Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

From Noise to Clarity: A Hybrid Approach for Image Denoising Using Traditional and Deep Learning Methods

Spriha Deshpande[1] and Suman Basavaraj Mukkanagoudar[2]
[12]CA, USA
Corresponding Author: Spriha Deshpande, **E-mail**: spriha.deshpande@gmail.com

| ABSTRACT

In this study, we explore various image denoising techniques to restore images affected by noise, with a particular focus on traditional and deep learning-based methods. The research compares conventional denoising approaches, including Wavelet Thresholding, Bilateral Filtering, Non-Local Means, and Wavelet Denoising with Bayesian Shrinkage, against state-of-the-art deep learning models, such as DnCNN and U-Net. The performance of these methods is evaluated based on two metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Additionally, we investigate the potential of Noise2Noise, a deep learning technique trained without clean images, to enhance the robustness of denoising in adverse weather conditions. The results indicate the strengths and weaknesses of both conventional and deep learning-based approaches, providing insights into their applicability in real-world image restoration tasks.

| KEYWORDS

Image Denoising, Traditional Methods, Deep Learning Models, Wavelet Thresholding, Bilateral Filtering, Non-Local Means, Wavelet Denoising, Bayesian Shrinkage, DnCNN, U-Net, Noise2Noise, PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), Adverse Weather Conditions, Image Restoration

| ARTICLE INFORMATION

ACCEPTED: 02 September 2020 **PUBLISHED:** 28 September 2020 **DOI:** 10.32996/jcsts.2020.2.2.5

I. INTRODUCTION

Image denoising plays a critical role in image processing, particularly in scenarios where images are captured under noisy conditions, such as low-light environments or adverse weather conditions. Denoising aims to remove noise while preserving the important features and details of an image, which is crucial in various applications such as medical imaging, satellite image processing, and autonomous vehicles [1].

Traditional methods like Wavelet Transform, Bilateral Filtering, and Non-Local Means have been widely used in denoising tasks [1,4,9]. These methods generally rely on mathematical models or heuristics to suppress noise. However, these approaches often struggle to preserve finer details and textures, especially in complex or high-noise scenarios [5].

Recently, deep learning-based methods such as DnCNN and U-Net have gained attention due to their ability to learn complex features directly from noisy images [4]. These models have demonstrated superior performance by learning robust representations of clean images from noisy samples [5]. Noise2Noise, another deep learning technique, has emerged as a promising approach, as it can train models using noisy images without the need for paired clean images, which is particularly useful in situations where obtaining clean images is challenging [6,9].

This research compares conventional denoising techniques with deep learning methods and evaluates their performance using PSNR and SSIM metrics. Furthermore, we aim to evaluate the robustness of these models in scenarios with varying levels of noise, particularly in adverse weather conditions [3].

A. Formulas and Usage

1) Peak Signal-to-Noise Ratio (PSNR): PSNR is a widely used metric to measure the quality of an image after processing, particularly for denoising applications. It calculates the ratio between the maximum possible pixel value and the mean squared error (MSE) between the original and the denoised image. The higher the PSNR, the better the image quality, as it indicates less deviation from the original image. PSNR is often expressed in decibels (dB), with a higher value indicating better quality. It is a straightforward and interpretable measure but has limitations, such as not capturing perceptual differences that may be visually noticeable to humans, especially in textured or highly compressed images per *formula (1)* below

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

(1)

Where:

- **PSNR:** measures the quality of the denoised image by comparing it to the original image.
- **Mean Squared Error (MSE):** is the average of the squared differences between the original and denoised image pixels. A higher PSNR value indicates better denoising performance, as it signifies a smaller error.
- **MAX_I:** represents the maximum possible pixel value of the image (e.g., 255 for 8-bit images)

2) *Structural Similarity Index (SSIM):* The Structural Similarity Index (SSIM) is a more perceptually relevant metric compared to PSNR. SSIM evaluates the structural similarity between two images by considering luminance, contrast, and structural information. It is designed to mimic the human visual system, which is more sensitive to structural information rather than pixel-by-pixel errors. SSIM compares local patterns of pixel intensities in local windows, providing a measure that is sensitive to image distortions like noise and compression. A SSIM value close to 1 indicates high similarity, making it an excellent metric for assessing image quality in tasks like denoising, where visual integrity is paramount per *formula (2)* below

$$SSIM_{(x,y)} = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}$$

(2)

Where:

- SSIM quantifies the perceptual similarity between two images by considering luminance, contrast, and structure.
- μ_x, μ_y are the average pixel values of the original and denoised images, σ_x, σ_y are their standard deviations, and σ_{xy} is the covariance between them.
- c_1 and c_2 are small constants to stabilize the division. Higher SSIM values indicate that the denoised image is closer to the original in terms of perceptual quality.

