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Image Denoising Using Deep Learning and Wavelet Transform

S Rakesh[1], Dr. K. Shahu Chatrapati[2]

[1] M.Tech Student, Department of Computer Science and Engineering, JNTUHUCEST Hyderabad, Telangana, India

[2] Professor of CSE, Department of Computer Science and Engineering, JNTUHUCEST Hyderabad, Telangana, India

Abstract

Image denoising is a critical task in image processing, aimed at improving visual quality by removing unwanted noise introduced during acquisition, transmission, or storage. Noise can degrade visual content and affect image analysis tasks such as edge detection, object recognition, and feature extraction. As digital images are widely used in fields like medical imaging, satellite imaging, and photography, developing efficient denoising techniques is essential. The core challenge lies in balancing noise reduction with detail preservation. Traditional methods like Gaussian and median filtering often blur important features. This project integrates Convolutional Neural Networks (CNNs) with wavelet transforms, leveraging multi-resolution analysis to separate noise from image features. CNNs further refine the output by learning complex patterns for enhanced denoising. By isolating noise through wavelet coefficients and reconstructing clean images using CNNs, this hybrid approach achieves high-quality denoising with minimal detail loss. This project seeks to advance image processing by offering a robust solution that balances noise reduction with detail preservation.

Keywords: Image Denoising, Deep Learning, Wavelet Transform, Convolutional Neural Networks, Noise Reduction

1. Introduction

Image noise, arising from factors such as sensor imperfections, low-light environments, and transmission errors, degrades visual quality and poses challenges for both human perception and automated image analysis. Effective denoising is crucial in domains like medical diagnostics, surveillance, and remote sensing, where image clarity is paramount. Traditional denoising techniques—such as Gaussian and median filtering can suppress noise but often at the cost of blurring important structures and fine details. Recent advances in deep learning have significantly improved denoising performance by enabling models to learn complex noise patterns and distinguish them from true image content. Convolutional Neural Networks (CNNs), in particular, excel at adaptively processing spatial features, allowing for the preservation of textures and edges while reducing noise. As a result, deep learning-based approaches offer enhanced accuracy and robustness across a wide range of noise types and imaging conditions.

2. Literature Survey

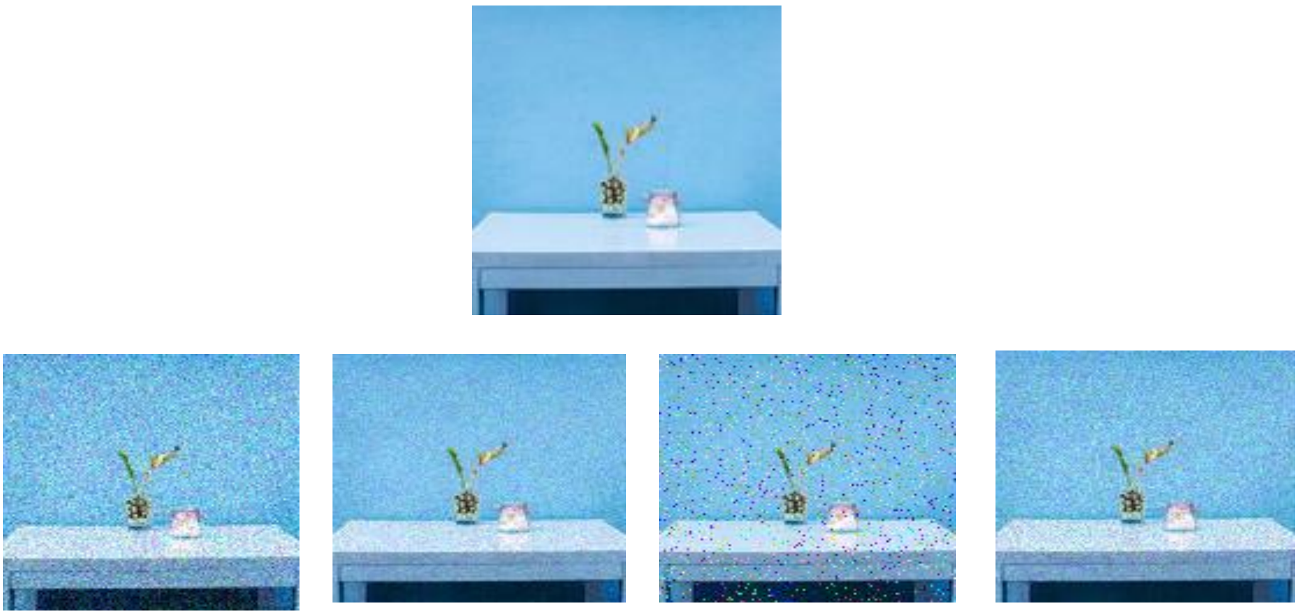
Traditional denoising techniques like Gaussian and median filters are fast and simple but tend to blur edges and fine textures along with noise [1]. Deep learning approaches, such as DnCNN [2], RED-Net [3], and FFDNet [4], improve performance by learning noise distributions through convolutional layers and residual connections. However, these models are typically trained on synthetic Gaussian noise and struggle to generalize to real-world, signal-dependent noise. FFDNet, for instance, introduces noise level maps for flexibility but underperforms in blind denoising tasks. Moreover, most deep models operate solely in the spatial domain and do not exploit frequency-domain cues, limiting their capacity to isolate high-frequency noise components. Wavelet-based models like WDnCNN [5] and hybrid approaches using Discrete Wavelet Transform (DWT) [7] attempt to bridge this gap by incorporating frequency decomposition, but challenges in generalization and computational efficiency persist. Many models also lack multiscale feature extraction, reducing their effectiveness in capturing context-aware details.

