Neural Nearest Neighbour Network

Project ID: 15 | Robot Chitti

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Github link

Prerequisites

1. *Dilated Convolution* - Dilated Convolution is a technique that expands the kernel (input) by inserting holes between its consecutive elements. In simpler terms, it is the same as convolution but it involves pixel skipping, so as to cover a larger area of the input.

2. *Receptive Field Size* - It is defined as the size of the region in the input that produces the features. To obtain bigger receptive fields we generally use more convolution blocks which give more complex features in the feature space.

3. *Self Similarity* - Properties of image structures tend to reoccur within the same image, giving rise to a strong prior for image restoration.

4. *Local Processing* - It involves methods which divide the image in patches and extract features from those patches to further process the image. Example- using convolution with a kernel for feature optimisation, or local histogram equalization.

5. *Non-local Processing* - It involves methods which look at the complete image. Example- global histogram equalization.

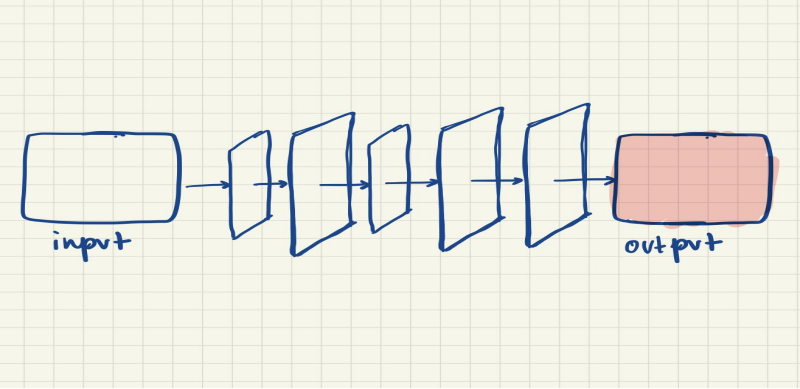
Aim

The aim of the paper is to construct an image denoising technique better than current methods. Traditional KNN cannot be integrated into a CNN, this is due to its non-differentiable nature. This is overcome by the proposal of a continuous relaxation of KNN, and based on this we develop a N^3 block (Neural Nearest Neighbours block) which when combined with local networks performs better than state of the art.

We have learnt about the basic KNN and CNN algorithms in SMAI, here we learnt how to integrate these further to make up a better algorithm.

Introduction

Local processing methods such as CNN's have been in extensive use because of their robustness. But they trade off between context size and localisation accuracy. This means that in local processing, for a fixed kernel size we need more number of layers to get better accuracy. This is what brings us to non local processing. Non-local processing exploits the property of self similarity of images which reduces the number of layers in the hourglass structure which in turn reduces the complexity.



KNN is one such non local processing method. But since KNN needs a sorting operation, which in terms of a mathematical model is not continuous, it is not a continuous function. Hence it is non-differential in nature.

Why do we need differentiability in our model?
Optimization in feature space (Backpropagation steps) in CNN requires functions to be differentiable for optimization algorithms like gradient descent to work.

So we will come up with a discrete relaxation of the KNN selection rule, which then we use to derive the continuous KNN rule. Later using this relaxation, we develop a Neural Nearest Neighbours block (N^3 block).

KNN selection rule

Given a query item q, a database of candidate items $(x_i)\ i \in I$ with indices $I = \{1, 2, \cdots, M\}$for matching, and a distance metric $d(.,.)$ between pairs of items.. Where $\pi_q : I \to I$be a permutation that sorts the database items by increasing distance to q:

$$\pi_q(i_1) < \pi_q(i_2)$$

This implies,

$$d(q, x_{i_1}) < d(q, x_{i_2})$$

Where

$$i_1, i_2 \in I$$

The KNN of q are then given by the set of the first $k$items w.r.t. the permutationπ_q

$$KNN(q) = \{x_i \mid \pi_q(i) \leq k\}$$

This rule is not differentiable. This does not allow us to derive gradients. So we will first show KNN as a limit of a parametric family of discrete stochastic sampling processes. Then we will derive continuous relaxations for the discrete variables. So we would eventually end up with a continuous deterministic relaxation.