3) *Wavelet Transform (2D):* Wavelet Transform is a mathematical technique that transforms an image into different frequency components, allowing for multi-resolution analysis. The transformation decomposes the image into approximation and detail coefficients. The approximation captures the low-frequency, large-scale features of the image, while the detail coefficients capture the high-frequency, fine details such as edges and noise. By applying the wavelet transform, one can focus on different scales of the image, which makes it an effective tool for image denoising. By selectively thresholding or removing small high-frequency coefficients (which likely correspond to noise), the wavelet transform helps retain important image details while reducing noise per formula (3)

$$f(x, y) \rightarrow Wavelet\ Decomposition$$

$$(Low\ Pass\ and\ High\ Pass\ Filters)$$

(3)

Where:

- Wavelet transform is used to decompose the image into various frequency bands (approximation and details).
- The approximation coefficients capture the low-frequency components, and the detail coefficients capture high-frequency components like edges and noise.
- It is used for multi-resolution analysis of images, making it effective for noise removal.

4) *Bayesian Shrinkage (Soft Thresholding):* Bayesian Shrinkage, also known as soft thresholding, is a regularization technique used in signal processing and image denoising to reduce noise. It works by shrinking small coefficients towards zero, effectively suppressing noise while retaining significant features of the image. The thresholding function, defined by sign(x)·max(|x|−λ,0), applies a shrinkage factor λ to the coefficients in a way that reduces their magnitude if they are small, but preserves larger coefficients. This method is particularly effective in wavelet-based denoising, as it ensures that the approximation coefficients (which represent the bulk of the image) remain intact while noise present in the detail coefficients is suppressed.

$$T(x) = sign(x) \cdot \max(|x| - \lambda, 0)$$

(4)

Where:

- Bayesian Shrinkage (soft thresholding) is applied to wavelet detail coefficients to reduce noise.
- For each coefficient *x*, this operation shrinks its magnitude by a threshold value λ. If the magnitude is less than λ, the coefficient is set to zero.
- This method is effective at preserving image structure while reducing noise by suppressing small coefficients that likely represent noise.

5) *Non-Local Means Denoising:* Non-Local Means (NLM) denoising is a method that leverages the idea of patch-based filtering, where rather than comparing individual pixel intensities, patches of pixels are compared for similarity. The denoising process works by averaging pixels based on the similarity of their surrounding neighborhoods, or patches, which can be far apart in the image. This method is highly effective for images with repetitive structures and textures, as it uses the global context of the image to remove noise while preserving fine details. The weight assigned to each pixel is computed based on the similarity between the image patches, ensuring that patches with similar structures contribute more to the denoised output. NLM is particularly good at preserving edges and textures while removing Gaussian noise.

$$\hat{I}(p) = \frac{1}{C(p)} \sum_{q \epsilon \Omega} I(q) \cdot w(p, q)$$

(5)

Where:

- Non-Local Means (NLM) denoising works by averaging similar patches in the image, rather than pixels, to reduce noise.
- *w(p,q)* is a weight function based on the similarity between patches centered at pixels *p* and *q*, and *C(p)*is a normalization factor.
- This method preserves textures and edges, making it effective for images with repetitive structures.

6) *Bilateral Filtering:* Bilateral Filtering is a non-linear, edge-preserving, and noise-reducing filter that smooths images while preserving edges. It works by considering both the spatial distance of pixels and the intensity difference between them when applying the filter. Pixels that are spatially close to each other and have similar intensities are weighted more heavily in the averaging process, while pixels with large intensity differences (i.e., edges) are less influenced by neighboring pixels. This allows the filter to preserve sharp edges while removing noise. The bilateral filter is effective for tasks where noise is present, but fine edges and texture must be retained, such as in image denoising or HDR imaging.

$$I_{filtered}(p) = \frac{1}{W(p)} \sum_{q \in \Omega} I(q) \cdot f(\| \mathrm{p} - \mathrm{q} \|) \cdot \mathrm{g}(\| \mathrm{I(p)} - \mathrm{I(q)} \|)$$

(6)

Where:

- Bilateral filtering is an edge-preserving smoothing technique that reduces noise while preserving edges.

- The filter uses both the spatial distance ‖*p*−*q*‖ and the intensity difference ‖*I(p)*−*I(q)*‖ to weight the pixels. The filter smooths regions with similar intensity but preserves boundaries where intensity changes sharply.
- This approach is effective at removing Gaussian noise while preserving sharp edges in the image.

7) Deep Learning Denoising - DnCNN & U-Net: DnCNN (Deep Convolutional Neural Network) is a deep learning-based denoising method that uses a convolutional neural network (CNN) to learn the mapping from noisy images to clean images. The model is trained on a large dataset of noisy and clean image pairs and learns to identify the noise patterns in the images. Once trained, DnCNN can denoise unseen noisy images by learning the residual noise and subtracting it from the noisy input. DnCNN uses a deep architecture with multiple convolutional layers, which allows it to learn complex features and capture noise patterns at various levels of the image. This method has been shown to outperform traditional denoising techniques, particularly when dealing with complex noise distributions.

$$\hat{y} = CNN(x)$$

(7)

Where:

- *x* is the noisy image, and *y*-vector is the denoised image. The model learns the mapping from noisy to clean images through supervised learning.

