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Image denoising using deep learning: Comparative study

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Abstract: Deep learning offers a flexible and effective approach to automated image denoising. This study investigated the residual learning capabilities of two recent deep learning networks: the Restoration Transformer (Restormer) network and the Deep CNN (DnCNN) network. We compared their denoising performance on the BSD68 dataset under varying levels of Gaussian noise against established algorithms such as block-matching and 3D filtering (BM3D) and trainable nonlinear reaction diffusion (TNRD). Our findings demonstrate that the Restormer algorithm excels in noise removal. This highlights the potential of transformer-based architectures in image restoration tasks, surpassing traditional methods in achieving superior denoising quality. Further research can explore the application of Restormer to other noise types and datasets.
Keywords: *Convolutional neural networks, Deep learning, Image denoising, Transformers.*

1. Introduction

Deep learning is a powerful tool that enables the automatic removal of noise from images in a flexible and effective manner. One of the most significant advantages of using deep learning for image denoising is its ability to learn and capture complex patterns in the data, unlike traditional image denoising techniques, which may not effectively remove noise in all cases. Deep learning-based approaches have been successfully applied in various fields, including low-light image enhancement, noise reduction in medical imaging, and image restoration. Noise reduction in images is the process of removing noise to improve the visual quality of an image. Noise can be introduced into an image through various means, such as capturing in low-light conditions, image compression, or transmission over a noisy channel. Removing noise from an image helps restore its original clarity and enhances its overall appearance [1].

Several techniques can be used to remove noise from images, including adaptive filters [2-5] and wavelet-based denoising [6-8]. Smoothing filters work by averaging the pixel values in an image, while median filters replace a pixel's value with the median value of its surrounding pixels. Wavelet-based denoising employs wavelet transforms to separate an image into different frequency bands, allowing noise to be distinguished from the signal and removed. Completely eliminating noise often requires sacrificing some level of detail, but with careful tuning, it is possible to minimize detail loss while achieving effective noise reduction.

Deep learning has recently emerged as a powerful tool for image noise reduction. In deep learning, a neural network is trained to learn the underlying structure of an image and predict a noise-free version from a noisy input [1]. This is typically achieved using a large image dataset containing both noisy images and their corresponding clean versions, which is used to train the network to learn the relationship between noisy and noise-free images.

One of the key advantages of using deep learning for image denoising is its ability to learn and capture complex structures within data. Traditional image denoising techniques rely on fixed filtering, which may not effectively remove noise in all situations. In contrast, deep learning-based approaches can

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adapt to different types of noise and denoise images more flexibly and effectively. Additionally, deep learning models can be trained in an end-to-end manner, allowing them to learn from large datasets and automatically determine the most suitable noise reduction technique for a given task. As a result, deep learning has the potential to enhance the performance of image denoising techniques and has already been successfully applied in various scenarios.

The rest of this work is structured as follows: The history and related work on image denoising are summarized in Section 2. Section 3 discusses and presents two recently introduced image denoising algorithms explored in this project—the Restoration Transformer (Restormer) network and Deep Convolutional Neural Networks (DnCNN) Residual Learning. The results and comparisons are presented and analyzed in Section 4. Finally, Section 5 concludes the project and discusses future work.

2. History and Related Work

2.1. Convolutional Neural Networks (CNNs)

CNNs have achieved remarkable success in image processing due to their plug-and-play network architectures [9-14]. As a pioneer in CNN technology, LeNet [15] utilized convolutional kernels of different sizes to extract features and achieve effective image classification. However, due to the use of the Sigmoid activation function, LeNet had a slow convergence rate, which posed a limitation in real-world applications.

Following LeNet, AlexNet Krizhevsky, et al. [16] and Daalah, et al. [17] became a milestone in deep learning (see Figure 1). Its success stemmed from its ability to address the overfitting problem and improve the speed of stochastic gradient descent (SGD) instead of using the Sigmoid activation function [18]. While AlexNet achieved high performance, its large convolutional kernels required significant memory usage, limiting its application in real-world scenarios such as smart cameras.