3. Project Scope

The project titled "Image Denoising Using Deep Learning and Wavelet Transform" introduces a hybrid technique that combines wavelet transforms with convolutional neural networks (CNNs) to effectively restore noisy digital images. This model is designed to handle various noise types, including Gaussian, Poisson, and real-world noise, while preserving important image textures and details. The approach enhances image quality through localized frequency analysis and deep feature learning, making it suitable for applications in medical imaging, remote sensing, and surveillance systems.

Dataset :The ground truth image dataset used in this study is sourced from Kaggle. To evaluate the robustness of the proposed denoising approach, synthetic noisy images were generated by corrupting each clean image with four different types of noise: Gaussian noise, Poisson noise, salt-and-pepper noise, and speckle noise. This multi-noise setup helps simulate diverse real-world noise conditions and ensures the generalizability of the model across varying noise distributions. Figure 1 illustrates examples of clean (ground truth) images alongside their corresponding noisy counterparts for each noise type.

Figure 1: Sample dataset images depicting Ground Truth (clean image), Gaussian Noise, Poisson Noise, Salt & Pepper Noise, and Speckle Noise.



4. Convolution Neural Network

A Convolutional Neural Network (CNN) is a type of deep learning model especially effective for image-related tasks such as classification, enhancement, restoration, and segmentation.

In this project, CNN is the core architecture used for processing and enhancing images. It instructs the model on how to:

- Extract spatial features (edges, textures, patterns)
- Enhance image quality by suppressing noise and restoring structure
- Function across both the spatial and wavelet domains

The Project uses CNNs in various modules:

1. Dynamic Convolution Block
   Learns adaptive filters based on input content.
2. Residual Dense Blocks (RDBs)
   Deep CNN layers with skip connections that retain features and improve gradient flow.
3. Wavelet Enhancement Block (WEB)
   CNN layers operate on decomposed (wavelet) frequency bands to enhance image details before reconstruction.
4. Final Convolution Layer
   Converts the processed feature map back into a high-quality RGB image.

5. Wavelet Transform

The Wavelet Transform is a mathematical technique used to break down an image into components at multiple resolutions or frequency bands. Unlike Fourier transforms, which analyze global frequency, wavelets are capable of capturing both spatial and frequency information, making them ideal for image processing tasks.