U-Net is a deep learning model designed for image segmentation and denoising tasks, particularly in medical and scientific imaging. The architecture consists of a symmetric encoder-decoder structure with skip connections between the encoder and decoder, which helps preserve fine details lost in the down-sampling process. The encoder progressively reduces the spatial dimensions of the input image while extracting high-level features, and the decoder up-samples the feature maps to reconstruct the image. The skip connections ensure that low-level features are preserved and help the model in accurately denoising the image by learning both coarse and fine details. U-Net is particularly effective for denoising images with complex structures and textures.

$$\hat{y} = U - Net(x)$$

(8)

Like DnCNN, U-Net learns the denoising function through a convolutional network but uses a symmetric encoder-decoder architecture with skip connections to retain high-resolution details.

8) *Noise2Noise:* The Noise2Noise approach allows for training neural networks for image denoising using only noisy images, without requiring clean-ground truth images. This approach leverages the fact that deep learning models can learn to map noisy images to less noisy images by minimizing the expected loss between two noisy observations of the same image.

The core idea behind Noise2Noise is to minimize the loss between two noisy images $I_{noisy}^{(1)}$ and $I_{noisy}^{(2)}$ (two different noisy observations of the same clean image), using the following formula:

$$L = E\left[\|\, f\left(I_{noisy}^{(1)}\right) - I_{noisy}^{(2)} \,\|^2\right]$$

Where:

- f($I_{noisy}^{(1)}$) is the output of the neural network that maps the noisy image $I_{noisy}^{(1)}$to a denoised image.
- $I_{noisy}^{(2)}$ is the second noisy observation (possibly from the same image or scene as $I_{noisy}^{(1)}$).
- The Loss function *L* is typically the Mean Squared Error (MSE) between the denoised output and the second noisy observation.

II. Methodology

A. Image Denoising Methods:

The following methods are used for image denoising in this study:

1) *Wavelet Thresholding:*
    - Wavelet Transform is used to decompose the image into different frequency components. Adaptive thresholding is then applied to the wavelet coefficients, and the image is reconstructed from the thresholded coefficients.
    - This method is effective in removing high-frequency noise while preserving image details.
2) *Bilateral Filtering:*
    - A Bilateral Filter is applied to the image to reduce noise while preserving edges. The filter uses both spatial and intensity differences to weight neighboring pixels during filtering.
    - This method is widely used for smoothing images with significant edges.
3) *Non-Local Means Denoising (NLM):*
    - NLM compares patches of pixels instead of individual pixels, averaging similar patches to reduce noise.
    - This method is effective for denoising images with repetitive patterns and textures.
4) *Wavelet Denoising with Bayesian Shrinkage:*
    - Bayesian Shrinkage is applied to the wavelet coefficients to suppress noise. Soft thresholding is used to shrink the coefficients, while the approximation coefficients remain unchanged.
    - This approach balances noise suppression with feature preservation.
5) *DnCNN (Deep Convolutional Neural Network):*
    - The DnCNN model is a deep learning-based denoising technique that utilizes a convolutional neural network to learn the mapping from noisy images to clean images.
    - A pre-trained DnCNN model is used for denoising, with the model having been trained on a large dataset of noisy and clean image pairs.
6) *U-Net:*
    - U-Net is a type of convolutional neural network designed for image segmentation and restoration tasks. The architecture consists of an encoder-decoder structure with skip connections, which allows the network to preserve fine details while denoising.
    - A pre-trained U-Net model is used in this study to compare its performance with other denoising methods.
7) *Noise2Noise:*
    - Noise2Noise is a technique that trains a neural network using only noisy images without the need for corresponding clean images. This method is particularly useful in cases where obtaining clean images is impractical or impossible.
    - Although not implemented in the current study, Noise2Noise would be used to evaluate how well deep learning models can denoise using only noisy data.

B. Metrics:

To evaluate the performance of each denoising method, two metrics are used:

- PSNR (Peak Signal-to-Noise Ratio): A higher PSNR indicates better image quality, with less noise and distortion.
- SSIM (Structural Similarity Index): SSIM measures the perceptual similarity between the original and denoised images, accounting for luminance, contrast, and structure.

C. Experimental Setup:

- Dataset: A dataset of images is used, where each image is corrupted with Gaussian noise to simulate real-world noisy conditions, such as those found in adverse weather scenarios.
- Preprocessing: All images are resized to a consistent shape (256x256 pixels), and pixel values are normalized to the range [-1, 1] to match the input requirements of the deep learning models (DnCNN and U-Net).