KNN is interpreted as the limit of k categorical distributions. Let$Cat(w_1|\alpha_1, t)$ be a categorical distribution, such that:

$$Cat(w_1 |\alpha_1, t) \ = \ P[w_1 = i \,|\alpha_1, t]$$

Where,

$$\alpha_1 =- \ d(q, x_i)$$

and

w= all zero vectors with 1 at the ith position.

In the limit $t \ \to 0$, $Cat(w_1 |\alpha_1, t)$ will converge to a deterministic distribution centred at the index of the database item with the smallest distance to q. Hence $Cat(w_1 |\alpha_1, t)$ is a stochastic relaxation of 1-NN. We need to generalise it for K-NN by constructing further distributions$Cat(w_{j+1} |\alpha_{j+1}, t)$.
Having derived KNN as a limit of a parametric family of discrete stochastic sampling processes, we will now derive continuous relaxations for the discrete variables.

Continuous deterministic relaxation

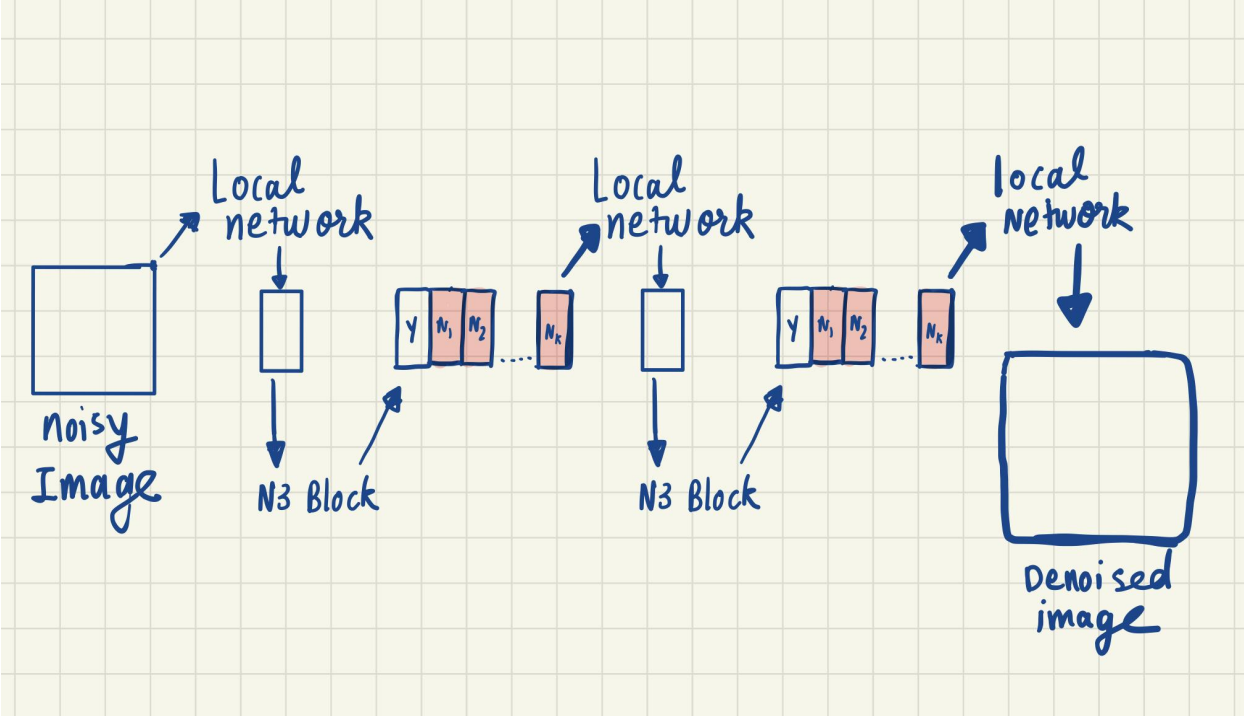
Replacing the weighted vectors w with their continuous expectations. This will give us a continuous relaxation of the stochastic nearest neighbours that still converges to the hard KNN selection rule in the limit case of $t \ \to 0$.