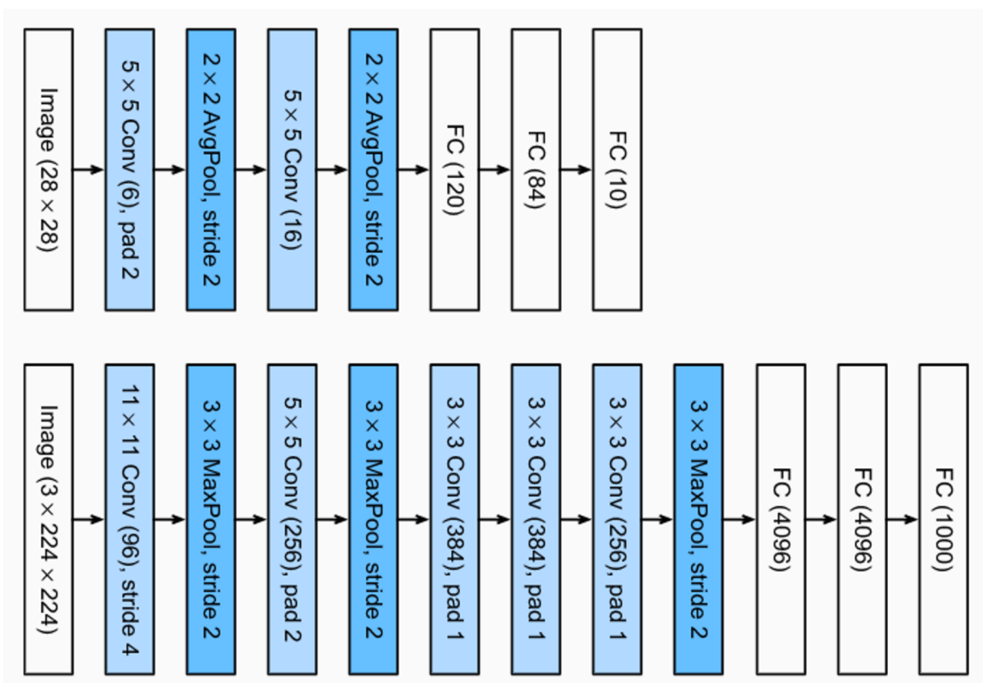

Figure 1.
LeNet (Top) and AlexNet (Bottom).

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To enhance performance and reduce computational costs, deeper network architectures with smaller filters were preferred. Specifically, VGG [19] stacked more convolutional layers with small kernel sizes, as illustrated in Figure 2.

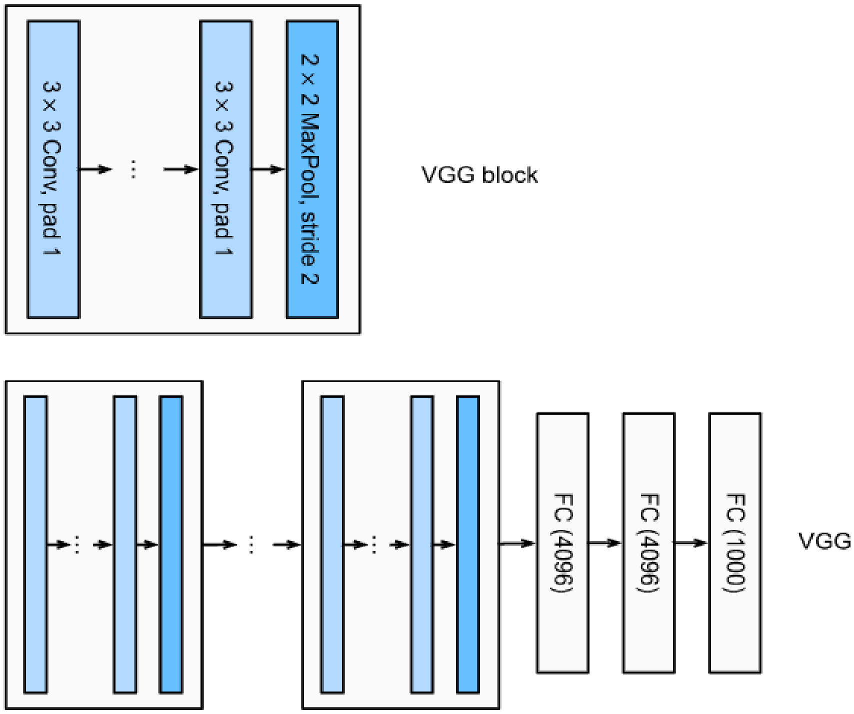

Figure 2.
The Architecture of the VGG.

As accuracy improved, research shifted toward increasing the width of networks. GoogleNet Szegedy, et al. [20] expanded the width of CNN architectures to enhance the performance of image-processing applications. Additionally, it reduced the number of parameters and computational costs by replacing large convolutional kernels with two smaller ones. The fundamental convolutional block in GoogleNet is called the Inception block (see Figure 3), and the GoogleNet architecture is shown in Figure 4.

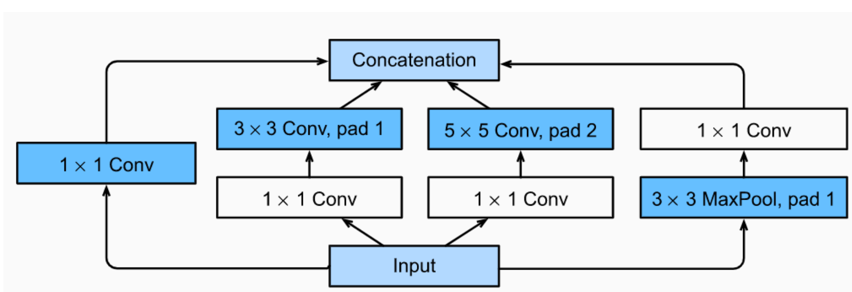

Figure 3.
The Inception Block.