The Wavelet Transform can be Mathematically Expressed as :

$$I(x,y) = \sum_{j,k} c_{j,k} \cdot \emptyset_{j,k}(x,y) + \sum_{x,y} d_{j,k} \cdot \varphi_{j,k}(x,y)$$

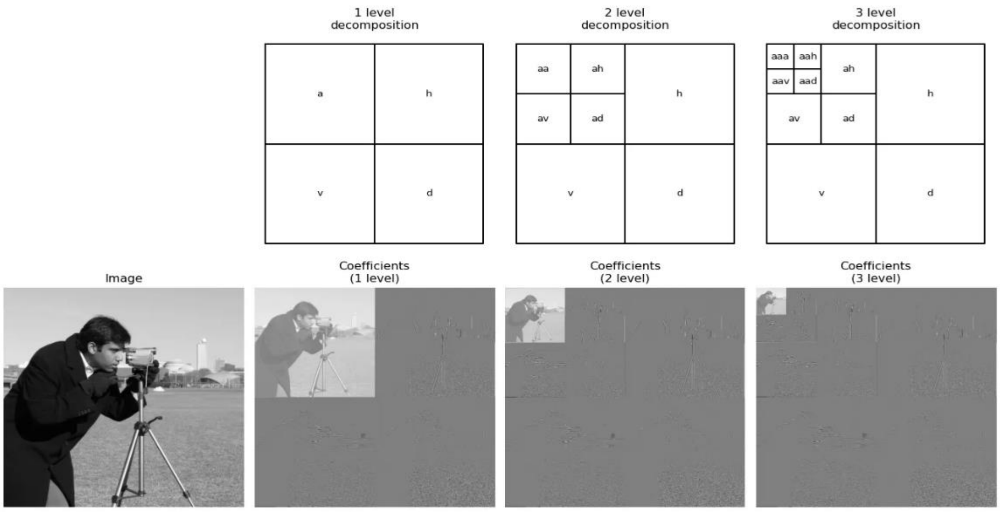
Where, $\emptyset_{(j,k)}$ (x,y)= Scalling Function captures Smooth ares

$\varphi_{j,k}(x,y)$=Wavelet Function captures edge, textures (high frequencies

$c_{j,k}$ = Approximation Coefficients

$d_{(j,k)}$=Detail Coefficients

Figure 2: Wavelet Decomposition



6. Implementation

The proposed denoising architecture leverages both spatial and frequency-domain information through the integration of dynamic convolutions, wavelet transforms, and residual dense feature learning. It is structured into three main modules: the Dynamic Convolutional Block (DCB), the Wavelet Transform and Enhancement Block (WEB), and the Residual Dense Block (RDB). Together, these components enable effective noise suppression while preserving important image details.

