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Denoising of Images Using Autoencoder

Shreya Shrikant Naik*, Sowmya, Preethika N K
Department of Information Science and Engineering, Srinivas Institute of Technology, Valachil, Karnataka, India

ABSTRACT

Image is the object that stores and reflects visual perception. Images are also important information carriers today. Acquisition channel and artificial editing are the two main ways that corrupt observed images. The goal of image restoration technique is to restore the original image from a noisy observation of it which is aiming to reconstruct a high quality image from its low quality observation has many important applications, like low-level image processing, medical imaging, remote sensing, surveillance, etc. Image denoising is common image restoration problems that are useful by many industrial and scientific applications. The application classifies images based on single image selected from user. The noise from the corrupted image is removed and original clear image is obtained. In our project we are making use of Auto-encoder. Auto-encoder do not need much data pre-processing and it is an end to end training process which helps to remove the noise present in some pictures using some data compression algorithms.

Keywords : Auto-Encoder, Data Compression, Deep Neural Network.

I. INTRODUCTION

Image denoising is a kind of feature representation extraction process. A good denoising algorithm should not just work well on removing all kinds of noises, but also should work effectively. Deep neuron networks is powerful in some image classification task nowadays, however, some noise of input images can change its performance. Some research such as one pixel attack for fooling deep neural networks from another aspect states the importance of image denoising. Some researchers have also work on the images denoising task. Method of Spatial Filtering learn a denoising technique in a traditional way by cleaning up the output of lasers, removing aberrations in the beam due to imperfect , dirty or damaged optics. Time-consuming is its main drawback and our method using encoder can have great efficiency improved. Ways like linear filter and non-linear filter improve the efficiency but makes the denoised images blurring. However, even sometimes images generated might have the blurring problems due to its mean squared cost function, it still have good images result than traditional linear and non-linear filters. AutoEncoder with convolution neuron network is one special non-linear filter as the convolution neuron network can be viewed as a big, non-linear and non-convex function. Another advantage that AutoEncoder over all other denoising techniques is that Auto Encoder doesn't need much data pre-processing and it is an end-to-end training process. Auto encoding is a data compression algorithm that has both the compression and decompression functions. AutoEncoders has their main properties that are data-specific, lossy and can learn core representations automatically from input examples without any supervision signals. Proposed paper makes use of Auto-encoder. Auto-encoder do not need much data preprocessing and it is an end to end training process which helps to remove the noise present in some pictures using some data compression algorithms.

II. RELATED WORK

Image denoising is a crucial pre-processing step in medical image analysis. Different algorithms are proposed in past three decades with varying denoising performances. More recently, having outperformed all conventional methods, deep learning based models have shown an excellent promise. These methods are however limited for requirement of huge training sample size and high computational costs. In the work [1] shows that using small sample size, denoising autoencoder constructed using convolutional layers are often used for efficient denoising of medical images. Heterogeneous images are often combined to spice up sample size for increased denoising performance. Simplest of networks can reconstruct images with corruption levels so high that noise and signal aren't differentiable to human eye. Partial differential equations (PDEs), domain transformations such as wavelets , DCT , BLS-GSM etc., Good denoising performance can be achieved using small training datasets, training samples as few as 300 are enough for good performance. It are often seen that as background level increases, this easy network has trouble reconstructing original signal. Recently a deep denoising auto-encoder has been proposed and shown excellent performance compared to conventional image denoising algorithms. In the work [2],studies the statistical features of restored image residuals produced by Denoising Auto-encoders and propose an improved training loss function for Denoising Auto-encoders based on Method noise and entropy maximization principle, with residual statistics as constraint conditions. Compare it with conventional denoising algorithms including original Denoising Auto-encoders, BM3D, total variation (TV) minimization, and non-local mean (NLM) algorithms. Experiments indicate that the Improved Denoising Autoencoder introduce less non-existent artifacts and are more robustness than other state-of-the-art denoising methods in both PSNR and SSIM indexes, especially under low SNR. Methods like the, Wavelet-based denoising method, Total Variate denoising model (TV) method. The benefit is real image information is retained and noise is removed effectively. The speech signal also has structural information; the IDEA is not only limited to image denoising, but also can be used in speech denoising. It's proved that the MSE and PSNR can only be seen as a simulation of the functional properties of early stages of human visual system (HVS), and are not very well characterization of perceived visual quality.