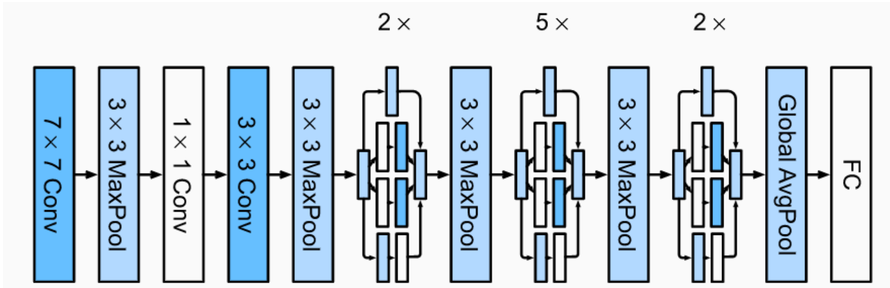

Figure 4.
GoogleNet Architecture.

Although VGG and GoogleNet methods are effective for image applications, they come with two main disadvantages: if the network is too deep, it may suffer from vanishing or exploding gradients; if the network is too wide, it may be prone to overfitting.

To overcome these issues, ResNet He, et al. [21] was proposed in 2016. To improve image recognition performance, residual learning was introduced into each block of the ResNet architecture. Figure 5 shows the structure of ResNet-18, while the basic building block of ResNet is illustrated in Figure 6.

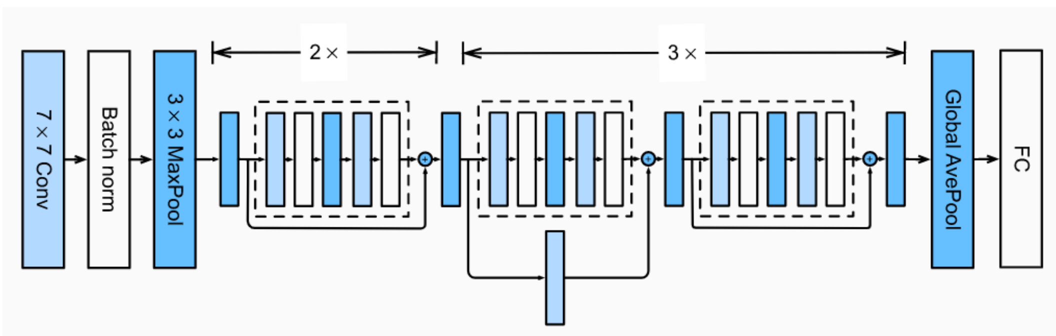

Figure 5.
ResNet-18 Architecture.

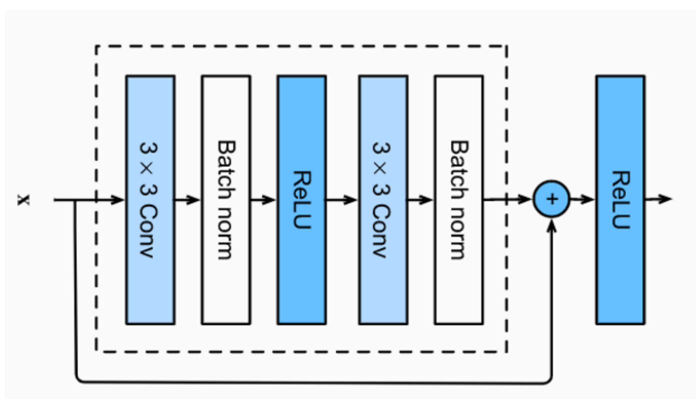

Figure 6.
ResNet Block.

Traditional machine learning algorithms have long been employed in diverse image processing applications [22-27]. For nearly a decade, deep networks have seen widespread use in real-world image

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applications, including face recognition [28-32] and medical diagnosis [33-37]. However, in many applications, such as real noisy image scenarios, the captured images are often insufficient in quality, and deep CNNs tend to show limited performance.

To address this, Generative Adversarial Networks (GANs) Radford, et al. [38] were developed. GANs consist of two networks: A Generator and a Discriminator. The generator is used to produce samples based on input data, while the discriminator evaluates the authenticity of both the input samples and the generated ones. These two networks work in opposition: if the discriminator can accurately distinguish real samples and the generator can produce convincing fake ones, the model is considered successfully trained. The architecture of a GAN is illustrated in Figure 7. Due to their ability to generate complementary training examples, GANs are highly effective in working with small datasets, especially in tasks like face recognition [39] and denoising complex noisy images [40].

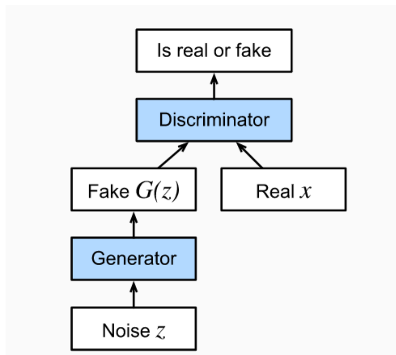

Figure 7.
GAN Architecture.

2.2. Deep Learning for Image Denoising

With the introduction of the networks mentioned above, deep learning techniques have attracted considerable attention in the field of image denoising. Researchers have explored deep neural networks to address the problem of noise removal. However, there are significant differences among various deep learning approaches to image denoising. Specifically, discriminative learning based on deep learning has proven effective in tackling the problem of Gaussian noise.

