Deep Neural Network Models for Image Denoising: DnCNN, GAN, and Unet

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Abstract. Image denoising is a fundamental task in the fields of image processing and computer vision, aiming to remove noise while preserving fine structural details. To address the limitations of traditional approaches that often struggle to balance noise suppression and detail preservation, this paper proposes two enhanced models based on the Deep Convolutional Neural Network for Denoising (DnCNN): DnCNN-GAN and DnCNN-UNet. The first incorporates a Generative Adversarial Network (GAN) to improve the perceptual quality and structural fidelity of denoised results, while the second leverages the multi-scale feature fusion capability of the U-Net architecture, achieving greater robustness and generalization under varying noise levels. For training, cropped patches from publicly available datasets were used, with Gaussian noise of random intensity added to simulate realistic scenarios. Experimental results demonstrate that both proposed models outperform the baseline DnCNN in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), validating their effectiveness and practical value for real-world image denoising applications.

1 Introduction

In processing and computer vision, denoising is one of the most essential and widely studied problems. Its goal is to remove unwanted noise while preserving important structural details as much as possible. It plays a key role in a wide range of applications such as medical imaging, remote sensing, low-light photography, and surveillance systems [1][2][3]. Noise may be introduced during image acquisition, transmission, or compression, and usually exhibits complex distribution characteristics, such as Gaussian noise, Poisson noise, or mixed noise patterns [4][5].

Traditional image denoising methods, such as mean filtering, bilateral filtering, and non-local means methods, rely on artificial priors and often find it difficult to strike a balance between noise suppression and detail preservation [6][7]. With the development of deep learning, convolutional neural networks (CNNs) have made significant progress in image restoration tasks, including denoising, super-resolution, and image inpainting [8][9][10]. Among them, the DnCNN model has demonstrated excellent performance by introducing residual learning to predict noise components [1].

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However, relying solely on residual learning may not be able to fully restore detailed textures under high noise levels. Generative Adversarial Networks (GANs) can promote the generator to output more realistic results by introducing a discriminator, thereby improving visual sharpness [3]. Moreover, the UNet architecture adopts a symmetric encoder–decoder framework in which skip connections are introduced to directly transmit feature maps from the encoder to the corresponding decoder layers. This design enables the effective fusion of multi-scale contextual and spatial information, thereby enhancing the network's capability to reconstruct fine-grained structural details and preserve image textures during the denoising process [4].

To address these challenges, this study not only analyzes the shortcomings of traditional denoising methods, but also proposes two innovative combination models: DnCNN-GAN, which improves the detail quality of denoising results by introducing a generative adversarial network; and DnCNN-UNet, which combines the multi-scale feature fusion capability of U-Net to more effectively suppress noise while preserving details. Under a unified training and evaluation framework, this paper systematically compares the performance of three deep neural network models: the baseline model DnCNN, the improved DnCNN-GAN, and the DnCNN-UNet variant. The conducted experiments highlight important observations regarding how different network architectures manage the inherent trade-off between reducing noise and maintaining fine structural details, offering a deeper understanding of their respective strengths and limitations.

2 Method

2.1 Overall process

This study aims to perform denoising on images contaminated with Gaussian noise using deep neural network models with different architectures. As shown in Figure 1, the clean images first undergo data preprocessing, including normalization, cropping, and format conversion. Gaussian noise is then added to simulate training input images, which are paired with the original images and fed into the training model. The network learns the distribution characteristics of the noise to predict the noise components in the images. Finally, the model subtracts the predicted noise image from the noisy image to produce a reconstructed image that is as close as possible to the original.

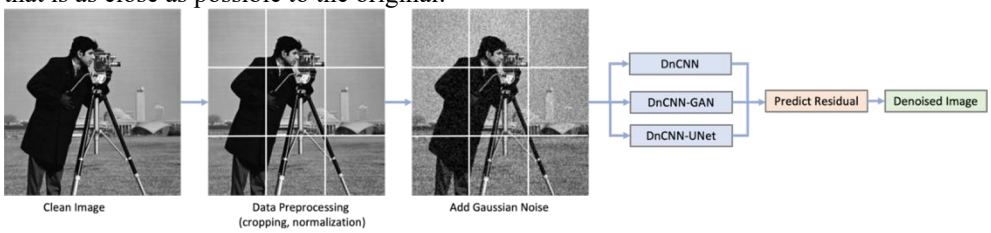

Fig. 1. Overall Process Diagram (Picture credit: Original).

