

# Removal of Gaussian White Noises from the image by probability map prediction based Deep learning approach

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## Abstract

Deep learning methods have gained an increasing research interest, especially in the field of image denoising. Although there are significant differences between the different types of deep learning techniques used for natural image denoising, it includes significant process and procedure differences between them. To be specific, discriminative learning based on deep learning convolutional neural network (CNN) may effectively solve the problem of Gaussian noise. Deep learning based optimization models are useful in predicting the true noise level. However, no relevant research has attempted to summarize the different deep learning approaches for performing image denoising in one location. It has been suggested to build the proposed framework in parallel with the previously trained CNN to enhance the training speed and accuracy in denoising the Gaussian White Noise (GWN). In the proposed architecture, ground truth maps are created by combining the additional patches of input with original pictures to create ground truth maps. Furthermore, by changing kernel weights for forecasting probability maps, the loss function may be reduced to its smallest value. Besides, it is efficient in terms of processing time with less sparsity while enlarging the objects present in the images. As well as in conventional

methods, various performance measures such as PSNR, MSE, and SSIM are computed and compared with one another.

**Keywords:** Image denoising, deep learning

## 1. INTRODUCTION

Machine learning has grown increasingly efficient over the last three decades, yet even with considerable efficiency, compactness, cost effectiveness and high-resolution image sensors are still underutilized due to their limited ability to function in low-light conditions. Without effective image enhancement and noise reduction, digital image processing is meaningless [1-4].

The widespread use of digital picture devices includes the use of these technologies for identifying people as well as remote sensing. A captured image is a damaged picture, which is caused by noise and lighting artifacts. During an unknown latent observation, noise is mostly produced during transmission and compression operations. Image denoising procedures must be used to recover the latent observation from the provided damaged image [5-8]. Figure 1 shows some standard sample images for training and testing purposes.

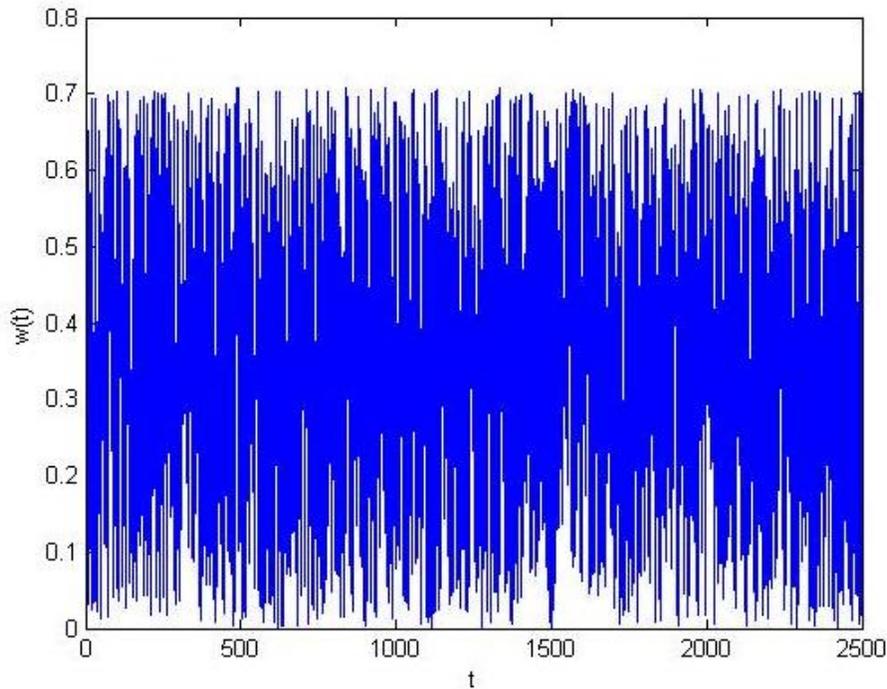
Image denoising techniques have gained increased popularity over the last half-century. The idea of nonlinear and non-adaptive filters was initially used in image processing applications. Nonlinear filters preserve image clarity and edge information while reducing noise but linear filters do not. To calculate an appropriate weighting factor for eliminating noise from a picture damaged by the mixture of additive random, signal-dependent, impulse noise, and additive random noise, adaptive nonlinear filters rely on local signal-to-noise ratios. Edge information and signal-to-noise ratio information may be concurrently used by non-adaptive filters [9]. Sparse-based machine learning techniques including early denoising approaches became effective over time.