In Jain and Seung [41] proposed using Convolutional Neural Networks (CNNs) for image denoising, arguing that CNNs can provide representations like, or even better than, those of Markov Random Field (MRF) models [42]. In Burger, et al. [43]. Multi-Layer Perceptrons (MLPs) were successfully applied to image denoising. In Xie, et al. [44] stacked sparse denoising autoencoders were adopted for Gaussian noise removal and achieved results comparable to K-SVD [45]. In Chen and Pock [46] a Trainable Nonlinear Reaction Diffusion (TNRD) model was proposed, which can be expressed as a feedforward deep network by unrolling a fixed number of gradient descent inference steps.

Among these deep neural network-based approaches, MLP and TNRD have shown promising performance and can approach the denoising quality of BM3D [47]. In Chen, et al. [48] researchers proposed NAFNet, a parameter-efficient network with nonlinear activation-free layers, which outperformed state-of-the-art (SOTA) methods and demonstrated computational efficiency.

Chen, et al. [49] proposed a simple GAN that takes Gaussian noise as input to generate noisy patches. However, as with most conventional methods, this GAN operates at the image level, treating images as samples and attempting to approximate the probability distribution of real-world noisy images.

To overcome the limitations of this approach, a new Pixel-level Noise-aware Generative Adversarial Network (PNGAN) was introduced in [50]. This novel method performs alignment in both the image space and noise space simultaneously during training, leading to more accurate noise modeling.

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In Zhang, et al. [51] the structure of feedforward denoising convolutional neural networks (DnCNNs) was explored for image noise removal. To enhance denoising performance and accelerate the training process, residual learning and batch normalization were employed. The proposed network was successfully applied to several common image degradation tasks, including Gaussian denoising, single-image super-resolution, and JPEG artifact removal.

Researchers in Zamir, et al. [52] developed an efficient Transformer-based model for image denoising and restoration, capable of handling high-resolution images. To reduce computational demands, they introduced key architectural elements such as a multi-input self-attention (SA) layer and a multi-scale hierarchical module with reduced computational complexity.

3. Restormer and Residual Learning of Dncnn Networks

This section focuses on two recently developed image denoising algorithms: The Restoration Transformer (Restormer) network and the Residual Learning of the Deep CNN (DnCNN) network. Convolutional Neural Networks (CNNs), which have demonstrated strong performance in image processing applications, will be utilized in the studied algorithms due to their accessibility to large-scale datasets.

3.1. Residual Learning of the Denoising CNN (DnCNN) Network

Discriminative model learning for image denoising has gained significant attention recently due to its superior denoising performance. In Zhang, et al. [51] researchers explored the construction of feedforward denoising convolutional neural networks (DnCNNs) by incorporating advancements in deep architectures, learning algorithms, and regularization techniques for image denoising. Specifically, residual learning and batch normalization are employed to both accelerate the training process and enhance denoising performance. Unlike conventional discriminative denoising models that are trained for a specific noise level (e.g., Additive White Gaussian Noise - AWGN), the DnCNN model can remove Gaussian noise with unknown noise levels (i.e., blind Gaussian denoising). Using the residual learning strategy, DnCNN indirectly estimates the clean image embedded in the hidden layers. The DnCNN Network Architecture is shown in Figure 8.

3.1.1. Residual Learning

Residual learning in CNNs was initially proposed to address the degradation of performance in very deep networks. As network depth increases, training accuracy can begin to degrade. With residual learning, deep CNNs can be trained more effectively, leading to improvements in tasks such as image classification and object detection [53]. The proposed DnCNN model adopts the residual learning principle by using a single residual unit to predict the residual image (i.e., the noise), rather than directly predicting the clean image.

3.1.2. Batch Normalization

Despite the simplicity and effectiveness of mini-batch stochastic gradient descent (SGD), the performance of trained CNN models can degrade due to internal covariate shift, that is, changes in the distribution of nonlinear activations during training. Batch Normalization was proposed to reduce this effect by adding a normalization step before each nonlinearity, along with a scale and shift operation. Batch normalization leads to faster training, better performance, and reduced sensitivity to weight initialization [21].

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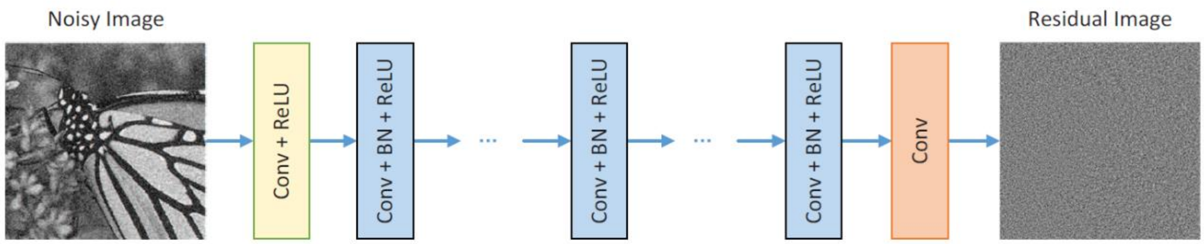

Figure 8.
DnCNN Network Architecture.

