Image Denoising Using Deep Convolutional Auto-Encoders

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Abstract— Image denoising is one of the fundamental problems in the image processing field since it is required by many computer vision applications like in medical, environmental, educational, and communication. Several methods have been applied in image denoising techniques in recent years from spatial filtering to model-based approaches. The neural network-based objective methods have gained popularity in recent years. However, most of these approaches still have trouble adapting to different noise levels and types. This work presents the denoising of images using the convolutional auto encoder model in deep learning. It has become an important task to remove noise from the image and restore a high-quality image in order to process the image further for a purpose like object segmentation, detection, tracking, etc. This work is done by adding 1% to 10% noise to the image and then applying the auto encoder model to denoise it. In this work there are two types of noise are applied, one is additive white Gaussian noise (AWGN) and another one is salt & pepper noise at different variance levels(σ=3,7,10). The denoised image is next subjected to qualitative and quantitative analysis using two metrics which are MSE (mean square error) and PSNR (peak signal to noise ratio). Here the auto encoder model mainly consists of the encoder and decoder network layers that will help in making the image to be denoised. The results from the analysis and simulation show that the auto encoder model can efficiently remove noise and restore the image details.

I. INTRODUCTION

Digitalized Visual Information has gained momentum as a prominent means of communication in the present era. Whenever digitized information (data and images) is transmitted through any media, it gets corrupted with noise. Denoising an image poses a challenge to society at a large number and prevails in the communities medical, environmental, educational, and other areas. To help these communities in the persistence of their analysis, has need to provide images with enhanced quality without noise.

An exploration in the field of internet and intranet applications during the last decade has resulted in increased usage of digital images. Various methods and technologies have been identified by eminent researchers and scholars to provide images without noise, clarity, and qualitative for the evaluation. The quality of an image is determined by the presence of noise in it, pixel resolution, and dimension. Traditional methods like noise filters and algorithms used for denoising the images offer moderate support for removing the noise.

Several characteristics of the image such as contrast, sensitivity, blur, and noise make certain information relating to the same will be invisible. In most cases, changing certain characteristics of an image can improvise the quality, yet adversely affect the other characteristics of an image. Hence, choosing a denoising procedure is dependent on the specific requirements of the applications for which the image is being used.

II. RELATED WORK

Kaur, Ravinder, Mamta Juneja, and A. K. Mandal [4] conduct a study to compare the capabilities of several notable and contemporary denoising techniques in the presence of different types of noise present in abdominal CT images. Computed Tomography (CT) is one of the effective imaging modalities in medical sciences that assist in diagnosing various pathologies inside the human body. Their algorithm scans a vast portion of the image in search of all the pixels that resemble the pixel in restoration. Sources of noise in an image mostly occur during storage, transmission and acquisition of the image. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. The image denoising technique will mainly depend on the type of the image and noise in cooperating with it. There have been several published algorithms and each approach has its assumptions, advantages, and limitations [3] [9] [12].

Another method called Block Matching and 3D Matching (BM3D), given by Dabov et al. [21], is a complex and an advance method for image denoising. This technique gathers comparative 2D image sections and utilizes inverse 3D transformations to accomplish fine details of denoising. The BM3D algorithm has been broadened (IDD-BM3D) to perform decoupled deblurring and denoising by using Nash Equilibrium Balance. It is moreover fascinating to see image denoising papers [9] that attempts to assess the characteristic limits of fix based denoising techniques. It guaranteed that BM3D is truly near those optimality limits.

One of the important method for image denoising is Discrete wavelet transform [11, 13-15] is used to find the approximation and detailed coefficients of a discrete signal. It basically represents the time frequency analysis of discrete signal. It gives information about spectral content of the signal at particular location [20].