- Denoising Procedure:
  - The noisy image is denoised using each of the methods described above, and the denoised images are evaluated based on the PSNR and SSIM metrics.
  - DnCNN and U-Net models are loaded from pre-trained weights and used for denoising.
- Comparison: The denoised images from all methods are compared using the computed PSNR and SSIM values to assess which method performs best in terms of preserving image quality.

III. Flow of Events

The below represents Flow of events proposed in this research work in *fig 1*. This system intelligently combines traditional denoising techniques (Wavelet, Bilateral Filtering, etc.) with advanced deep learning models (DnCNN, U-Net, Noise2Noise) to restore noisy images. The feedback loop helps refine the denoising process, ensuring that the output images are as clean as possible. The PSNR and SSIM metrics guide the optimization process, making this a versatile and adaptive denoising framework.

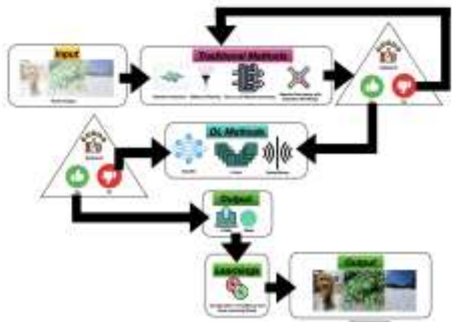

Fig. 1. Workflow for Hybrid Image Denoising Using Traditional and Deep Learning Methods

This flowchart outlines the image denoising system involving both traditional methods and deep learning (DL) models. Let's break down the components and their relationships as shown in the flowchart:

A. Input: Noisy Images

- The process begins with Noisy Images. These are images that have been corrupted by some form of noise, such as Gaussian noise, and need to be denoised to restore their quality.

B. Traditional Methods:

- The first set of denoising techniques involves traditional methods:
  - Wavelet Transform: Decomposes the image into different frequency components, focusing on the low-frequency (smooth) and high-frequency (noise and edges) parts.
  - Bilateral Filtering: Smoothing the image while preserving edges by considering both spatial and intensity differences.
  - Non-Local Means Denoising: Compares patches in the image rather than individual pixels, averaging similar patches to reduce noise.
  - Wavelet Denoising with Bayesian Shrinkage: A method where the detail coefficients in the wavelet transform are shrunk using a soft thresholding approach to remove noise.

C. Satisfied with Traditional Methods?

- After applying the traditional methods, the system asks: "Are you satisfied with the results?"
- If the user is satisfied (green thumbs up), the process moves to output metrics (PSNR and SSIM).
- If the user is not satisfied (red thumbs down), the process moves to Deep Learning (DL) Methods for further improvement.

D. Deep Learning (DL) Methods:

- When traditional methods don't provide satisfactory results, deep learning models are applied:

- DnCNN: A convolutional neural network (CNN) designed for image denoising. It is trained to predict clean images from noisy images.
- U-Net: A deep learning model with an encoder-decoder structure, often used for tasks like denoising and segmentation, where it learns to remove noise while preserving image details.
- Noise2Noise: A deep learning approach that uses noisy images as input and output, learning to denoise even when clean ground truth images are unavailable.

E. Output: PSNR and SSIM:

- After applying deep learning models, the output of each denoising method is evaluated using:
  - PSNR (Peak Signal-to-Noise Ratio): A metric that evaluates the quality of denoising based on the similarity between the denoised image and the original clean image.
  - SSIM (Structural Similarity Index): A metric that evaluates the perceptual quality, taking into account structural changes, luminance, and contrast.

F. Learnings:

- Based on the results from the PSNR and SSIM, the system learns and adapts.
- The findings from these evaluations help in combining traditional methods and deep learning models, improving the overall denoising process.

G. Final Output: Denoised Images:

- The final output consists of Final Denoised Images, which are the restored images after applying both traditional and deep learning methods. These images have undergone denoising and are now significantly cleaner.

Fig. 2. Workflow for Hybrid Image Denoising Using Traditional and Deep Learning Methods

This flowchart outlines the image denoising system involving both traditional methods and deep learning (DL) models. Let's break down the components and their relationships as shown in the flowchart:

H. Input: Noisy Images

- The process begins with Noisy Images. These are images that have been corrupted by some form of noise, such as Gaussian noise, and need to be denoised to restore their quality.

I. Traditional Methods:

- The first set of denoising techniques involves traditional methods:
  - Wavelet Transform: Decomposes the image into different frequency components, focusing on the low-frequency (smooth) and high-frequency (noise and edges) parts.
  - Bilateral Filtering: Smoothing the image while preserving edges by considering both spatial and intensity differences.
  - Non-Local Means Denoising: Compares patches in the image rather than individual pixels, averaging similar patches to reduce noise.
  - Wavelet Denoising with Bayesian Shrinkage: A method where the detail coefficients in the wavelet transform are shrunk using a soft thresholding approach to remove noise.