**Figure 1.** Standard Sample Images for Training and Testing Purposes

Many of the aforementioned techniques have obtained acceptable image denoising results but they have several shortcomings, including the need for optimization methods during the testing phase, set parameters that must be manually tuned and a single denoising job model. As architectures have become more adaptable, deep learning methods have recently acquired the capacity to overcome the limitations that have hindered their use in the past [10-13]. An ergodic and stationary random process with zero mean is known as Gaussian white noise (GWN). It has the following basic property: no matter how close two values of GWN are in time, they are statistically independent. Figure 2 shows Gaussian white noise spectrum.

Due to the development of deep learning, significant steps have been achieved in computer vision in recent years. The large quantity of data available in many computer vision tasks underestimate the impact of denoising inputs on CNNs. Any technique that may improve model performance without extending the dataset is of considerable value in areas such as medical imaging, where data is frequently sparse. Pre-processing the input is considered as a popular technique.



**Figure 2.** Gaussian White Noise Model

When using medical imaging equipment such as X-ray machines, visual noise is inevitably present in the images. While denoising these images is undeniably useful in improving radiologists' diagnostic abilities, wherein others have questioned its ability to improve the performance on computer-aided diagnosis tasks based on convolutional neural networks (CNNs). On the other

hand, denoising reduces the amount of explanation in an image or that the CNN can learn to manage the noise on its own, even with a reduced training set [14, 15].

## **2. Organization of the Research**

The remaining part of this paper is organized as follows: Section 3 summarizes the current research works on picture denotation processes based on deep learning. Section 4 describes the suggested image denotation framework. Section 5 provides the outcomes of the framework suggested. The last section ends the proposed research study with a future improvement.

## **3. Preliminaries**

Dodge et al. dealt with different noises with blurring effect of contrast images on the performance of various image classification algorithms in this research. Furthermore, it was shown that CNNs trained on images were susceptible to Gaussian noise [16].

Comparable research by Nazare et al. confirm this point while also demonstrating that CNNs have difficulty in dealing with kinds of noise that they were not taught to deal with. Training on denoised images improves performance on the same image distribution for certain types of noise [17]. Koziarski et al. confirm the classification impact of noise and demonstrate that denotation and increasing noise training data may improve the classification performance [18].

An end-to-end architecture for combined denoising, deblurring, and image categorization is proposed by Diamond, et al. A pipeline is created by first learning to denoise pictures using a CNN, which in turn is utilized for classification. The analysis shows that, compared to architectures that separate the preprocessing and classification phases, this design is better when emulating raw camera sensor data. To see if their better-looking denoised pictures were linked to

improved image classification, the researchers found that for the job in question, the appearance of images did not affect their classification accuracy [19].

To circumvent this situation, Karam and Dodge came up with an ensemble of CNNs, each trained on a different kind of additional noise. Finally, an input picture is sent to a gating network, which uses a CNN to classify the image. As a consequence, a resilient model remains unaffected by various types of noise is produced [20].