The expectation $\bar{w_1}$ of $w_1$is given by:

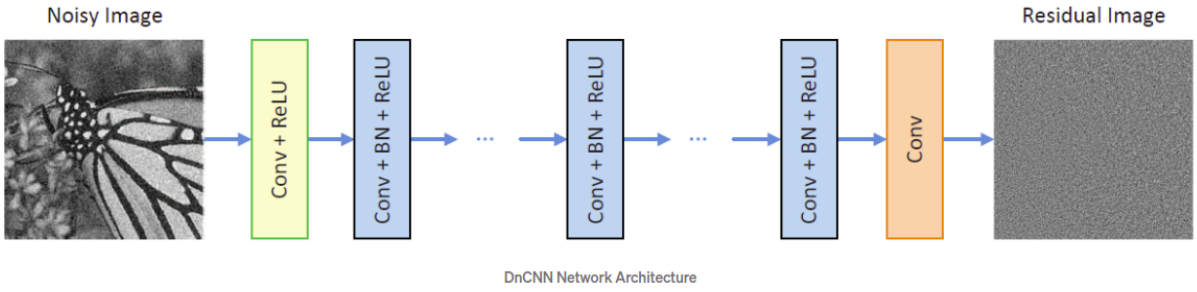
$$\bar{w_1} = \ P[w_1 = i \,|\alpha_1, t]$$

Neural Nearest Neighbour (N^3) Net

This is the main architecture that combines Local and Non-Local processing techniques to denoise a given image. It consists of DnCNN blocks and N3 blocks in sequence, where the implementation of the individual blocks is described below.



Local Processing - DnCNN

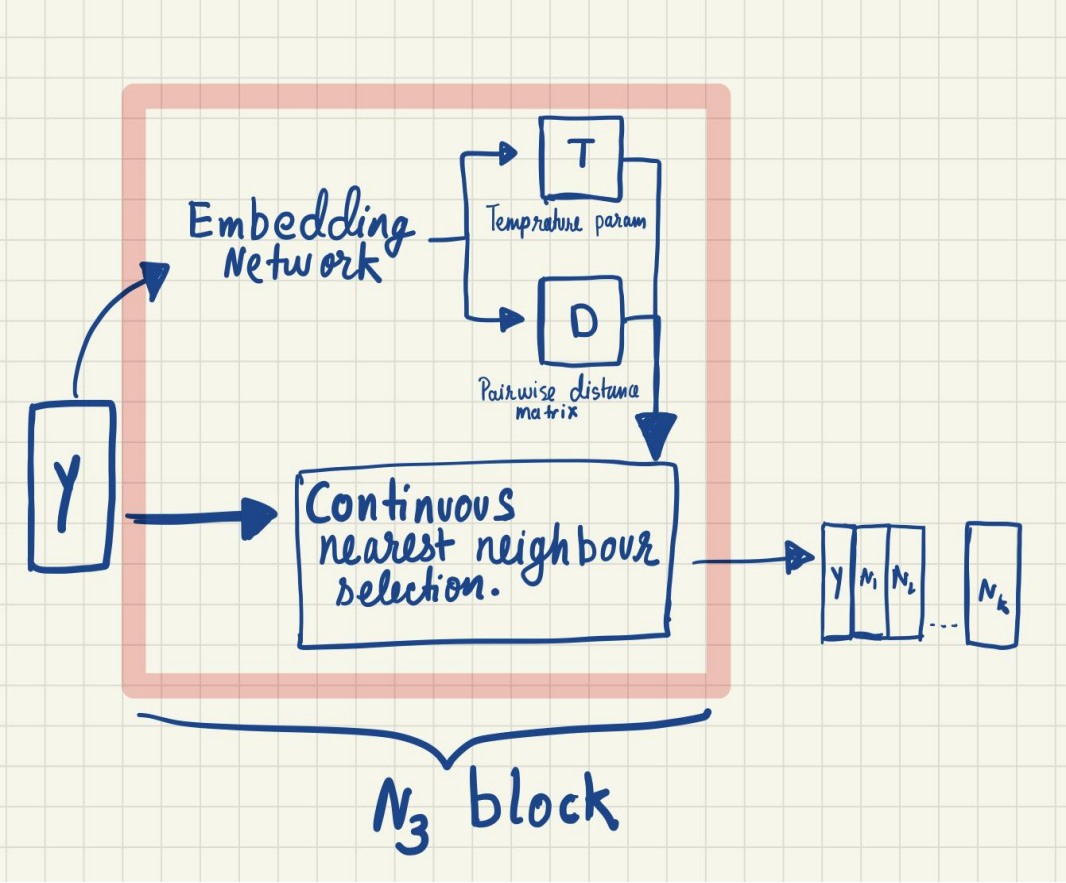


DnCNN Network Architecture

DnCNN is a feed-forward denoising convolutional neural network to embrace the progress in very deep architecture, learning algorithm, and regularization method into image denoising. Specifically, residual learning and batch normalization are utilized to speed up the training process as well as boost the denoising performance.
The size of convolutional filters are set to be 3×3 and all pooling layers are removed. Therefore, the receptive field of DnCNN with a depth of d should be (2d+1)(2d+1).