Another method in Deep Learning is DnCNN model for denoising the image. The idea of CNN model came from vision processing in living organism. In 2004 it was proven by K. Jung and K. S. Oh that Graphic Processing Units (GPUs) can implement neural networks 20 times faster than on CPU. In 2018 Liu, Zhe, Wei Qi Yan, and Mee Loong Yang: Proposed a work on the comparison of image denoising is performed for a CNN model and the other traditional techniques without using Deep Learning in digital image processing [5]. Another variety of deep neural network model that gave outstanding results, known as denoising auto encoder [17]. It is used for image denoising that inputs noisy images and tries to produce denoisy version of it. A variety of denoising auto encoders called as stacked denoising auto-encoder are some amongst the deep neural system models that can be utilized for image denoising. In this network, the reconstruction error is minimized at each layer with respect to inputs. Xie, Linli and Chen [6] presented an approach for low level vision problems that used sparse coding with deep auto encoders. They suggested the different training methods that adapts denoising auto encoders for image denoising and image inpainting. For better performance, they used KSVD (K-means Single Valued Decomposition), which is widely used sparse coding method. For image inpainting, there is no need of any prior information about the region requiring inpainting. Their proposed work encompasses the stacked denoising auto encoders with sparse representation.

Generally, the strategies based on deep neural network derive the necessary parameters from the training data. This becomes progressively compelling in real world image reconstruction applications.

III. IMAGE DENOISING USING CNN

This method is introduced for denoising the image using the convolutional neural network (CNN) model in deep learning [1]. To analyze the image further for purposes like object segmentation, detection, and tracking, it has become a critical task to remove noise from the image and restore a high-quality image. Denoising the image with deep learning's convolutional neural network (CNN) model of analysis is done by adding Gaussian white noise to the image and then applying the CNN model to denoise it.

Further, qualitative and quantitative analysis of the denoised image is performed. Under qualitative analysis comes the quality of image where edge factor, texture, uniform region and non- uniform region, smoothness, structure of objects is considered. The quantitative analysis is done using the three metrics which are PSNR (peak signal to noise ratio), SSIM (structural similarity index measurement), and MSE (mean square error).

IV. PROPOSED METHOD

The proposed model improves the denoising of the image using the Auto encoders and decoders of the convolutional neural network (CNN) model in deep learning. This analysis is done by adding 1% to 10% noise to the image and then applying the Convolutional auto encoder and decoder model to denoise it. Further, qualitative and quantitative analysis of the denoised image is performed. The block diagram of the proposed model is shown below.

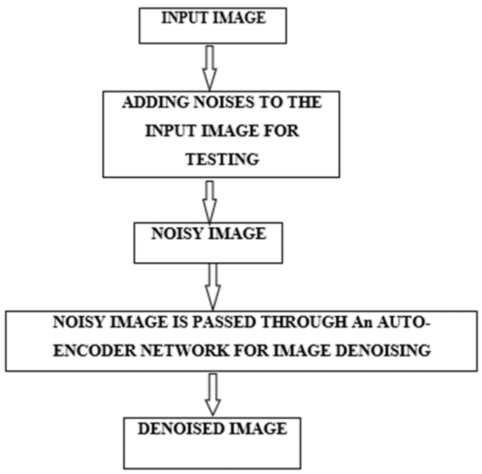

Figure 1: Flow chart of Image denoising using proposed model

4.1 IMAGE DENOISING

Estimate denoised image from noisy image using a denoising deep convolutional auto encoder and decoder network specified by net. Net loads the pre-trained denoising convolutional auto encoder and decoder network. Build-in convolutional auto encoder network to learn the meaningful representation of these images their significantly important features. It is mainly designed to remove noise from images.

Created this network using Tensor Flow's Sub classing API. Inherited the Model class in our Conv_AutoEncoder class and defined the network as individual methods to this class (self. Encoder and self. Decoder).

By default, auto encoder and decoder network has convolutional layers with stride equal to 1 and padding equal to 1 with activation function ReLu and a batch normalization with 64 channels after each convolutional layer. There is a Final Regression Layer that uses mean square error to give the regression output.