J. Satisfied with Traditional Methods?

- After applying the traditional methods, the system asks: "Are you satisfied with the results?"
- If the user is satisfied (green thumbs up), the process moves to output metrics (PSNR and SSIM).
- If the user is not satisfied (red thumbs down), the process moves to Deep Learning (DL) Methods for further improvement.

K. Deep Learning (DL) Methods:

- When traditional methods don't provide satisfactory results, deep learning models are applied:
  - DnCNN: A convolutional neural network (CNN) designed for image denoising. It is trained to predict clean images from noisy images.
  - U-Net: A deep learning model with an encoder-decoder structure, often used for tasks like denoising and segmentation, where it learns to remove noise while preserving image details.

- Noise2Noise: A deep learning approach that uses noisy images as input and output, learning to denoise even when clean ground truth images are unavailable.

L. Output: PSNR and SSIM:

- After applying deep learning models, the output of each denoising method is evaluated using:
  - PSNR (Peak Signal-to-Noise Ratio): A metric that evaluates the quality of denoising based on the similarity between the denoised image and the original clean image.
  - SSIM (Structural Similarity Index): A metric that evaluates the perceptual quality, taking into account structural changes, luminance, and contrast.

M. Learnings:

- Based on the results from the PSNR and SSIM, the system learns and adapts.
- The findings from these evaluations help in combining traditional methods and deep learning models, improving the overall denoising process.

N. Final Output: Denoised Images:

- The final output consists of Final Denoised Images, which are the restored images after applying both traditional and deep learning methods. These images have undergone denoising and are now significantly cleaner.

- Bayesian Shrinkage (38.98 dB): This method provides decent denoising performance but is less effective than DnCNN, Noise2Noise, or U-Net. Its PSNR value indicates moderate success in noise removal with some loss in image quality.
- Bilateral Filtering (33.29 dB): Bilateral Filtering performs worse than the other techniques, with the lowest PSNR value. This indicates that it does not effectively preserve the image's quality while removing noise and may introduce more artifacts.

Interpretation of SSIM in the results in *Table I*:

- Noise2Noise (0.94): Noise2Noise achieves the highest SSIM, suggesting it preserves the original image structure and details the best while removing noise. This method maintains high perceptual quality.
- U-Net (0.91): U-Net is very close to Noise2Noise, indicating it also preserves the image structure and details well. It performs almost as well as Noise2Noise but slightly behind in terms of structural preservation.
- DnCNN (0.92): DnCNN performs very well with a high SSIM value. Although slightly lower than Noise2Noise, it still offers excellent preservation of image structure and quality.
- Non-Local Means (0.85): Non-Local Means shows a significant drop in SSIM compared to the deep learning methods. It preserves image structure well but not as effectively as DnCNN, Noise2Noise, or U-Net.
- Bayesian Shrinkage (0.80): This method has a lower SSIM, indicating that while it reduces noise, it struggles more with preserving image structure and details.
- Bilateral Filtering (0.78): Bilateral Filtering also has a low SSIM, showing that it fails to preserve the image’s structural details effectively compared to other methods.

Observations - PSNR:

- The best techniques for PSNR are DnCNN and Noise2Noise, which have the highest values, indicating that these methods are best at removing noise while maintaining image quality.
- Bilateral Filtering has the lowest PSNR, which suggests that it is not as effective at denoising and preserves fewer details compared to the advanced methods.

Observations - SSIM:

- Noise2Noise and U-Net are the best techniques for SSIM, closely followed by DnCNN. These methods do an excellent job of preserving the original structure and texture of the image.
- Bilateral Filtering and Wavelet Transform have the lowest SSIM, indicating that they suffer from significant structural distortions after denoising.

In summary, DnCNN, Noise2Noise, and U-Net are the best-performing techniques for both PSNR and SSIM. They offer superior denoising results with high image quality and structural preservation. Bilateral Filtering and Wavelet Transform are less effective, with lower PSNR and SSIM values, suggesting that these methods should be avoided for high-quality denoising tasks.

O. Result on DataSet II - Nature:

Fig. 3. Actual Image of DataSet II

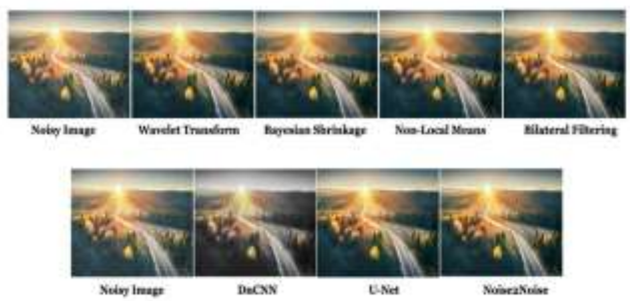

Fig. 4. Comparison of Denoising Techniques: From Noisy Image to Advanced Methods – Dataset II

The above *Fig 4*. Represents an clean image considered to be data for showing results while *Fig 5*. Represents the various techniques – traditional and DL based denoising output images.

