arxiv.org/pdf/1512.03385.pdf

- IMDB-WIKI Dataset
  https://data.vision.ee.ethz.ch/cvl/rrothe/imdb-wiki/

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THANK YOU

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