4.2 Auto encoder:

An auto encoder is a special type of neural network that tries to learn identity functions. An auto encoder consists of two parts, encoder and decoder. The encoder part is responsible for encoding the input into a compressed approximation. The decoder part then tries to reconstruct the input using the compressed representation. An example of auto encoder architecture is shown in Fig.2.

Here layer L1 is the input layer, layer L2 is called bottleneck which contains the encoded input and layer L3 is the output layer. Input is reconstructed in L3 using the representation in the L2. It is important to use fewer hidden units than inputs in auto encoder. By doing that, the network is forced to learn a compressed representation of the input in the hidden layer. If there are more hidden layers than the inputs in the auto-encoder, the risk of learning the identity function occurs where the output becomes equal to the input.

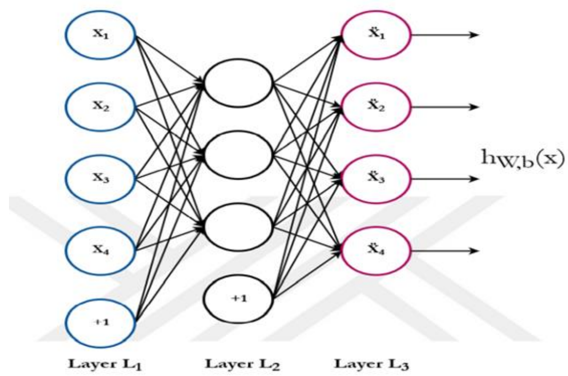

Figure 2: Example auto encoder architecture

Here layer L1 is the input layer, layer L2 is called bottleneck which contains the encoded input and layer L3 is the output layer. Input is reconstructed in L3 using the representation in the L2. It is important to use fewer hidden units than inputs in auto encoder. By doing that, network is forced to learn a compressed representation of input in the hidden layer. If there are more hidden layers than the inputs in the auto-encoder, the risk of learning the identity function occurs where the output becomes equal to the input.

4.3 Denoising Auto encoder:

Denoising auto encoder is an extension to the basic auto-encoder which introduces stochasticity to the network. The denoising auto encoder then reconstructs the original data from the corrupted input, assisting in the identification of robust representations while avoiding the learning of less essential identities. The data is partially contaminated by noises added to the input vector in a random way in the case of a Denoising Auto encoder. The model is then trained to predict the uncorrupted original data point as its output. In denoising auto encoder, input is randomly corrupted in the beginning and the network is forced to reconstruct the clean version of the input. The corruption process randomly sets some of the input units to zero. An example of denoising auto encoder architecture is shown in Fig. 3.

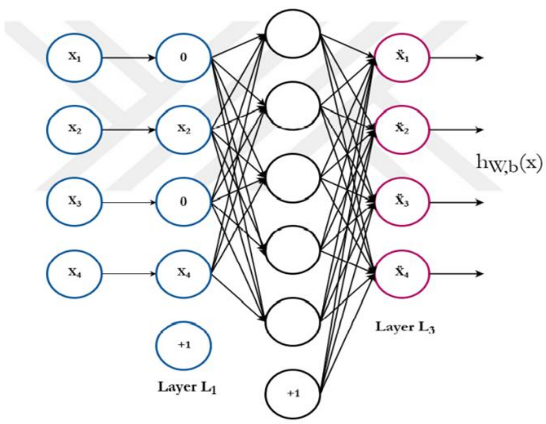

Figure 3: Example denoising auto encoder architecture

4.4 Convolutional Auto encoder:

Convolutional auto encoders are based on standard auto encoder architecture and convolutional layers are used in the network. This type of auto encoders are better suited for processing 2D data such as images since they can utilize methods in the convolutional neural networks field [17].