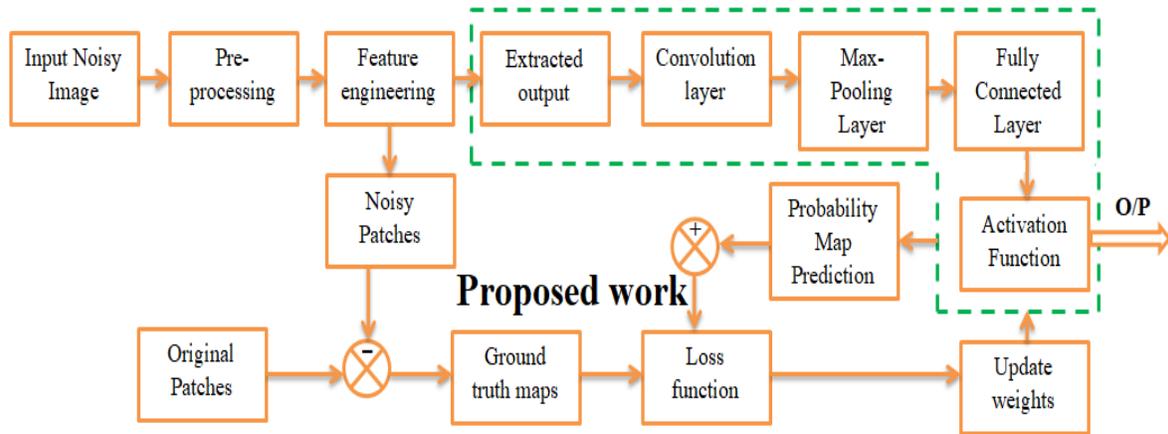
Inception-v is used as the model for the dual-channel CNN proposed by Yim and Sohn. The final model is made up of two different models. The first model accepts the original and unprocessed image, whereas the second model accepts the denoised image, which has been denoised using several methods. Feature summation and concatenation are used to merge the results of all the features into a single categorization, which is achieved via a fully linked layer. This had two objectives: to ensure that the findings on the original dataset were preserved while also providing higher accuracy in distinguishing between distinct images, which is feasible due to the model that takes raw images and the denoising module [21].

The learning research group comprises Kai Zhang's DnCNN, et al., and NVIDIA Research's Noise2Noise CNN. Both CNNs have been selected since they are one of the most popular CNNs for image denotation [22].

### **3.1 Research Gap**

Several deep learning denoising methods have been developed that do not take into account sparsity phenomena while enlarging denoised image. We are taking this into consideration and developing a CNN that includes a probability map prediction method.

#### 4. Proposed Framework



**Figure 3.** Overall Proposed Framework

The main goal of this study is to design a CNN architecture that can identify Gaussian white noise levels. As an input, the system uses a degraded picture with a particular amount of Gaussian noise. A convolutional filter (or kernel) is used to extract low-level features by convolving those using convolutional layers (or kernels). The overall proposed framework has shown in the figure 3.

Back propagation will be used to train these filters repeatedly until a set of filters with the highest recognition performance is obtained. A pooling layer is often required to downsample the sample feature map since the convolutional layer's output is so much bigger than the input. This reduces the computational expense, time commitment, and difficulty [23-25]. By the time of training this layer, a collection of output feature maps can be used as input for the next two convolutional and sampling layers. The maximum feature response of that area is selected for both the down sampling layers due to the implementation of max-pooling [26-29].

Two convolution layers are then applied to the image data for extracting higher-level features that better describe the image data. To make the training process faster, a Rectified Linear Unit (RELU) activation layer is sandwiched between these two convolution layers. To categorize the pictures, a softmax classifier is used in the final layer, which is a completely linked layer with the most responsiveness [30].

### ***Step 1***

Determine the ground truth maps from subtracting between noisy and original patches.

### ***Step 2***

Determine loss function to update the weights in the probability maps.

$$L(\Theta) = \frac{1}{N} \sum_{i=1}^N (M_i - \hat{M}_i)^2$$

Where  $\Theta$  denotes a set of training parameters.  $M_i$  and  $\hat{M}_i$  are patches from noisy and original.

### ***Step 3***

The pre trained model will be updated with our proposed work is defined as follows;

$$\mathbf{Output} = \begin{cases} (v_1, v_2, v_3), & \text{probability maps(at initial condition)} \\ x_i, & \text{probability maps (at separation of patches)} \end{cases}$$

## **5. Results & Discussion**

As a result of this experiment, we were able to determine how different dataset types and sizes affect the final network's performance. The PASAL VOC2007 dataset and the Google Open

Images Dataset V4 (GoogleV4) is introduced for Gaussian white noise detection were added to the original datasets for this study. The 500 images are randomly selected from each dataset, and they are all of excellent quality [31].

In this case, we are using certain common pictures referred to as "cameraman", as shown in figure 4. The picture with Gaussian noise introduced is seen in Figure 4b. Figure 4 c has been denoised by using a different technique, which results in some sparsity in the picture when the image is magnified. Furthermore, the suggested method exhibits null sparsity phenomena while expanding the picture, as shown in figure 4d. Figure 4 c depicts the impact of sparsity over the items present in the scene.