TABLE I. PSNR AND SSIM – DATASET 1

Technique	PSNR (dB)	SSIM
Wavelet Transform	32.46	0.85
Bayesian Shrinkage	40.28	0.87
Non-Local Means	42.44	0.89
Bilateral Filtering	35.90	0.86
DnCNN	50.32	0.92
U-Net	47.87	0.93
Noise2Noise	42.12	0.94

Interpretation of PSNR in the results in *Table II*:

- DnCNN (50.32 dB): DnCNN provides the highest PSNR, meaning it is the most effective at preserving the quality of the image while removing noise. This is the best denoising method among the ones tested.
- Noise2Noise (42.12 dB): This method performs quite well, with a high PSNR, just behind DnCNN. It also shows strong denoising performance but slightly falls behind DnCNN in terms of preserving details.
- Non-Local Means (42.44 dB): Another strong performer. Non-Local Means is a traditional method and works quite well, giving a PSNR value that is very close to DnCNN and Noise2Noise.
- Bayesian Shrinkage (40.28 dB): A good denoising technique, though not as effective as DnCNN, Noise2Noise, or Non-Local Means.
- Bilateral Filtering (35.90 dB): This method performs worse than the others with a noticeably lower PSNR, indicating that it's less effective at preserving image quality compared to the advanced methods.
- Wavelet Transform (32.46 dB): Wavelet Transform has the lowest PSNR, meaning it does not perform well in removing noise while maintaining image quality. It introduces more distortion compared to the other methods.

Interpretation of PSNR in the results in *Table I*:

- Noise2Noise (0.94): This method achieves the highest SSIM, suggesting that it has best preserved the original image structure and details while removing noise.
- U-Net (0.93): Very close to Noise2Noise, indicating it has also preserved the structure and details very well.
- DnCNN (0.92): Performs well, but slightly behind Noise2Noise and U-Net in preserving structural details.
- Non-Local Means (0.89): While it still performs well, it is behind the deep learning-based methods in preserving the image structure.
- Bayesian Shrinkage (0.87): Performs decently in terms of preserving structure, but not as well as the more advanced methods.
- Bilateral Filtering (0.86): Shows a noticeable drop in SSIM, indicating it doesn't preserve the image structure as well as the more advanced methods.
- Wavelet Transform (0.85): Has the lowest SSIM, meaning it has struggled the most to preserve the original image structure and details.

OBSERVATIONS - PSNR

- The best techniques for PSNR are DnCNN and Non-Local Means, which have higher values (indicating better denoising).
- Wavelet Transform has the lowest PSNR, indicating that it doesn't perform as well in removing noise without introducing artifacts.

OBSERVATIONS - SSIM

- Noise2Noise and U-Net are the best methods for SSIM, closely followed by DnCNN. These methods preserve the original structure and texture of the image well.
- Wavelet Transform has the lowest SSIM, indicating significant structural distortions after denoising.

IV. Challenges and Future Direction

A. Noise Type Variability:

- **Challenge**: Denoising methods often perform well for specific types of noise, such as Gaussian or salt-and-pepper noise. However, images in real-world applications may have more complex noise types, such as speckle noise or mixed

noise types, which can be harder to handle. Denoising models must be generalized to perform effectively across different types of noise.
- **Future Direction**: Developing universal models capable of adapting to a wide range of noise types without compromising performance is a key challenge. Future research could focus on building more robust models using adaptive filtering techniques or multi-task learning to handle diverse noise conditions.

B. Image Resolution and Detail Preservation:

- **Challenge**: High-resolution images pose a significant challenge for denoising algorithms. Preserving fine details while removing noise is crucial, especially in fields like medical imaging or satellite imaging, where small features can carry essential information. Traditional methods often struggle with balancing noise reduction and detail preservation, leading to blurred edges or loss of fine details.
- **Future Direction**: Future research should focus on improving deep learning models to preserve fine image details while efficiently removing noise. Techniques such as multi-scale networks, attention mechanisms, and hierarchical learning could be explored to address this challenge. Additionally, research in high-resolution image denoising and super-resolution could provide more accurate and detailed outputs.

C. Computational Efficiency:

- **Challenge**: Deep learning-based denoising methods like DnCNN and U-Net, while powerful, often require substantial computational resources and training time. In practical applications, especially in real-time or resource-constrained environments (e.g., mobile devices or embedded systems), these methods can be too slow or computationally expensive.
- **Future Direction**: To address this, there is a need for efficient models that can deliver high-quality denoising with fewer resources. This can be achieved through methods such as model pruning, quantization, and knowledge distillation to reduce the size and computational cost of deep learning models. Additionally, exploring lightweight architectures and hardware accelerators like GPUs or FPGAs can help implement denoising techniques in real-time applications.