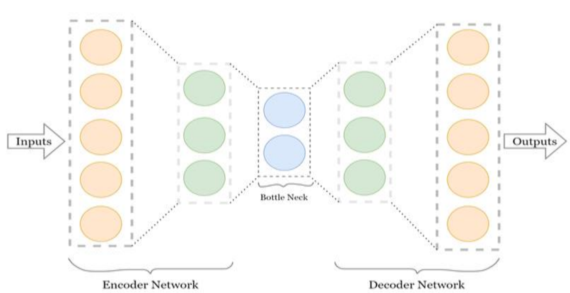

Figure 4: Auto encoder Network

4.5 Image Quality Metrics:

Image quality metrics can be divided into objective and subjective methods [10]. Subjective methods are based on human evaluation and they work without any reference or defined criteria. Objective methods on the other hand evaluate the quality of the image using a reference image and several criteria. This section will discuss two commonly used objective quality metrics, namely peak signal-to-noise ratio (PSNR).

4.6 Peak Signal-to-Noise Ratio (PSNR):

PSNR uses mean square error (MSE) to compare the error between the clean image and noisy image. Given a noisy image x and clean image y, both of size WxH, PSNR is calculated as:

$$PSNR(x,y) = 10\log\frac{255^2}{MSE(x,y)} \quad (1)$$

Where 255 is the maximum pixel value in the image and mean square error between x and y is defined as:

$$MSE(x,y) = \frac{1}{WH}\sum_{i=1}^{W}\sum_{j=1}^{H}(x_{ij} - y_{ij})^2 \quad (2)$$

Where x_{ij} and y_{ij} are the pixel values of images.

PSNR value approaches to infinity as MSE approaches to zero. That is why images with higher PSNR values are assumed to have a higher quality. It should be noted that PSNR does not correlate well with human perception of image quality. However, thanks to its simple structure and performance at capturing noise in images, PSNR is commonly used in image denoising applications as an evaluation metric.

V. RESULTS AND DISCUSSION

The proposed method gives good MSE and PSNR values when compared with existing methods. So,the results obtained have visually good PSNR and MSE values. The proposed method resulting images are shown in figures 5, 6, 7, 8, 9, and 10.

From fig.5 to fig.7 shows the denoised images with different noise levels of additive white Gaussian noise.