III. SYSTEM IMPLEMENTATION

Proposed system uses deep convolutional neural networks to learn the mapping $x_i \rightarrow y_i$ where x_i are noisy images (our data/observations) and y_i are clean images (our labels/ground-truth). The system will consider the images of the BSDS dataset as our clean/ground-truth images: y_i. For each of them, system will generate noisy versions by adding white Gaussian noise: $x_i = y_i + w_i$ where w_i is an image where each pixel is an independent realization of a zero-mean normal distribution with variance $\sigma = 30$. Since images have different sizes, system will consider random crops of size of 180×180.In the proposed denoising CNN model, i.e., DnCNN, and extend it for handling several general image denoising tasks.

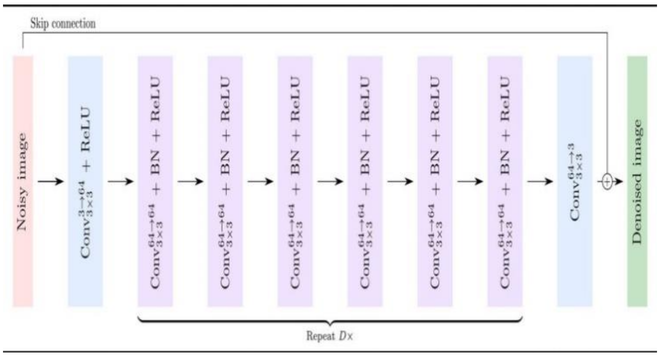

Figure 1. Model Architecture of the system.

For network architecture design system will implement Convolution layers o make it suitable for image denoising, and set the depth of the network based on the effective patch sizes used in state-of-the-art denoising methods. For model learning, the proposed systems adopt the residual learning formulation, and incorporate it with batch normalization for fast training and improved denoising performance. First, the proposed system set the size of convolutional filters to be 3×3 but remove all pooling layers. For better trade-off between performance and efficiency, one important issue in architecture design is to set a proper depth for DnCNN.By fixing the noise level σ= 25, system will analyze the effective patch size of several leading denoising methods to guide the depth design of our DnCNN. The input of our DnCNN is a noisy observation y = x + v For DnCNN, system will adopt the residual learning formulation to train a residual mapping R(y)≈v, and then have x = y − R(y). Given the DnCNN with depth D, there are three types of layers, shown in Fig with three different colors. (i) Conv+ReLU: for the first layer, 64 filters of size3×3×care used to generate 64 feature maps, and rectified linear units (ReLU,max(0,·)) are then utilized for nonlinearity. Here c represents the amount of image channels, i.e. ,c = 1 for gray image and c = 3for color image. (ii)Conv+BN+ReLU: for layers 2∼(D−1), 64 filters of size3×3×64are used, and batch normalization is added between convolution and ReLU. (iii) Conv: for the last layer, c filters of size3×3×64are used to reconstruct the output. To sum up, our DnCNN model has two main features: the residual learning formulation is adopted to learn R(y), and batch normalization is incorporated to speed up training as well as boost the denoising performance. The network shown in Fig. 1 can be used to train either the original mapping F(y) to predict x or the residual mapping R(y)to predict v.

A. Block Diagram

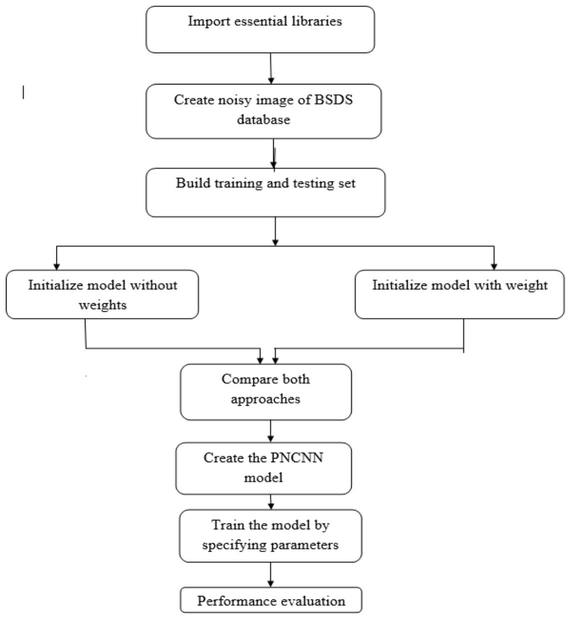

Figure 2. Block Diagram for Denoising of Images

The below given Figure 2 represents the block representation of our project, Where it starts from importing the library functions and then creating the noise for the images which we get from the datasets. Here some images are to be tested where those images will be compared with the training datasets to obtain the clear image. Model will be trained by using the specific parameters and then will be sent for the performance evaluation.