Non Local Processing - Neural Nearest Neighbour (N^3) Block

Here we have implemented the neural nearest network block, in which First, an embedding network (a collective term used for mapping graph nodes of a vector to a multidimensional space) takes the output Y of the previous layer as input and calculates a pairwise distance matrix D between elements in Y as well as a temperature parameter(T).



Embedding network:

- Calculates ($E = f_e(Y)$) (feature embedding)
- Calculates distance matrix D such that $D_{ij} = d(E_i, E_j)$
- Another branch will calculate the temperature tensor ($T = f_t(Y)$)
- Now using these parameters, we can calculate the Continuous relaxation of the KNN rule and apply it in the next step.

Continuous nearest neighbour selection:

- K continuous nearest neighbours can be estimated using D and T
- Ni and Y have the same dimensionality, this means we can perform element wise operations to get a feature but this can lead to early fusion of the features which can result in a bad accuracy for the model since we don't have that many features at this stage.
- To avoid reduction at this stage we will concatenate Y with k N_i

Classes and Functions used in code

- `def cnn()` - This is the cnn processing required in the embedding network.
  - Variable ksize shows the size of the kernel.
  - The padding determines the variables excluded from the edges of the image
  - cnn_bn is the batch normalisation flag.
  - This emirates for the range of (cnn_depth -1) to extend cnn_layers from nn.Conv2d
  - If the depth of CNN is greater than 0 our function will append nn.conv2d to it,
  - Lastly, it will return the variable net which is just the CNN layers in sequential order.

- `Class N3Block()` - This is the implementation of the N3Block
  - It defines two things: Embedding network and Continuous KNN

    - It requires nn.Module as input.
    - First it defines the embedcnn function using cnn(), then finds the T tensor and D matrix. Secondly, it uses KNN (from non_local.py) to get the final output of N3Block.
    - The structure as given in image above is defined in forward() function.

- `Class DnCNN()` - This is the implementation of Local network using DnCNN architecture.
    - It is a standard and effective architecture
    - It mainly consists of the hourglass-like structure in the order from left to right as : *conv - relu - layers - conv.* This is defined in forward().

- `Class N3Net()` - This is the final class that binds all the substructures and blocks together to finally get the main net.
    - Takes *nblocks* as input, and defines *nblocks* numbers of DnCNN and N3Block in sequence as per the diagram given above.

- `non_local.py` consists of various classes and functions that the n3net needs for basic tasks like continuous K nearest neighbours implementation.
    - `def compute_distances` function computes the differentiable distance between two feature vectors (euclidean distance) which is further used to model the continuous KNN as a weighted average of features.
    - `class NeuralNearestNeighbours` consists of the implementation of the continuous and differentiable version of the KNN model as discussed in the paper.
    - This differentiability helps in integrating the KNN block in the CNN model without any difficulties during backpropagation.

Experiment

Our model is trained using the BSDS500 dataset, while it is tested on Urban-100 dataset.

The experiment involved gaussian denoising of grayscale images. We are using the Urban-100 dataset. It is tested on our architecture. The process is as follows: First, the images are converted to grayscale, then gaussian noises are added to the images. We experimented by using gaussian noises with σ =25,50 and 75. Based on this, we get the noisy image which is then used to test our model. The outputs are attached below:

<u>Image-1:</u>

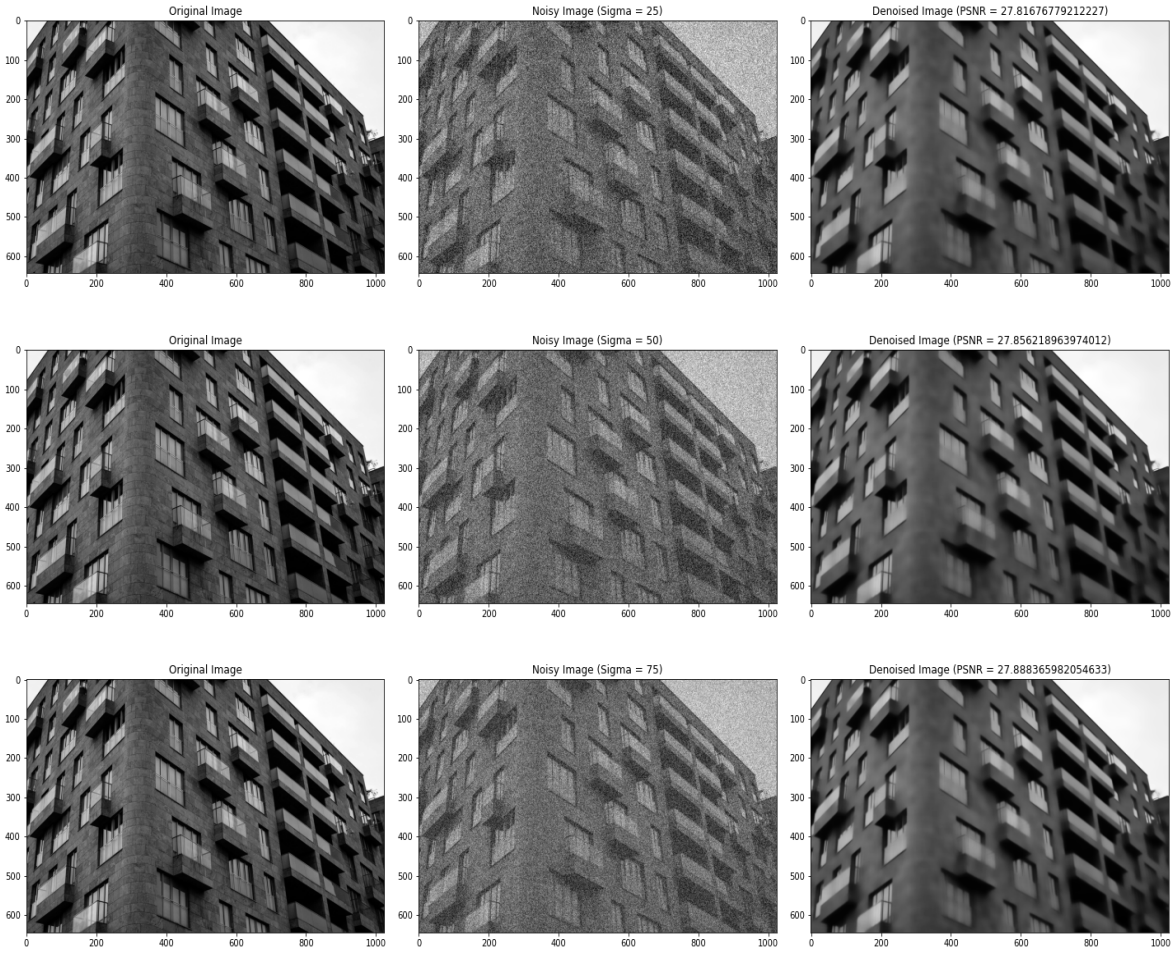


Image-2:

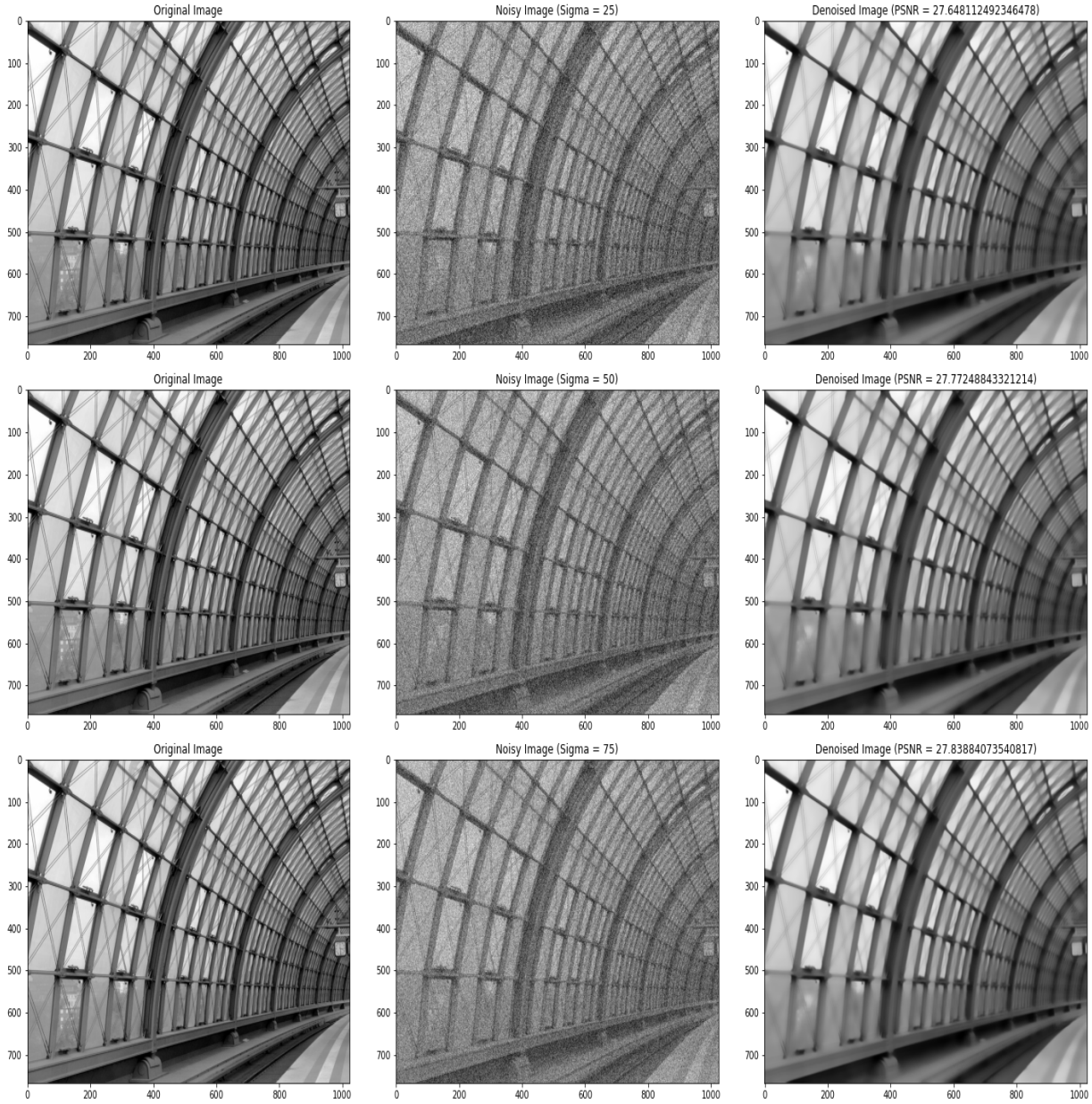

Original Image
Noisy Image (Sigma = 25)
Denoised Image (PSNR = 27.648112492346478)
Original Image
Noisy Image (Sigma = 50)
Denoised Image (PSNR = 27.77248843321214)
Original Image
Noisy Image (Sigma = 75)
Denoised Image (PSNR = 27.83884073540817)

Image-3:

Conclusion:

As we saw in the experiments, our N3 block algorithm is able to denoise images and could be used in image restoration when used as a building block with other neural networks, this has vast applications in not only improving the visual quality of images but also upgrades performance in several computer vision tasks like classification and object detection tasks in images. It is also a core prerequisite for density estimation. This could potentially also be used in end to end trainable tasks like text detection or any kind of sequence-valued data.

Work Distribution

Abhigyan Gargav : Code (N3 block and N3 Net architecture implementation)
Raj Singh Parihar : Code (N3 net and the gaussian image denoising experiment)
Rohan Lahane : Worked mainly on understanding the theory and developing the report.
Kartik Mehta : Worked mainly on understanding the theory

References:-

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3.https://www.math.ucla.edu/~lvese/285j.1.09f/NonlocalMethods_main.slides.pdf

4.https://www.ipol.im/pub/art/2012/l-bm3d/article.pdf