Maya Hussein and Nada Badawi

CSCE-4606

September 2022

Image Restoration

1 Problem Statement

The resolution of image capturing has been improving as technology progresses. Nowadays, most images are highly detailed and pixelated ranging from a standard 72 dpi (dots per inch) all the way up to 300 dpi. However, historical images and prints tend to have noisy resolutions in comparison to present day. Other images, online or in-print, might have distorted colors or deteriorated segments. Images as such can be enhanced and restored back to its original format if not better through deep machine learning.

Figure 1: Input/Output

2 Motivation

Image Restoration is a widely requested tool nowadays. Denoising these images can help advance the medical field such as enhancing the scans, purify discolored underwater shots, aid in the advancement of old scientific experiments, and even retain the memories of loved ones in proper formatting.

3 Current State of the Art Results

The state of the art that primarily utilized for Gaussian Denoising was

1. Block-matching and 3D filtering, a 3D block-matching algorithm used for image restoration along with convolutional neural networks, that is proposed to produce better results.
2. Trainable Non-Linear Reaction Diffusion, a model used to change pixels during the denoising process from motion iteration.[4]

Both were utilized as a method of comparison along with BSD dataset introduced below for performance testing. It is also assumed that the noise level is unknown within every picture.

For the single image super-resolution,

1. Trainable Non-Linear Reaction Diffusion (TNRD)
2. Very-Deep Super-Resolution (VDSR), deep learning approach for enlarging images. It has 20 weighted layers which is much deeper compared SRCNN (Super-Resolution Convolutional Neural Network).

It is noted that the TNRD is trained with each up-scaling factor while VDSR trained a single model for three up-scaling factors. The datasets introduced were Set5, Set14, BSD, and Urban100. [1]

Below are the results of the state of the art in terms of PSNR. The experiment was carried out with different noise levels, sigma. As shown in the the table, the DnCnn models show the best results in terms of PSNR (DB), where the DnCNN-S exhibited the highest PSNR averages on most images. Furthermore, it is noticed that the -S Method outperforms other methods at least by 0.2DB; however, it fails to support only two images of repetitive structures: "House" and "Barbara" images.

TABLE II
THE AVERAGE PSNR(DB) RESULTS OF DIFFERENT METHODS ON THE BSD68 DATASET. THE BEST RESULTS ARE HIGHLIGHTED IN BOLD.

Methods	BM3D	WNNM	EPLL	MLP	CSF	TNRD	DnCNN-S	DnCNN-B
$\sigma = 15$	31.07	31.37	31.21	-	31.24	31.42	**31.73**	31.61
$\sigma = 25$	28.57	28.83	28.68	28.96	28.74	28.92	**29.23**	29.16
$\sigma = 50$	25.62	25.87	25.67	26.03	-	25.97	**26.23**	**26.23**

Figure 2: Average PSNR of Different Methods

4 Survey of Available Models

After some research, a total of 3 different models were found suitable to solve the problem of image restoration. The following are details of each model.

4.1 Denoising Convolutional Neural Networks

The Denoising Convolutional Neural Network (DnCNN) model is used to detect patterns in images, such as noises and based on the detection, a higher quality of the image can be produced. This method is the most accurate so far and has been tested on multiple datasets, such as Set12, BSD, Urban100, Set14, Set5, BSD CBSD68, LIVE1, and Classic5 [1]. This makes the results of the model accurate on various data sets, which in turn, makes it reliable. The following is the public repository link for this model: https://github.com/cszn/DnCNN. Below is a representation of the explained architecture of the DnCNN model:

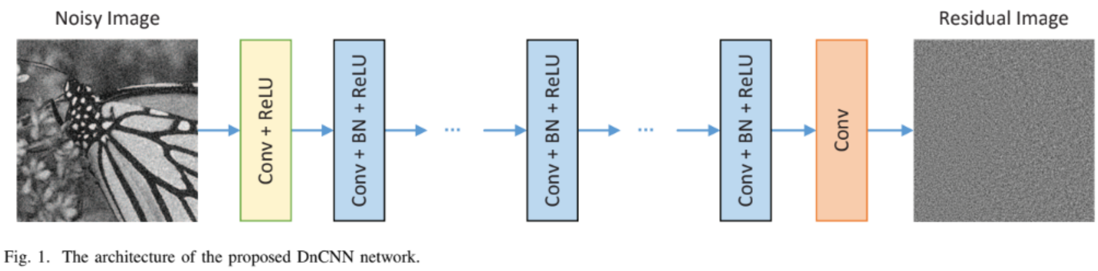


Figure 3: DnCNN Architecture

4.2 Variational Autoencoder

This autoencoder involves two main networks; the first one is the encoder network and the second one is the decoder network. The former is aimed to result in a latent vector as an output that describes the image but in a condensed form. The decoder then takes in that vector to expand back in a high resolution similar to the input of the encoder. The decoder network is the one used to resolve the issue of image denoising to expand an image to a high resolution. However, the way the authors of the paper have used the model did not include batch-normalization, which may be helpful in training the model. Moreover, the only dataset used to train the model is DIV2K. Therefore, this option has been eliminated as a state-of-the-art [2]. The following is the GitHub link to the corresponding research paper proposing the model: https://github.com/microsoft/Bringing-Old-Photos-Back-to-Life. Below is

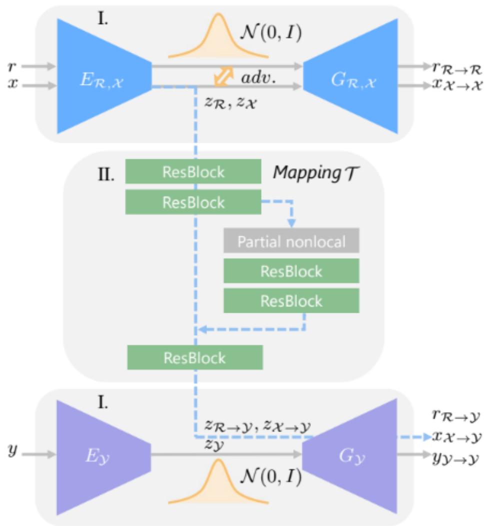


Figure 4: VAE Architecture

a representation of the architecture of the Variational Autoencoder (VAE):

4.3 Diffusion Model

The diffusion model is a type of a generative model. It is used to generate noisy images in order to train the model. Convolutional layers are used to denoise the images back and restore them into a higher quality. The datasets used to train the model are ImageNet, COCO, Places, FFQH, and CelebA-HQ. These are not as much as the ones used in the DnCNN. According to the paper the model is hard to retrieve highly precised results and it is slower than the Generative Adversarial Network (GAN) regarding the sampling rate [3]. Therefore, it is not the state-of-the-art result. The following is the repository link for this model: https://github.com/compvis/latent-diffusion. The above figure illustrates the architecture of the diffusion model:

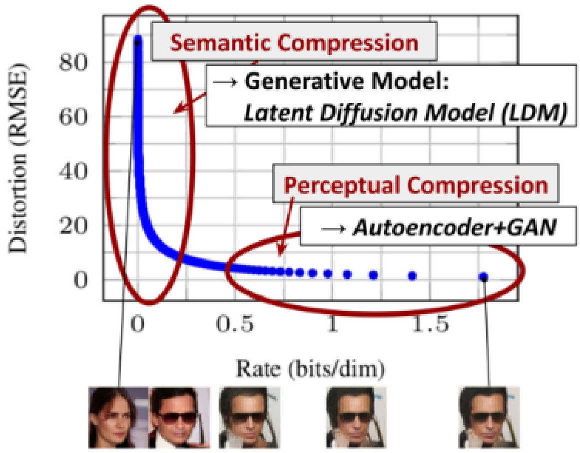


Figure 5: Diffusion Model

All three sources of code use the PyTorch framework.

5 Model Description

The DnCNN model uses filters in its layers to be able to spot patterns that are in images. For example, there is a filter that is used to detect the edges in images. The method used to tackle the problem included the use of batch-normalization and residual learning. Both of these are used to speed up the learning process. This is the only model out of the other two that uses batch-normalization, which enhances the learning process. This type of model is useful to restore images since we can use a filter called the 'Gaussian' filter, which can remove noise in any image to restore it. As the paper claims, the

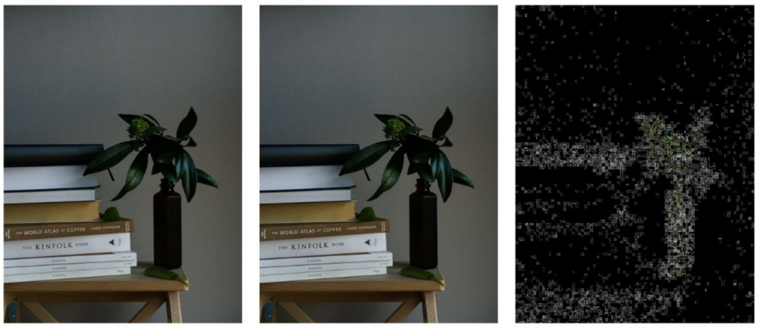
Gaussian denoising is a blind one. This means that the filter works regardless of the noise level.