2.2 Random noise modeling

Additive Gaussian white noise is used as the image corruption method. The noise term follows $\mathcal{N}(0, \sigma^2)$, where σ is the standard deviation that determines the noise intensity. The noisy training image can be expressed as:

$$I_{noisy} = I_{clean} + N \tag{1}$$

During training, the network aims to recover I_{noisy} from I_{clean} .. A residual learning approach is employed, in which the model predicts the noise component $f_\theta(I_{\text{noisy}})$, and the clean image estimate is obtained as:

$$\widehat{I_{clean}} = I_{noisy} - f_\theta(I_{noisy}) \tag{2}$$

This modeling approach has the advantage that the network does not directly predict the clean image but only learns the relatively simpler noise structure, thereby improving training stability and denoising performance. The Gaussian noise addition process is illustrated in Figure 2 which shows the complete generation procedure from a clean image to a noisy training input.

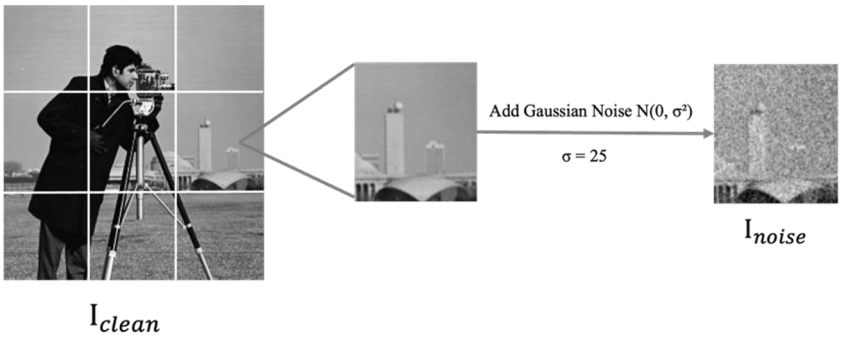

Fig. 2. Gaussian Noise Addition Process (Picture credit: Original).

This random noise mechanism simulates real-world noise conditions, such as sensor noise and compression noise, making the training more representative of actual application scenarios.

2.3 Network architectures and methods

To verify the effectiveness of the proposed method, three models are compared: DnCNN, DnCNN-GAN, and DnCNN-UNet.

2.3.1 DnCNN basic model

Denoising Convolutional Neural Network (DnCNN) is an end-to-end convolutional neural network designed to learn the residual between the noisy and clean images. Its architecture typically consists of multiple convolutional layers, ReLU activation functions, and batch normalization layers, as shown in Figure 3. The model predicts the noise directly, and the clean image is obtained via residual learning:

$$\widehat{I_{clean}} = I_{noisy} - f_\theta(I_{noisy}) \tag{3}$$

Here, f_θ denotes the noise predicted by the neural network.

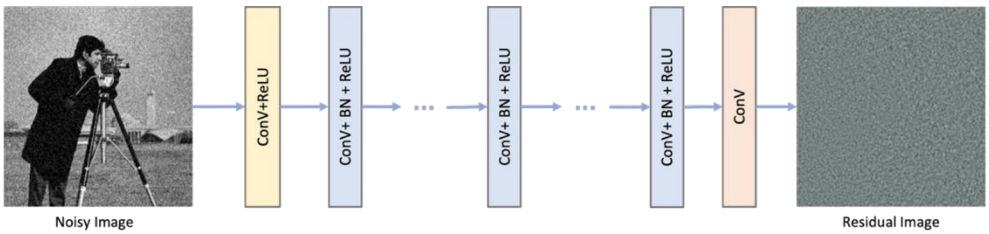

Fig. 3. DnCNN Basic Model (Picture credit: Original).

