DLCV Fall 2019 Final Project : Dunhuang Image Restoration

Team 8

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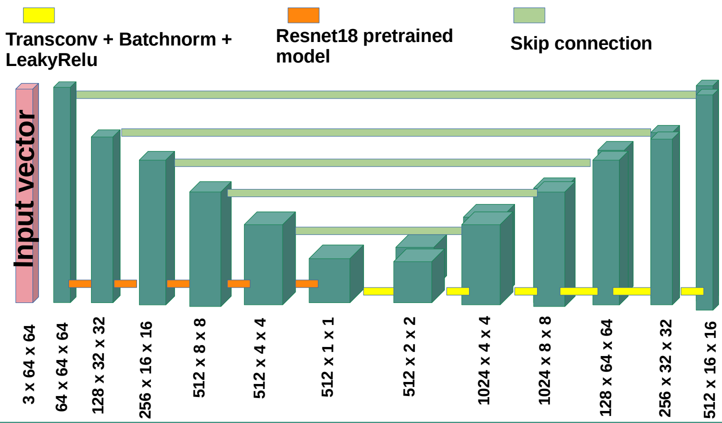
Motivation

Search for a deep learning strategy to restore images such as :
* the ground truth does not exist
* a diverse panel of patterns because of the various artists so that there is a lot of info to generate
* the sample dataset for training is very small

Base model architecture



Performance enhancer

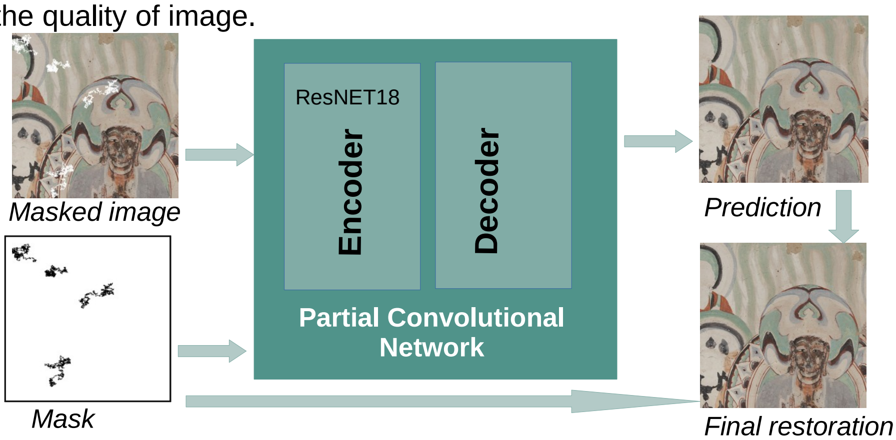
1) Image augmentation

* Need to be applied to groundtruth, masks and masked image
* Sequence of scaling, flipping, cropping, resizing

2) Putting not only the deteriorated images but also the masks through the model

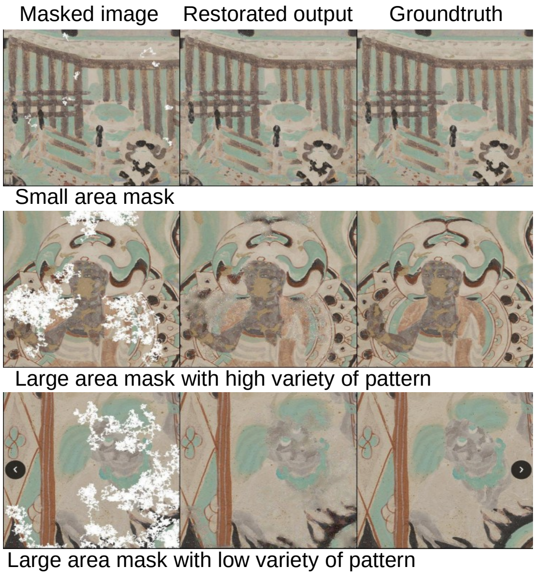
Method

In the preprocessing part we increase the size of the original dataset through data augmentation
The network model process the newly generated data (ie a pair of mask and masked image) and outputs a first restorated image on which we apply the mask to preserve the undeteriorated part of the image to refine the quality of image.



Use of skip connections :
The 6 downsampling layers implies a loss of information so when we want to upsample, the decoder may not have enough features to effectively recover most details for an end-to-end image generation task A skip connection builds up a pipeline for sharing the low-level features from layers in the encoder to the corresponding layers in decoder.
We then recover more details in the output.

Experiment Results



	Average
MSE	34.40395
SSIM	0.79630

Final score = 1.4523

* quality of the output heavily dependent on variety of style, texture and content hidden by masks

* implementable solution would have been to change the MSE loss function whose results don't correlate well with human's perception of image quality by a multi variable loss

$$L = \lambda_{content} L_{content} + \lambda_{style} L_{style} + \lambda_{TV} L_{TV}$$