6 Proposed Updates

The experiment can be carried out on different DnCNN architectures to test which one is the best out of VGG Net, ResNet, Dense Net, Inception Net, or Xception Net. Another suggestion would be testing the data set after amplifying it by making minor changes to the original input to train the model better, such as rotation. It would also be an adequate idea to try playing with the hyperparameters to obtain better PSNR results, such as changing the filters (weights) or the number of filters without significantly reducing the output size with respect to the input size. It is expected to come up with a

7 Result Evaluation

Of the many metrics utilized in image restoration, differential images determine the accuracy of the model since it illustrates how much noise is removed from the input (noisy image) to produce the expected output (clean image). Moreover, it could also provide the extent of corruption in each image and the amount of damage done. Figure (c) below is an example of differential imaging metric with figure (b) being the noisy input image and figure (a), the denoised output image. As for the comparison, the plot, a bar chart, will consisted of the normalized factor of denoisiness across different datasets on both models.


(a) (b) (c)

8 Survey of Available Datasets

All the datasets provided below are used frequently in image denoising and super-resolution.[1]

The dataset presented in the lead research paper consisted of:

- Set12 - 12 greyscale images, 256x256 pixels each - 5.6MB
- BSD - 100 test images ranging from landscapes to object-specific images - 70MB
- Urban100 - 100 test images of urban spaces - 190MB
- Set14 - 14 test images from a variety of contexts - 7.26MB
- Set5 - 5 test images (”baby,” ”bird,” ”butterfly,” ”head,” ”woman”) - 1.3MB

The upcoming sets were used in the testing phase.

- LIVE1 - a set of images and videos whose quality is ranked by human subjects using Quality Assessments.
- Classic5 - 5 classical greyscale images

9 Dataset Description

In addition to the described datasets, another dataset, DIV2K, was allocated with various samples of images, some with noise, discoloration, and missing fragments, while others are with high resolutions and clear formatting. The dataset also introduced a variety of color intensities, including but not limited to: binary, greyscale, full color, and multispectral images. The set consists of around 1000 images, 800 which will be used for training, and 200 for testing and validation. This dataset has a size of 3.06 GB.

10 Contributions

Both the research and proposal have been implemented by both students equally. For a detailed outlook: Maya has researched the *DnCNN* paper, model, and its corresponding datasets, along with the other datasets. Nada has researched the two other models (Diffusion and Variational Autoencoder Models), and the *High-Resolution Image* Paper. The third paper *Old Photo Restoration via Deep Latent Space Translation* was brought by both students.

11 Links

- Google Drive:
- https://drive.google.com/drive/u/0/folders/1It_UTz0EMBo4k0jcUHbgUc0heA8pIwXd
- Set12: https://paperswithcode.com/dataset/set12
- BSD Dataset: https://paperswithcode.com/dataset/bsd
- Urban100 Dataset: https://paperswithcode.com/dataset/urban100
- Set14: https://paperswithcode.com/dataset/set14
- Set5: https://paperswithcode.com/dataset/set5
- LIVE1: https://paperswithcode.com/dataset/live1
- Classic5: https://paperswithcode.com/dataset/classic5

References

[1] Zhang, K., Zuo, W., et al. *Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising*. Papers With Code, 2016.

[2] Wan, Z., Zhang, B., et al. *Old Photo Restoration via Deep Latent Space Translation*. Papers With Code, 2020.

[3] Rombach, R., Blattmann, A., et al. *High-Resolution Image Synthesis with Latent Diffusion Models*. Papers With Code, 2022.One of the

[4] Yuanxiu Xing, et al. *Image Denoising Algorithm Based on Local Adaptive Nonlinear Response Diffusion* IOP Conf. Ser.2020

[5] Plachta, M., Kremien, M., et al. *Image Restoration Using Deep Learning and Ensemble Classifiers*. MDPI, 2022.