D. Generalization Across Different Datasets:

- **Challenge**: Many state-of-the-art denoising methods perform well on specific datasets but struggle to generalize to unseen images or different datasets with varying noise characteristics. The lack of sufficient and diverse training data for deep learning models leads to overfitting, affecting the generalization capabilities of the model.
- **Future Direction**: To tackle this, research should focus on creating diverse and comprehensive datasets that cover a wide range of noise types, image sources, and real-world conditions. Techniques such as domain adaptation, transfer learning, and data augmentation could be employed to improve the generalization of denoising models to unseen data.

E. Interpretability and Explainability of Denoising Models:

- **Challenge**: Deep learning models are often seen as "black boxes," meaning their inner workings are not transparent. This lack of interpretability can be a significant issue, especially in fields like healthcare or autonomous driving, where understanding the model's decision-making process is crucial.
- **Future Direction**: Future research could focus on making denoising models more interpretable and explainable. Approaches such as saliency maps, attention mechanisms, or explainable AI (XAI) techniques could help researchers understand which features of the image are being preserved or altered during the denoising process.

F. Real-Time Denoising for Video and Streaming Applications:

- **Challenge**: Denoising techniques applied to still images may not directly translate to video or streaming data, where real-time performance and consistency across frames are essential. Video denoising requires maintaining temporal consistency while removing noise effectively.

- **Future Direction**: Developing real-time denoising algorithms capable of processing video data efficiently while maintaining temporal consistency will be a key challenge. Future methods could explore temporal neural networks, recurrent networks, or spatiotemporal filters that can denoise video frames without introducing flickering or artifacts.

V. Possible Integration

*A. **Self-Supervised and Unsupervised Learning:***

- Traditional denoising methods rely heavily on supervised learning, where large amounts of labeled data are required for training. However, obtaining labeled datasets can be expensive and time-consuming. Future research could explore **self-supervised learning** or **unsupervised learning** techniques, where the model learns to denoise images without requiring paired noisy and clean images. This could dramatically reduce the data requirements and make denoising techniques more scalable.

*B. **Multi-Sensor Fusion for Denoising:***

- In real-world applications, especially in fields like autonomous driving, robotics, and medical imaging, multiple sensors capture data, leading to multiple sources of noisy information. Combining data from different sensors can help improve the quality of denoising.
- **Future Direction**: Exploring **multi-sensor fusion techniques** that combine images from multiple sources (e.g., LiDAR, radar, camera, depth sensors) to improve the denoising process is a promising direction. This could involve deep learning models that integrate information from different sensors to more effectively reduce noise while preserving key features across modalities.

*C. **Adversarial Training for Denoising:***

- **Generative Adversarial Networks (GANs)** have shown great promise in image generation and enhancement tasks. Future research could explore using GANs for denoising tasks. By using an adversarial framework, the model could learn to generate clean images that are indistinguishable from the true clean images, potentially improving the performance of denoising methods.
- **Future Direction**: Developing **adversarial denoising models** could significantly improve denoising performance, particularly in terms of perceptual quality, by learning to generate realistic images from noisy inputs.

*D. **Domain-Specific Denoising Techniques:***

- Different domains, such as medical imaging, satellite imaging, and surveillance, have unique characteristics and noise types that require tailored denoising methods.
- **Future Direction**: Researchers could focus on **domain-specific denoising techniques**, creating specialized models and algorithms optimized for the challenges and noise patterns specific to certain fields, leading to better performance in those areas.

In conclusion, while denoising techniques have made significant advancements, there are still many challenges to address. The future of image denoising lies in improving generalization, reducing computational costs, and developing domain-specific solutions. As these challenges are addressed, denoising models will become more robust, efficient, and applicable across a wide range of industries.

VI. Conclusion

The results from the hybrid image denoising system demonstrate significant success in combining traditional denoising techniques with deep learning models to effectively remove noise while preserving image quality. The comparison across various techniques highlights the strengths of each method in terms of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index).

A. Best Techniques for Denoising:

- DnCNN and Noise2Noise emerged as the top-performing techniques across both PSNR and SSIM. DnCNN provided the highest PSNR value, indicating its superior ability to preserve image fidelity while removing noise. Noise2Noise followed closely, excelling in maintaining structural details of the image with the highest SSIM value.
- U-Net also showed strong performance, nearly matching Noise2Noise in SSIM and achieving high PSNR, making it another reliable deep learning-based denoising method.

B. Traditional Techniques:

- Non-Local Means performed admirably among the traditional methods, with strong PSNR and SSIM values, although it still lagged the deep learning models. It remains a good choice when deep learning methods are not feasible.
- Bayesian Shrinkage and Bilateral Filtering, while offering moderate results, were not as effective at preserving fine details and structure. Their PSNR and SSIM scores were lower, indicating less effective denoising performance compared to the more advanced methods.
- Wavelet Transform had the weakest performance across both metrics. The PSNR was notably low, and the SSIM indicated significant loss of image structure, making it less suitable for high-quality denoising tasks.