**Figure 4.** Obtained Results

In the PASCAL VOC2007 dataset, pictures depict 20 different object types. Only 50 out of the 600 classes in the GoogleV4 dataset were used in our study. As a result, although the content of the test dataset is considerably larger, where both the datasets include only restricted textural samples (e.g. pictures depicting just trains). We additionally reduced the original resolution four

times for the GoogleV4 dataset in order to maintain a consistent resolution across all training and test sets [32].

**Table 1.** Computed Performance Metrics

S.No	Transform Domain	PSNR	MSE	SSIM	Processing Time (sec)
1	Image processing method	24.71	0.1340	0.499	9.592
2	Auto Encoder based De-noising	26.98	0.0160	0.791	17.53
3	Proposed CNN approach	33.34	0.0004	0.922	15.38

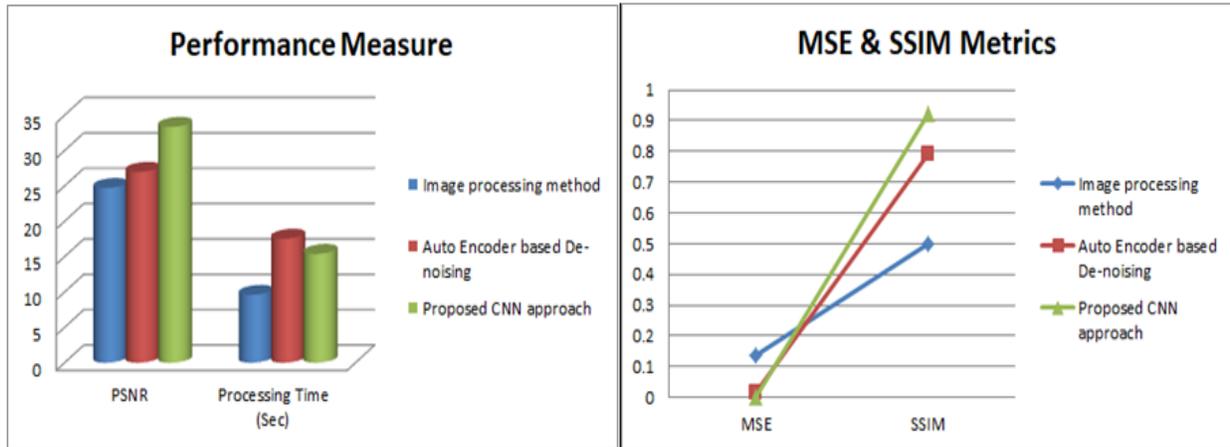
The following performance indicators are specified in this section:

$$PSNR = 10 * \log \left( \frac{255^2}{MSE} \right)$$

$$MSE = \frac{1}{M * N} \sum_{i=1}^N \sum_{j=1}^M [I(i, j) - \hat{I}(i, j)]^2$$

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

To train the model, we used 100 epochs and a mini-batch size of 100 photos, for a total of 100 images. The total processing time for our suggested framework is shown in the following table 1. To speed up the training process, we have included a graphic processing unit (GPU), which can complete a training cycle within 15 minutes. Figure 5 shows the overall performance measure, which shows less processing time with higher clarity images, PSNR and SSIM.



**Figure 5.** Overall Performance Measure

## 6. Conclusion

As a result, the GWN has been removed from all the image artifacts by utilizing the proposed framework. Further, the image patches of size 8\*8 are considered successful when tested with input and ground truth images, which generate almost zero GWN from the provided matrix. On the other hand, the traditional methods are unable to identify the noisy patches in the input picture that result in lower PSNR and SSIM scores than those obtained by using the suggested framework. As a result, the suggested framework outperforms conventional techniques when expanding denoised pictures, which is where standard methods fail. A novel measure or an existing one that has been used to estimate the effect of denoising algorithms on medical image classification framework performance can be implemented. Future work will concentrate on altering the suggested neural network design to find and repair pixels that have been polluted by impulsive noise in a single-stage network. Alternatively, a novel efficient denoising method may be used in the future [33].

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