2.3.2 DnCNN-GAN extended model

To enhance the detail quality of the generated images, a GAN structure is incorporated into the DnCNN framework. The generator retains the DnCNN architecture, while the discriminator distinguishes between generated images and real images, thereby improving generation quality. The model structure is illustrated in Figure 4. The training objective consists of a weighted sum of reconstruction loss and adversarial loss:

$$L_{total} = L_{MSE} + \lambda \cdot L_{GAN} \tag{4}$$

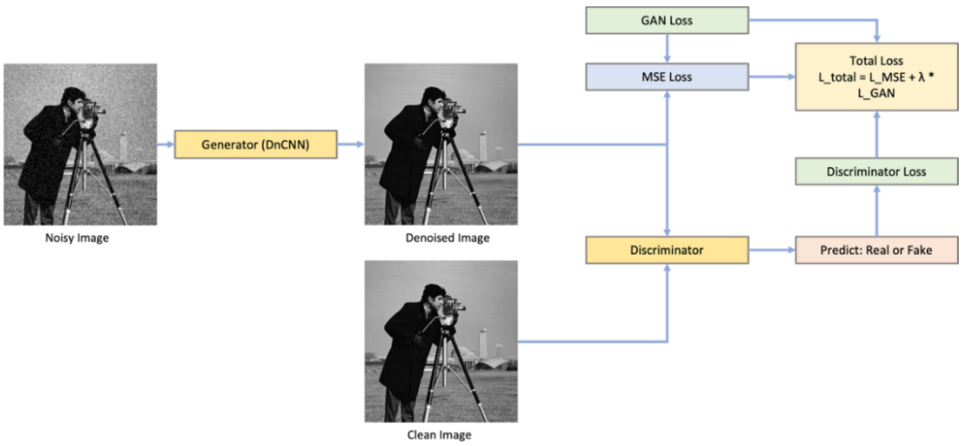

Fig. 4. DnCNN-GAN Extended Model (Picture credit: Original).

2.3.3 DnCNN-UNet fusion model

To further improve denoising performance, the generator in the original model is modified. While retaining the overall GAN architecture, the original DnCNN generator is replaced with a DnCNN-UNet structure. The generator preserves the encoder convolutional modules but adds a symmetric decoder and employs skip connections to fuse multi-scale features. This design preserves more image details during denoising. Figure 5 shows the structure of the improved generator (DnCNN-UNet).

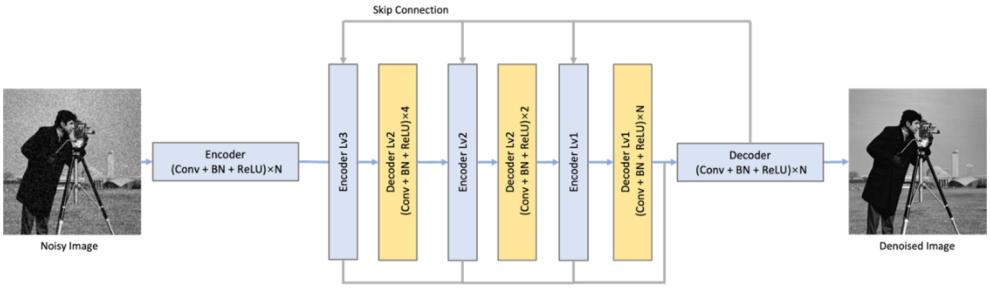

Fig. 5. DnCNN-UNet Fusion Model (Picture credit: Original).

This architecture extracts local features at shallow layers and aggregates global semantics at deeper layers, enabling better restoration of image details under complex noise interference.

3 Experiment

3.1 Dataset

In this study, experiments were conducted using a training set constructed from publicly available image datasets, together with a publicly accessible validation set. The training set was generated by cropping original PNG images from high-quality public datasets (e.g., BSD500, DIV2K) using a sliding-window approach to produce image patches of size 40×40, resulting in a total of 238,400 patches. To enhance the generalization ability of the model, Gaussian noise with a random standard deviation σ was added to the training images. The noise standard deviation for each image was randomly sampled from a predefined range to simulate the varying noise levels encountered in real-world scenarios. The validation set consisted of images from the public Set12 dataset for performance evaluation.

The validation set is the public dataset Set12, which includes 12 standard images widely used in image denoising research. These images are untrimmed and are used to evaluate the model's performance on full-image denoising tasks at different training stages.