IV. EXPERIMENTAL RESULT

System is being implemented and following outputs is being obtained as results.

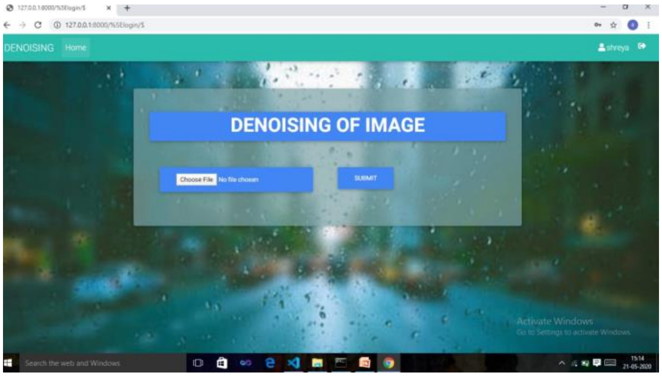

Figure 3. Selection of noised image screen.

Figure 3 shows screen depicting user to insert noisy image to the system.

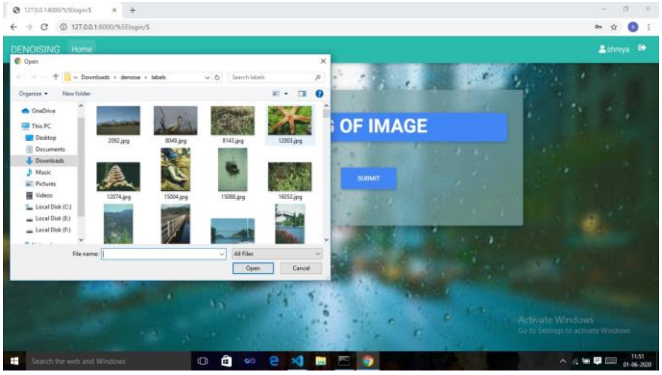

Figure 4. Loading of noised image to the model.

Figure 4 shows system providing console to upload image to the model via File explorer.

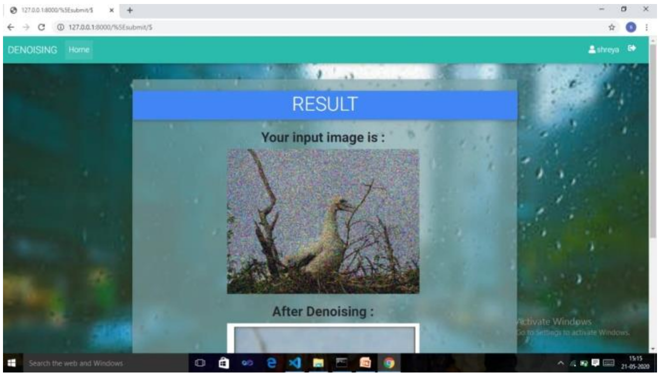

Figure 5. Result Screen depicting Input image.

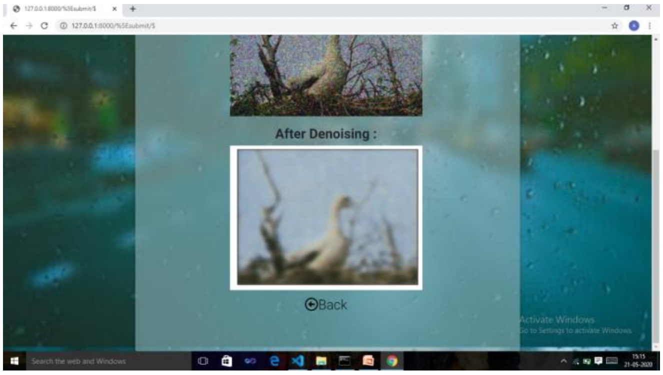

Figure 6. Output screen.

Figure 5 shows system showing the uploaded image and Figure 6 shows the noises being cleared by the system.

V. CONCLUSION

The system is being implemented and provides a web interface to clear images containing noises and obtain a clear image. The GUI is being designed to have user friendly environment and easy to maintain.

VI. REFERENCES

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