3.2. Restoration Transformer (Restormer) Network

Image restoration is the task of reconstructing a high-quality image by removing degradations (e.g., noise, blur, rain streaks) from a corrupted input. Convolutional Neural Networks (CNNs) have become the preferred choice over traditional restoration approaches due to their strong performance in learning generalizable priors from large-scale data [52]. The core operation in CNNs is convolution, which offers local connectivity and translation equivariance. While these properties provide efficiency and generalization, they also introduce two key limitations:

To address these issues, the self-attention (SA) mechanism was introduced, which computes a pixel's response based on a weighted sum of all positions in the input [54, 55]. SA has become a fundamental component in Transformer models, which are optimized for parallelization and effective representation learning [56]. Transformers have demonstrated state-of-the-art performance in natural language processing [57] and high-level computer vision tasks [58, 59]. Although SA is highly effective at capturing long-range pixel interactions, its computational complexity increases quadratically with spatial resolution, making it impractical for high-resolution image processing, common in restoration tasks. Research on adapting Transformers to image restoration is still limited [60, 61]. To reduce computational burden, some methods apply SA in small 8×8 spatial windows or divide the input image into non-overlapping 48×48 patches to perform attention independently within each patch. However, limiting the spatial scope of SA conflicts with the goal of capturing true long-range pixel relationships, especially in high-resolution images.

In Zamir, et al. [52] researchers proposed an efficient Transformer model capable of handling high-resolution images for restoration tasks. To manage computational demands, they introduced a multi-head self-attention layer and a multi-scale hierarchical module, which requires fewer resources than a single-scale network [58]. A progressive training strategy was adopted to help the model learn image statistics from large datasets, enhancing contextual understanding and improving quality during inference [52].

The Restormer architecture for high-resolution image restoration is shown in Figure 9. It consists of a multi-scale hierarchical design with efficient Transformer blocks. The core modules of a Transformer block include:

- Multi-Dconv Transpose Attention (MDTA): MDTA enables spatially enriched channel-wise query-key interactions, rather than operating across spatial dimensions.
- Gated-Dconv Feed-Forward Network (GDFN): GDFN performs controlled feature transformation, allowing more effective propagation of useful information.

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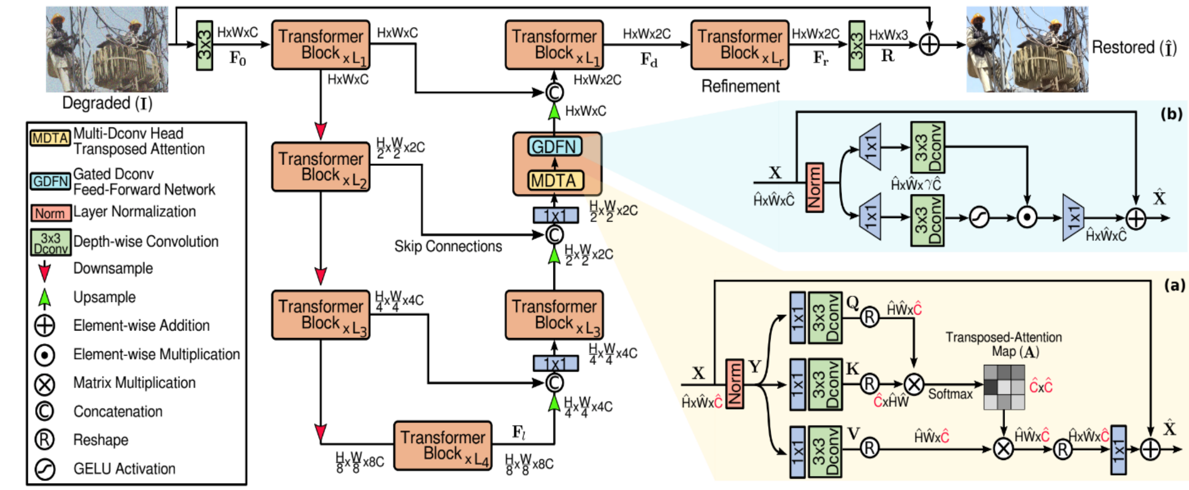


Figure 9.
Restoration Transformer (Restormer) network architecture Zamir, et al. [52].

4. Experimental Results and Discussions

Since noise reduction in images is an indispensable step in many practical applications, it remains a classic yet active topic in low-level vision. The goal of image denoising is to obtain a clean image x from a noisy signal y that follows the image degradation model $y = x + v$. A common assumption is that v is additive white Gaussian noise (AWGN) with standard deviation σ. From a Bayesian perspective, when the probability distribution is known, modeling the prior of the image plays a central role in noise removal.

In this section, comparisons are made between two recently introduced algorithms for image denoising, as discussed in the previous section. Different images from the BSD68 dataset were used for the comparisons. For each resulting image, the Peak Signal-to-Noise Ratio (PSNR) was calculated.