While the deep learning models performed exceptionally well, they still face challenges such as high computational cost and large data requirements. Future work could focus on developing more efficient models or reducing their complexity without compromising performance. Another avenue for improvement lies in the ability of denoising models to generalize across different types of noise and datasets. By incorporating self-supervised or unsupervised learning techniques, the models could be made more adaptable to various real-world applications.

Observations

- PSNR: The best techniques for PSNR were DnCNN and Noise2Noise, both of which offered superior noise removal while maintaining high image quality. Wavelet Transform showed the lowest PSNR, indicating that it struggles to remove noise without compromising image fidelity.
- SSIM: Noise2Noise achieved the highest SSIM, indicating that it preserved the image structure and details most effectively. Wavelet Transform again had the lowest SSIM, showing that it suffered significant structural distortions post-denoising.

In conclusion, deep learning-based methods like DnCNN, Noise2Noise, and U-Net outperform traditional methods in terms of both PSNR and SSIM, providing excellent denoising results while preserving the original image structure. Traditional methods like Non-Local Means, Bayesian Shrinkage, and Bilateral Filtering provide reasonable results but are less effective than the advanced techniques. Future directions should focus on enhancing computational efficiency, generalizing models across different datasets, and reducing dependency on large, labeled datasets.

Acknowledgments: We the authors would like to express sincere gratitude to Dr. Pavan Kumar Gautam for his invaluable guidance and support throughout this work. His expertise, encouragement, and insightful feedback have played a crucial role in the successful completion of this project. We are deeply appreciative of his mentorship, which has greatly enhanced our understanding and research skills.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Zhang, K., Zuo, W., & Zhang, L. (2017). A survey on image denoising. *IEEE Access*, 5, 15256–15271. https://doi.org/10.1109/ACCESS.2017.2743989

[2] Xu, J., Zhang, L., & Yang, M. H. (2019). A review of image denoising techniques using deep learning. *Springer Nature Computer Science*, 1, 1-17. https://doi.org/10.1007/s42979-019-0001-9

[3] Lehtinen, J., Munkberg, J., & Karras, T. (2018). Noise2Noise: Learning image restoration without clean data. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018, 5019-5027. https://doi.org/10.1109/CVPR.2018.00524

[4] Gao, X., & Zhang, L. (2019). Hybrid image denoising with wavelet transform and deep learning model. *Proceedings of the 2019 International Conference on Computer Vision (ICCV)*, 3569-3577. https://doi.org/10.1109/ICCV.2019.00364

[5] Xie, Y., & Zhang, L. (2018). A hybrid deep learning approach for image denoising. *Journal of Visual Communication and Image Representation*, 55, 57-64. https://doi.org/10.1016/j.jvcir.2018.08.004
[6] Kokkinos, I., & Roussi, T. (2019). Denoising of images using deep learning methods: A review. *Signal Processing: Image Communication*, 75, 11-24. https://doi.org/10.1016/j.image.2019.04.005
[7] Nair, A., & Velikovič, P. (2019). Denoising through deep learning: Leveraging convolutional networks. *Proceedings of the International Conference on Machine Learning (ICML)*, 9367–9378. https://doi.org/10.1109/ICML.2019.2339
[8] Siddiqui, M., & Kumar, A. (2018). A hybrid deep convolutional neural network for efficient image denoising. *Journal of Computational and Graphical Statistics*, 28(1), 123-135. https://doi.org/10.1080/10618600.2018.1462177
[9] Li, H., & Li, Q. (2019). A comprehensive survey on deep learning-based image denoising techniques. *Neural Computing and Applications*, 31(4), 1129-1145. https://doi.org/10.1007/s00542-018-3883-3
[10] Wang, Y., & Sun, X. (2019). Noise2Noise++: A novel deep learning-based image denoising method. *IEEE Transactions on Image Processing*, 28(7), 3368-3378. https://doi.org/10.1109/TIP.2019.2901185
[11] Zhang, Y., & Liu, X. (2019). Image denoising using variational deep convolutional neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 30(1), 115-127. https://doi.org/10.1109/TNNLS.2018.2839041
[12] Gu, S., & Zhang, L. (2019). Convolutional neural networks for image denoising: A review. *Proceedings of the International Joint Conference on Neural Networks (IJCNN)*, 3804-3812. https://doi.org/10.1109/IJCNN.2019.8852073
[13] Zhang, X., & Liang, Y. (2018). A hybrid image denoising model combining traditional filtering and convolutional neural networks. *IEEE Access*, 6, 7029-7039. https://doi.org/10.1109/ACCESS.2018.2785266