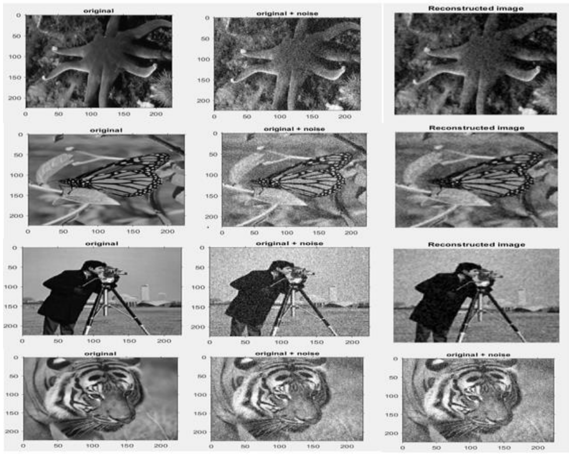

Figure 5: Denoised images with noise level σ= 3

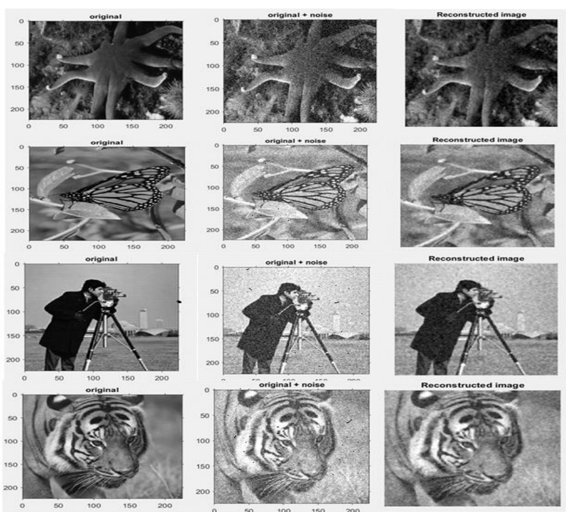

Figure 6: Denoised images with noise level σ= 7

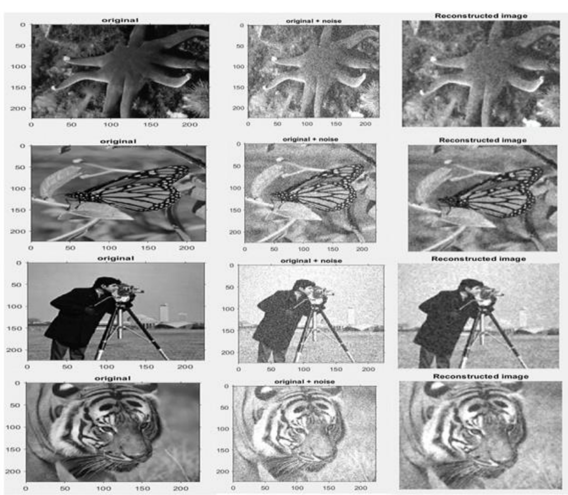

Figure 7: Denoised images with noise level σ=10

Fig 8 to fig 10 shows denoised images with different levels of salt & pepper noise. The below noise Images having dark pixels in bright region and bright pixels in dark regions are considered as having salt and pepper (Impulse) noise. The main causes of this noise are by deceased pixel, analog to digital converters error, and bit error during transmission.

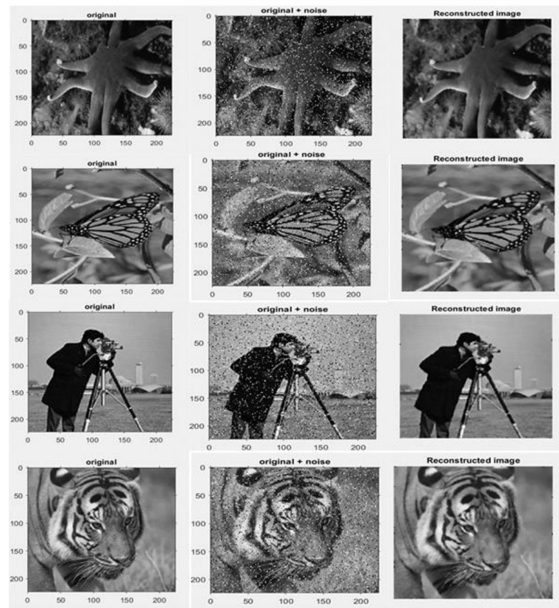

Figure 8: Denoised images with noise level σ=3

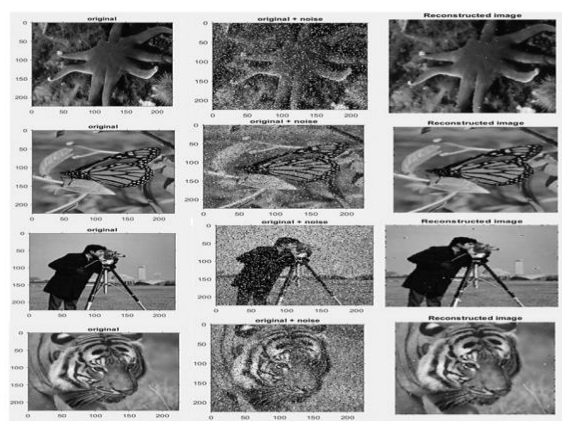

Figure 9: Denoised images with noise level σ=7

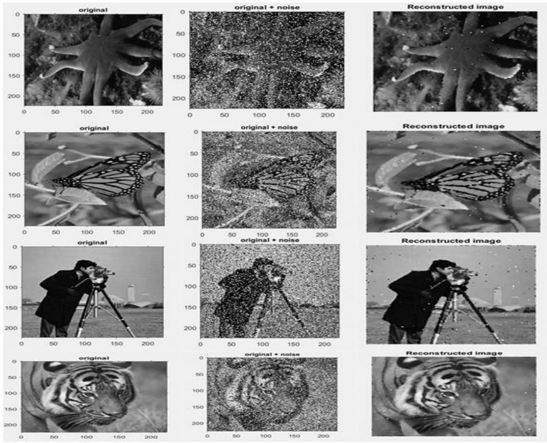

Figure 10: Denoised images with noise level σ=10

The loss levels and accuracy levels of the proposed model is indicated in Figure 11. The results show that the proposed model accuracy rate is high. Epoch and loss represents terms of neural networks, an epoch refers to one cycle through the full training dataset and loss refers to the loss value over the training data after each epoch.