3.2 Experiment setup

3.2.1 Hardware configuration

All experiments are conducted on a high-performance Linux server equipped with an NVIDIA RTX 3090 GPU (24 GB memory, supporting CUDA version 12.2). The server uses 8 cores of an AMD EPYC 7601 32-core processor, with 63 GB RAM. The system disk capacity is 20 GB, and the data disk is a 50 GB NVMe SSD. The network bandwidth is 700 Mbps for both upload and download.

3.2.2 Software configuration

The software environment is based on Ubuntu 20.04 with Python 3.8 and PyTorch 1.12, along with NumPy, Matplotlib, h5py, and TensorBoardX for data processing and visualization.

To ensure fair comparison, the same training strategies and parameter settings are used for all three models whenever possible. Optimizer, learning rate, number of epochs, and other

core hyperparameters are kept consistent, with differences only in the loss function and network architecture. Table 1 summarizes the training configurations.

Table 1. Loss Values at Key Epochs.

Configuration Item	DnCNN / DnCNN-Unet	DnCNN-GAN
Optimizer	Adam	Adam
Initial Learning Rate	0.001	0.001
Learning Rate Scheduler	StepLR	StepLR
Loss Function	MSE Loss	MSE Loss + GAN Adversarial Loss
Batch Size	128	128
Number of Epochs	50	50

In the testing phase, all three models are evaluated on the same Set12 validation set, and the original, noisy, and denoised results for each validation image are saved for visual comparison.

3.3 Results and analysis

This experiment compared the performance of the three models using two dimensions: quantitative indicators (Loss, PSNR) and visual results.

The convergence trends and stability of the three models are compared by recording the loss values at the 10th, 20th, 30th, 40th, and 50th epochs. As shown in Table 2, the UNet-based model maintains faster convergence and lower loss values throughout training, indicating stronger feature representation ability that improves denoising performance.

Table 2. Loss Values at Key Epochs.

Epoch	DnCNN	DnCNN-GAN	UNet
10	1.3661	1.3652	1.1939
20	1.3161	1.3154	1.1547
30	1.2739	1.2717	1.1100
40	1.2713	1.2703	1.1068
50	1.2704	1.2706	1.1064

The loss curves in Figure 6 show that incorporating GAN does not significantly alter the convergence speed compared to the base model, whereas the UNet-based model achieves the lowest loss.

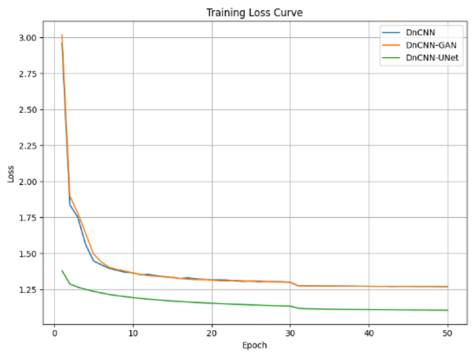

Fig. 6. Loss Curves of Three Models (Picture credit: Original).

To evaluate image reconstruction quality, the peak signal-to-noise ratio (PSNR) values are recorded at the same key epochs. As shown in Table 3, DnCNN-GAN achieves slightly higher PSNR in multiple stages, suggesting that the adversarial loss enhances visual quality.

Table 3. PSNR (dB) at Key Epochs.

Epoch	DnCNN	DnCNN-GAN	UNet
10	29.67	30.12	28.55
20	29.75	30.34	28.83
30	30.38	30.52	28.51
40	30.45	30.49	28.46
50	30.34	30.30	28.57

As shown in Figure 7, DnCNN-GAN achieves better PSNR performance on the validation set, demonstrating superior capability in restoring fine details.

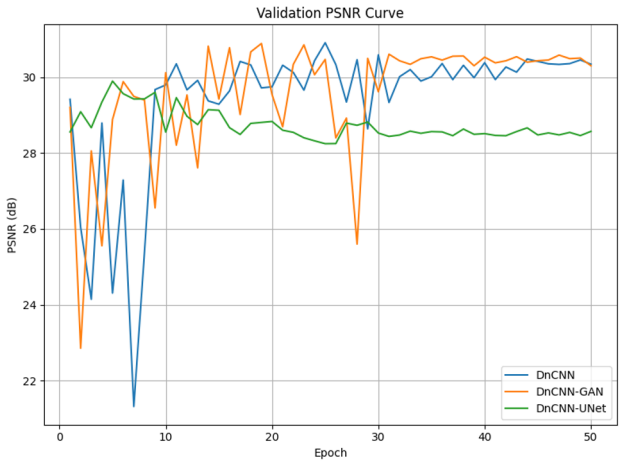

Fig. 7. PSNR Curves of Three Models (Picture credit: Original).