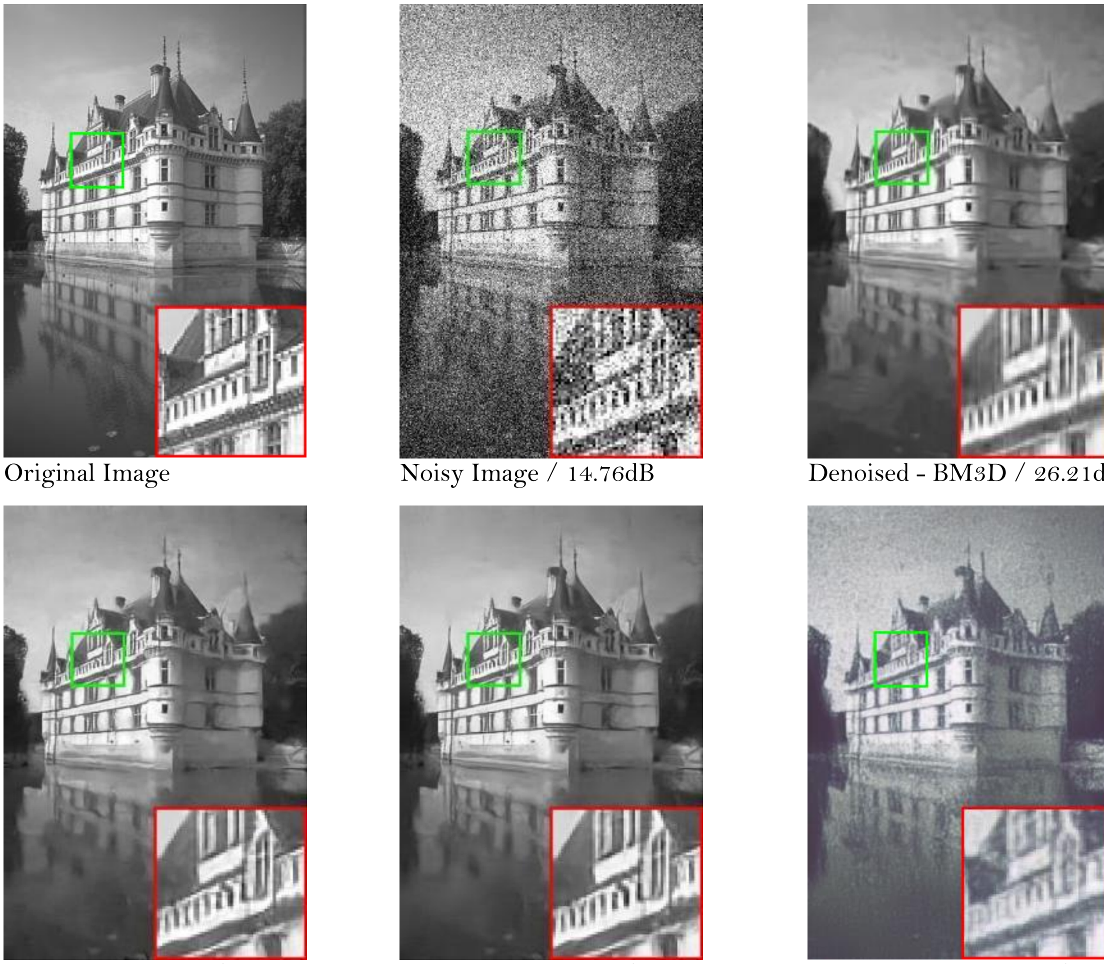
PSNR calculates the peak signal-to-noise ratio between two images in decibels. This ratio is used as a quality metric between the original image and the compressed or denoised version. The higher the PSNR value, the better the quality of the denoised image. To compute PSNR, the Mean Squared Error (MSE) is first calculated using Equation (1):

$$MSE = \frac{\sum_{M,N} \quad [I_1(m,n) - I_2(m,n)]^2}{M \times N} \tag{1}$$

In the above equation, M and N represent the number of rows and columns in the image matrix. Then, using Equation (2), the PSNR is calculated as follows:

$$PSNR = 10 \, log_{10} \left(\frac{255^2}{MSE} \right) \tag{2}$$

The PSNR results for an image from the BSD68 dataset with Gaussian noise added at a level of 50 were observed and compared using different denoising algorithms, as shown in Figure 10. Among the five algorithms compared, BM3D had the lowest performance with a PSNR of 26.21 dB, while Restormer achieved the highest PSNR value with 27.849 dB.



Original Image | Noisy Image / 14.76dB | Denoised - BM3D / 26.21dB

Denoised - TNRD / 26.59dB | Denoised - DnCNN / 26.90dB | Denoised - Restormer / 27.849 dB

Figure 10.
Comparison of denoising results for image 0010 from the BSD68 dataset at Gaussian noise level 50.