Figure 3: Architecture Diagram

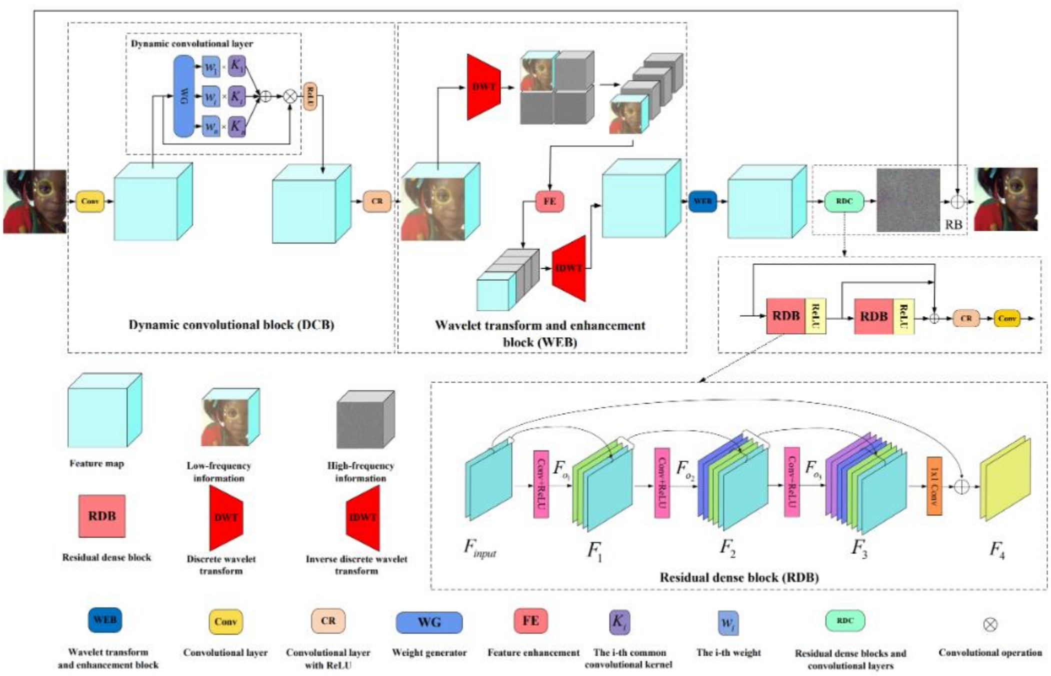
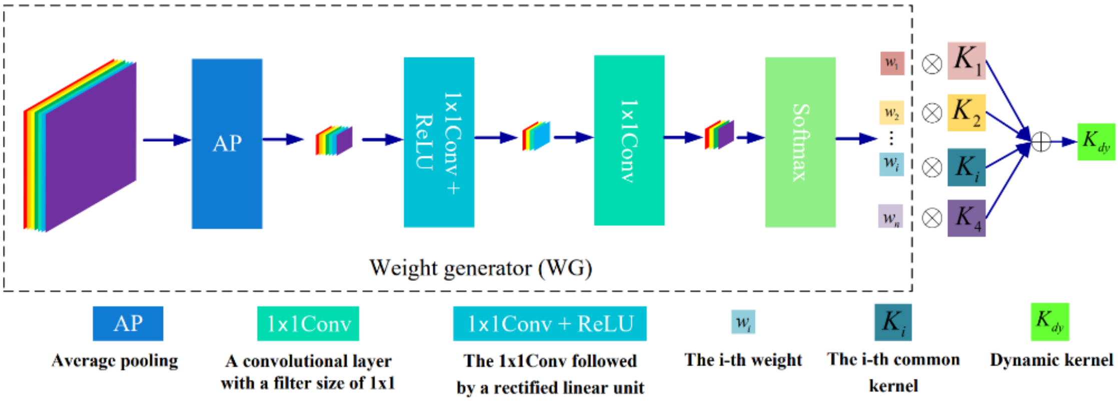


Figure 4: Architecture of weight Generator



Dynamic Convolutional Block (DCB):

The DCB is responsible for adaptive feature extraction in the spatial domain. This block generates dynamic convolutional kernels by combining multiple fixed kernels using weights produced by a Weight Generator (WG). The dynamic kernels are applied to the input feature map, allowing the network to adjust its receptive field and feature extraction behavior based on the image content. The resulting features are then refined through a convolutional layer followed by a ReLU activation.

Wavelet Transform and Enhancement Block (WEB)

The WEB processes features in the frequency domain by applying the Discrete Wavelet Transform (DWT), which decomposes the feature map into low-frequency and high-frequency components. A Feature Enhancement (FE) module improves these components by emphasizing important structures and suppressing noise. The processed features are then recombined using the Inverse Discrete Wavelet Transform (IDWT), effectively restoring spatial details while benefiting from frequency-domain noise isolation.

Residual Dense Block (RDB)

Deep feature extraction is performed by the RDB, which stacks multiple densely connected convolutional layers with residual connections. Intermediate feature maps (F1,F2,F3,F4)(F1,F2,F3,F4) are produced sequentially and concatenated, facilitating multiscale feature learning and retaining fine-grained details. Residual connections within and across blocks support stable gradient flow, enabling the network to model complex noise distributions effectively.