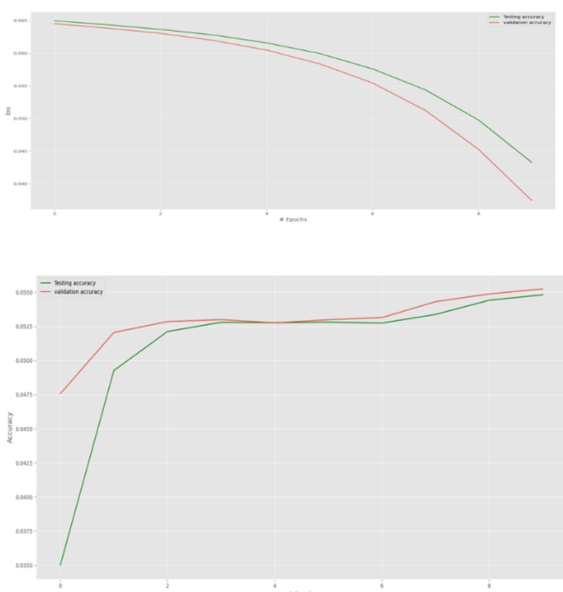

Figure 11: loss levels and accuracy levels of the proposed model

5.1. QUALITATIVE ANALYSIS:

PSNR and MSE is calculations for the proposed method with existing methods and the results are shown in table1

Table 1. Comparison of MSE and PSNR between existing and proposed method

Image Denoising methods		Image Quality assessment Parameters	
		MSE	PSNR(dB)
Wiener filtering		84.98	25.00
Bilateral filtering		83.62	25.90
PCA		80.98	26.78
Wavelet based transform method		81.87	26.12
CNN based denoising		78.46	28.71
Auto encoder and Decoder based denoising	Additive white Gaussian noise	72.78	29.75
	Salt and Pepper noise	69.50	30.88

From the above tables and figures in the proposed method, it is evident that for the images at noise level 10 with AWGN, PSNR value of 29.75 and with salt and pepper noise PSNR value 30.88 is achieved. Using this approach, for images the PSNR value achieved is greater than the existing methods.

MSE value of the proposed method achieves the value of 72.78 at a noise level of 10 dB of AWGN and achieves value of 69.50 at noise level 10dB of salt and pepper noise for the images. In terms of subjective visual quality, the proposed model is comparable with CNN, Wavelet based transform method and PCA, auto encoders is more pleasing visually in comparison with the earlier models.

VI. CONCLUSION & FUTURE SCOPE

In order to study the image denoising have implemented a new algorithm technique. Images are an important medium to represent meaningful information. It may be difficult for computer vision techniques and humans to extract valuable information from noised images. The model use for image enhancement perform these tasks such as preserving details, improving contrast, and noise suppression. Here, the different types of images are tested by this proposed implementation in order to achieve the performance capabilities. Finally, the image quality will be improved by using this proposed implementation which is produced by the numerous devices. The devices which are belongs to the real time or specific incomplete hardware conditions. The proposed method gives good PSNR and MSE value when compared with existing methods, so the results obtained have visually well.

The scope of this work can be extended in several directions based on the process of image denoising with reference to the model presented. Images effected with salt and pepper noise and Gaussian noise can be analyzed based on the denoising algorithm presented in this work. Research is being done on the new neural network-based techniques, auto encoder technique used in this proposed work has much potential to de-noising the images, but by introducing any new artificial neural network techniques it is possible to produce better and efficient results.

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