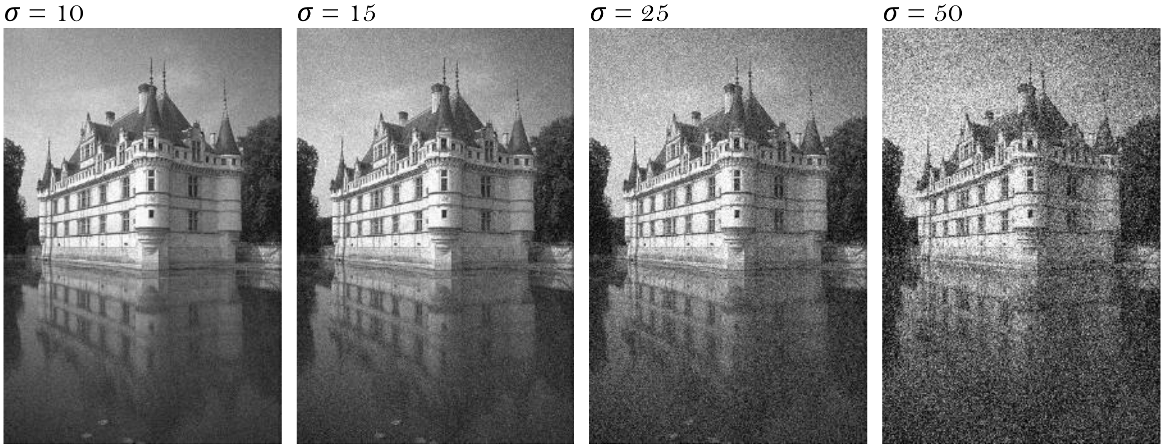
Another comparison was carried out on the images "Cameraman," "BSD68-10," and "BSD68-09" with different levels of Gaussian noise (10, 15, 25, and 50) using the Restormer denoising algorithm. It is evident that the PSNR value increases inversely with the noise level. The higher the Gaussian noise, the lower the PSNR value, and vice versa. The PSNR results for the denoised images are presented in Figures 11, 12, and 13. For a better comparison, a summary of the denoising results is listed in Table 1.

$\sigma = 10$ $\sigma = 15$ $\sigma = 25$ $\sigma = 50$

PSNR 30.50 dB PSNR 29.30 dB PSNR 27.97 dB PSNR 27.96 dB

Figure 11.
Gaussian image denoising on the Cameraman image using the Restormer algorithm at noise levels 10, 15, 25, and 50.

$\sigma = 10$ $\sigma = 15$ $\sigma = 25$ $\sigma = 50$



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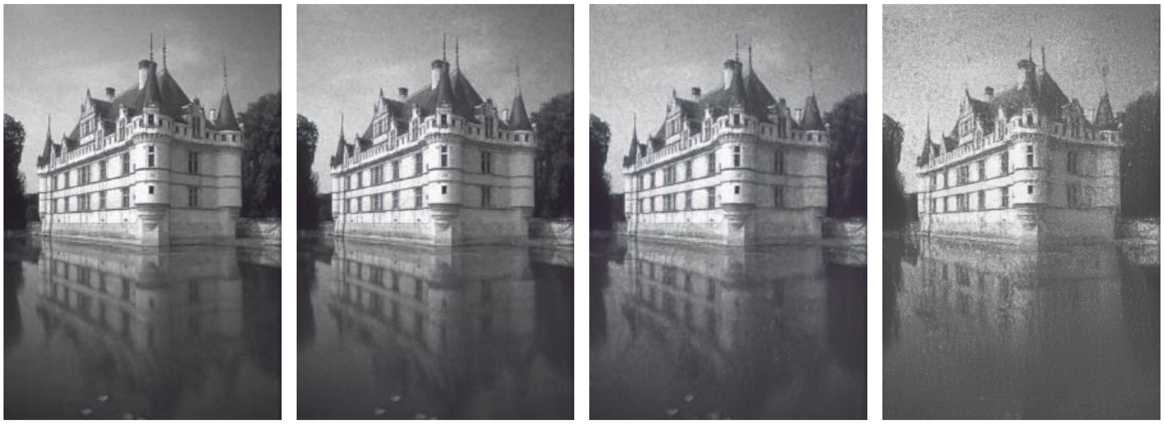
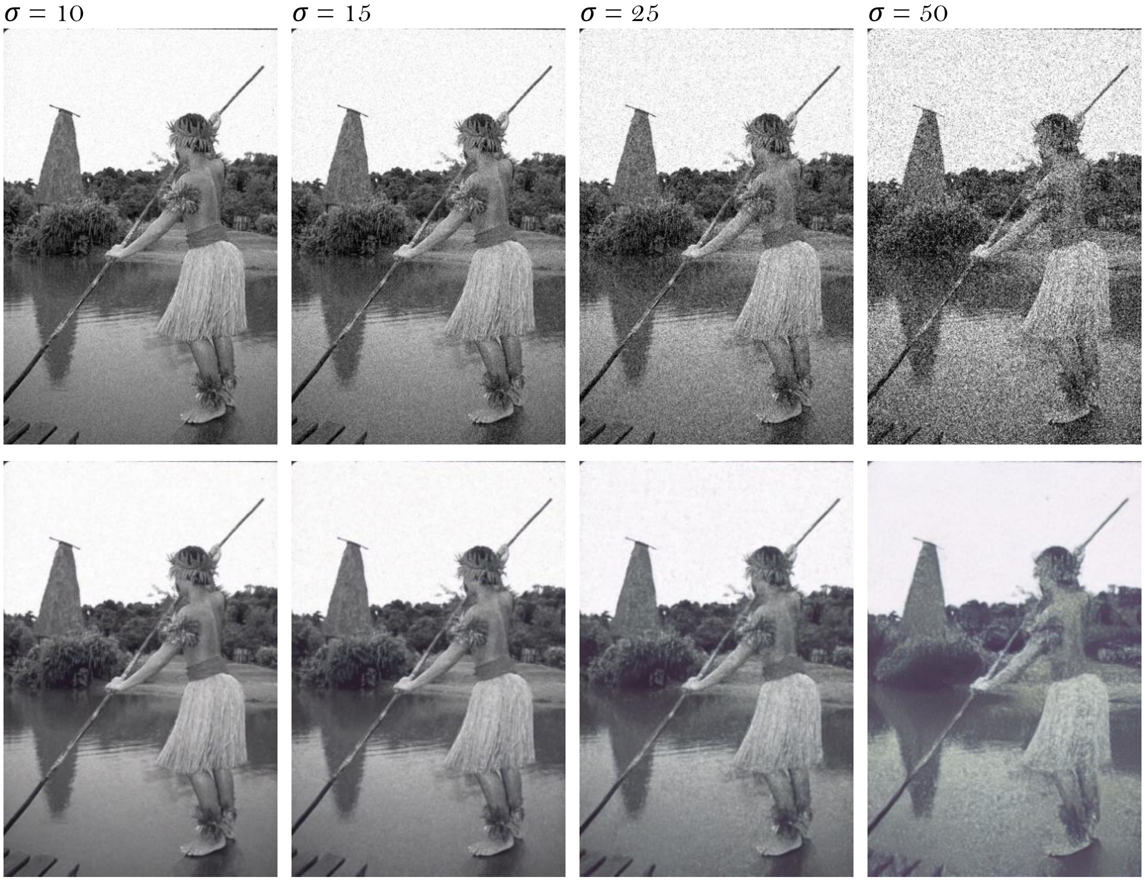