Denoising Reconstruction

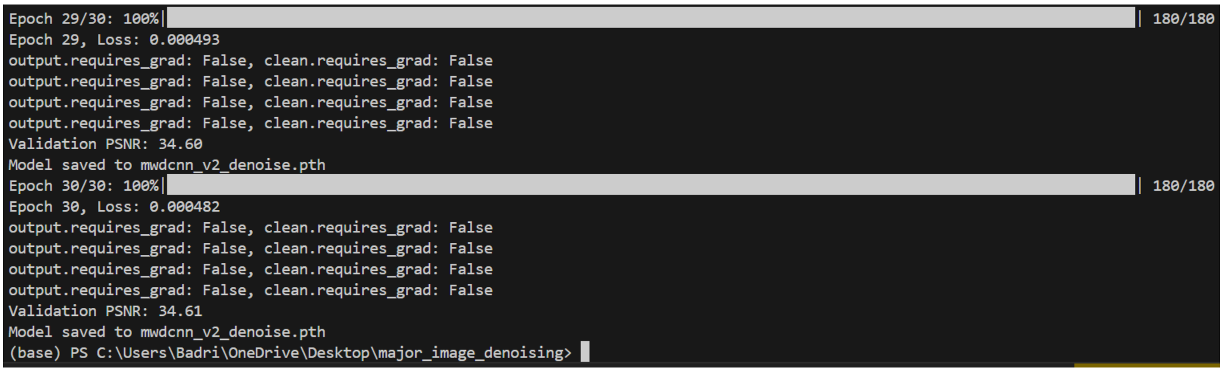
The outputs from the WEB and RDB modules are fused and passed through reconstruction layers, which progressively refine the features to suppress noise and restore image content. A final convolutional layer generates the denoised output image.

7. Results

Training and Validation Performance

The proposed model was trained on a dataset of clean images corrupted with four different types of synthetic noise: Gaussian, Poisson, salt & pepper, and speckle. The model was trained for 30 epochs using the Adam optimizer and a mean squared error loss function. As shown in Figure 5, the training loss consistently decreased across epochs, and the model achieved a validation PSNR of 34.61 dB in the final epoch, indicating strong noise suppression capability.

Figure 5: Training log showing convergence and final validation PSNR of 34.61 dB.



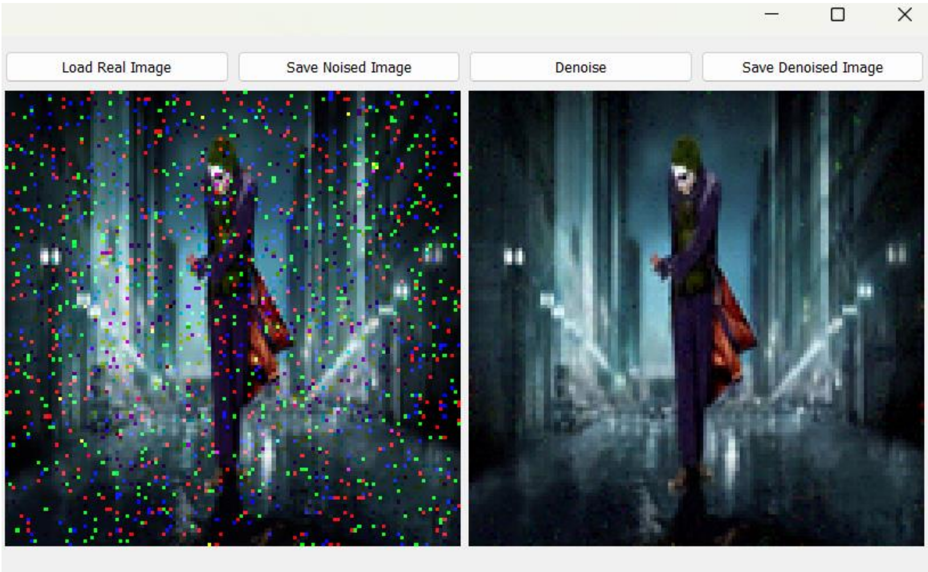
```
Epoch 29/30: 100%|████████████████████████████████| 180/180
Epoch 29, Loss: 0.000493
output.requires_grad: False, clean.requires_grad: False
output.requires_grad: False, clean.requires_grad: False
output.requires_grad: False, clean.requires_grad: False
output.requires_grad: False, clean.requires_grad: False
Validation PSNR: 34.60
Model saved to mwdcnn_v2_denoise.pth
Epoch 30/30: 100%|████████████████████████████████| 180/180
Epoch 30, Loss: 0.000482
output.requires_grad: False, clean.requires_grad: False
output.requires_grad: False, clean.requires_grad: False
output.requires_grad: False, clean.requires_grad: False
output.requires_grad: False, clean.requires_grad: False
Validation PSNR: 34.61
Model saved to mwdcnn_v2_denoise.pth
(base) PS C:\Users\Badri\OneDrive\Desktop\major_image_denoising>
```

Qualitative Denoising Results

To evaluate the model's performance in real-world scenarios, a custom GUI was developed to allow users to interactively load, corrupt, and denoise images. The visual denoising results are displayed below.