3.4 Visual comparison analysis

Representative test images are selected for visual comparison among the three models. Figure 8, Figure 9, and Figure 10 respectively display the original clean image, the noisy image, and the denoised results from DnCNN, DnCNN-GAN, and DnCNN-UNet.

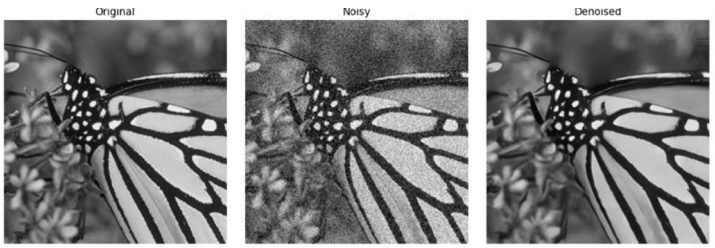

Fig. 8. DnCNN denoising comparison (original image, noisy image, and denoised result) (Picture credit: Original).

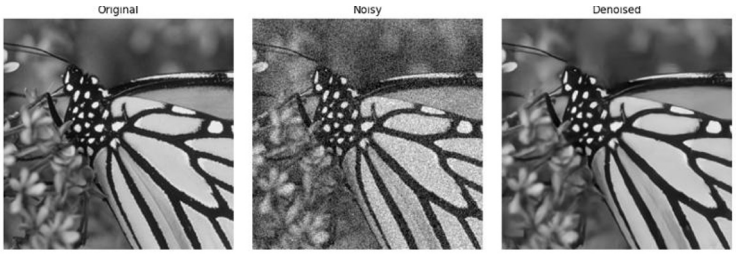

Fig. 9. DnCNN-GAN denoising comparison (original image, noisy image, and denoised result) (Picture credit: Original).

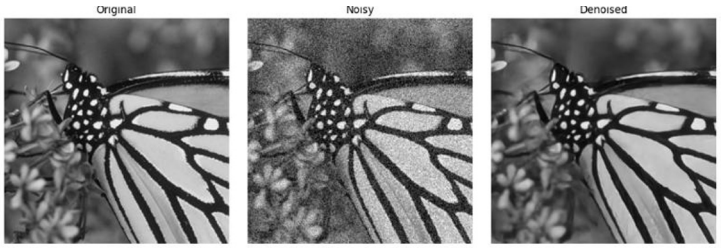

Fig. 10. DnCNN-UNet denoising comparison (original image, noisy image, and denoised result) (Picture credit: Original).

The visual results show that DnCNN-GAN preserves image texture details more effectively, while DnCNN-UNet achieves the highest overall clarity and edge restoration. DnCNN exhibits some blurring in complex texture regions.

In summary, DnCNN demonstrates good training stability and basic denoising capability. DnCNN-GAN, through adversarial learning, enhances the realism of generated images. DnCNN-UNet, leveraging the U-shaped structure for multi-scale feature fusion, offers strong potential for further improvement in image restoration quality.

4 Conclusion

This paper presented a comparative study of three deep learning-based image denoising models: DnCNN, DnCNN-GAN, and DnCNN-UNet. Using additive Gaussian noise as the corruption model, trained and evaluated the models under identical experimental settings to ensure a fair comparison.

Experimental results show that the DnCNN baseline achieves stable convergence and solid denoising performance, making it a reliable choice for general scenarios. The DnCNN-GAN variant introduces adversarial loss, which improves visual realism and texture preservation, leading to slightly higher PSNR values in most cases. The DnCNN-UNet model, with its multi-scale feature fusion capability, exhibits faster convergence and lower loss values, excelling in retaining fine structural details.

Overall, the study highlights that different network architectures offer distinct strengths: residual learning ensures stability, GANs enhance perceptual quality, and UNet structures boost detail recovery. Future work may explore hybrid approaches combining attention mechanisms, multi-noise training, and perceptual loss functions to further enhance both quantitative and qualitative denoising performance.

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