PSNR 30.65 dB | PSNR 29.4 dB | PSNR 28.5 dB | PSNR 27.91 dB

Figure 12.
Gaussian image denoising on image 0010 from the BSD68 dataset using the Restormer algorithm at noise levels 10, 15, 25, and 50.

$\sigma = 10$ | $\sigma = 15$ | $\sigma = 25$ | $\sigma = 50$



PSNR 31.51 dB | PSNR 30.17 dB | PSNR 29.05 dB | PSNR 27.93 dB

Figure 13.
Gaussian image denoising on image 0009 from the BSD68 dataset using the Restormer algorithm at noise levels 10, 15, 25, and 50.

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Table 1.
PSNR (dB) results obtained using the Restormer algorithm at noise levels 10, 15, 25, & 50.

Noise Level	Cameraman	BSD68-09	BSD68-10
10	30.50	31.51	30.65
15	29.30	30.17	29.4
25	27.97	29.05	28.5
50	27.96	27.93	27.91

Denoising was performed on the BSD68 dataset (consisting of 68 grayscale images) with noise levels of 15, 25, and 50 using different methods. The average PSNR (dB) results were calculated and are presented in Table 2. The best results for each noise level are highlighted in bold. The comparison shows that the DnCNN and Restormer algorithms produce results competitive with the BM3D and TNRD algorithms from the literature. While Restormer outperforms DnCNN at higher noise levels (σ = 50), DnCNN yields better performance at lower noise levels (σ = 25 and σ = 15).

Table 2.
PSNR (dB) results obtained using different methods on the BSD68 dataset at noise levels 15, 25, & 50.

Noise level	BM3D	TNRsD	DnCNN	Restormer
15	31.08	31.42	31.46	30.71
25	28.57	28.92	29.02	28.82
50	25.62	25.97	26.10	27.95

5. Conclusions

This study thoroughly investigated image denoising performance using two cutting-edge deep learning networks: the Restoration Transformer (Restormer) and the Deep CNN (DnCNN) with Residual Learning. The denoising process was rigorously applied to images from the BSD68 dataset and the classic Cameraman image, both corrupted with various levels of Gaussian noise.

To quantitatively assess denoising effectiveness, Peak Signal-to-Noise Ratio (PSNR) values were calculated. These values serve as a crucial metric for measuring the fidelity between the original and denoised images. The denoising capabilities of DnCNN and Restormer were directly compared against two established algorithms in image denoising literature: BM3D and TNRD.

Our findings revealed that DnCNN and Restormer consistently achieved the highest PSNR results for images subjected to Gaussian noise levels of 15, 25, and 50. These results underscore the significant potential of both deep learning architectures, particularly highlighting the superior performance of transformer architectures like Restormer in image restoration tasks. Their capabilities were shown to surpass those of traditional methodologies in terms of denoising quality.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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