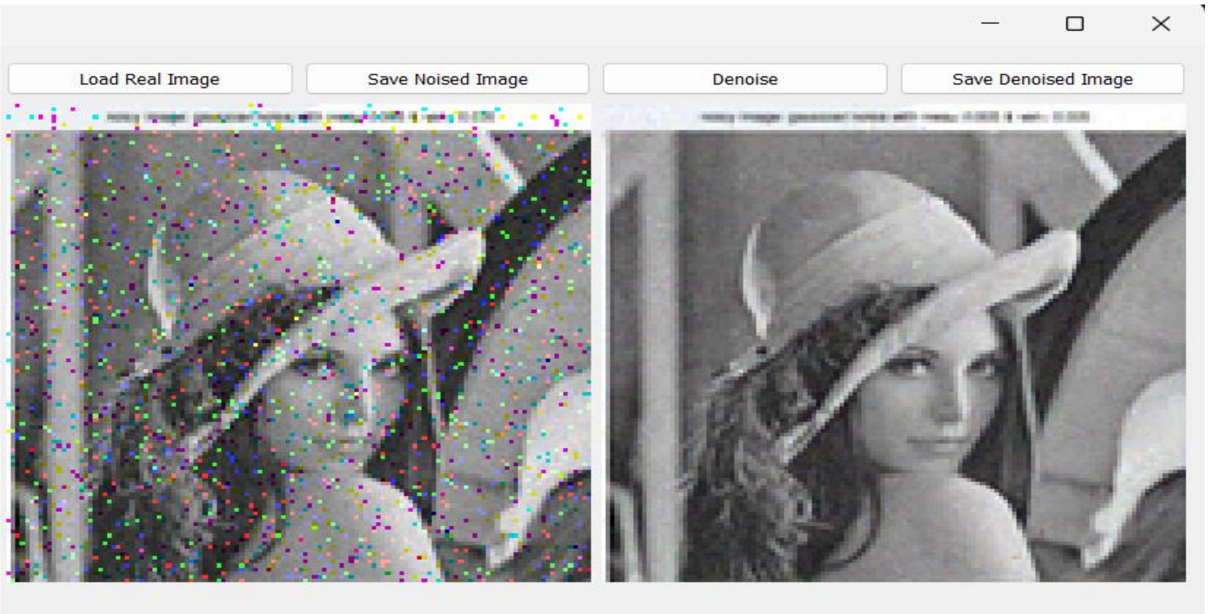
In Figure 6, an image corrupted with salt and pepper noise is shown on the left. The denoised output (right) demonstrates that the proposed model significantly removes the noise while preserving structural details like edges and textures.

Figure 6**:** Salt & pepper noise removal using the proposed model. Left: Noisy input. Right: Denoised output.



In Figure 7, the well-known grayscale Lena image is corrupted with salt and pepper noise. After denoising, the output image clearly shows restored sharpness and reduced noise artifacts, verifying the model's ability to handle even classic test cases effectively.

Figure 7**:** Denoising result on Lena image. Left: Noisy image. Right: Denoised image using the proposed model.



The denoising results demonstrate that the proposed architecture can handle a variety of noise types and preserve fine image structures. By integrating dynamic convolutional layers, wavelet transforms, and residual dense blocks, the model efficiently captures both spatial and frequency-domain features. It avoids the over-smoothing commonly associated with traditional filters and achieves superior perceptual quality.

8. Conclusion

The hybrid method by Nitin and Satinder Bal Gupta achieved a PSNR of 25.80 dB, showing that combining Gaussian filtering with wavelet transforms improves denoising over traditional techniques. In contrast, this project integrates wavelet transforms with deep CNNs, achieving a higher PSNR of 34.61 dB. This demonstrates the model's ability to preserve textures and restore image quality more effectively.

Future work includes integrating blind noise estimation for adaptive denoising and extending the method to video denoising by leveraging temporal consistency across frames.

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