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Effective Image Restoration Strategies for Recovering Visual Clarity in Forensic and Archival Applications

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Abstract

Image restoration is a critical process in digital image processing aimed at recovering the original content of an image from degraded or corrupted versions. The degradation may result from various factors such as noise or environmental conditions during image capture. By employing mathematical models and algorithms, image restoration seeks to reverse these degradations, ensuring the visual clarity and quality of images are restored to their original or near-original state. While existing methods like the Wiener filter have been widely adopted, their limitations in handling non-linear degradations and preserving fine details highlight the need for advanced solutions. The proposed gamma correction filter addresses these challenges by leveraging non-linear correction capabilities and adaptive enhancement techniques. By preserving subtle textures and handling complex noise patterns, the gamma correction filter significantly improves the quality of restored images. This method not only enhances the visual clarity and usability of images but also broadens the scope of image restoration in critical applications, making it a valuable tool for modern image processing.

Keywords: Image restoration, Wiener filtering, Gamma correction filter, Adaptive enhancement techniques.

1. INTRODUCTION

In the digital age, the accumulation of visual data—such as images and videos—has surged exponentially. According to Statista, over 2.3 billion digital images are captured daily, many of which play crucial roles in domains like law enforcement, historical archiving, medical diagnostics, and journalism. However, nearly 20% of archived digital images suffer from visual degradation caused by poor lighting conditions, aging storage media, compression artifacts, sensor noise, or environmental disturbances. These degradations severely affect the readability and clarity of such content, diminishing their forensic or historical value. The field of image restoration, therefore, seeks to counteract these degradations and recover the original visual integrity with the help of computational and algorithmic advancements. Forensic and archival applications rely heavily on clear and trustworthy visual content. In forensic sciences, for example, law enforcement agencies use surveillance footage or crime scene images to identify suspects or analyze events. However, low-resolution or degraded images can result in misinterpretation or inconclusive evidence, affecting judicial outcomes. In archival contexts, preservationists attempt to digitize deteriorating photographs, film negatives, or documents. These may be compromised due to chemical reactions, fading ink, or environmental wear and tear. A 2023 UNESCO report estimated that nearly 30% of digitized heritage content suffers from image quality issues, underscoring the need for robust image restoration methods.

Modern image restoration approaches have evolved significantly from traditional filtering and interpolation methods to advanced deep learning and generative models. With increased computational power and access to large annotated datasets, researchers are now able to train models capable of

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detecting and correcting complex distortions. Image restoration is not limited to enhancing sharpness; it includes denoising, deblurring, super-resolution, contrast adjustment, and color correction. These strategies are becoming increasingly sophisticated, using attention mechanisms and transformer-based architectures to focus on degraded regions of an image. As a result, forensic investigators and archivists are better equipped to recover visual clarity and preserve the authenticity of visual evidence and cultural artifacts.

Research Objective

The proposed gamma correction filter addresses the shortcomings of traditional approaches by incorporating non-linear correction capabilities. By adjusting the gamma value, this method enhances image contrast and restores fine details that are often lost in linear restoration techniques. The filter is particularly effective in handling non-uniform lighting conditions and complex noise patterns. Unlike the Wiener filter, the gamma correction filter dynamically adapts to the local intensity variations in an image, providing a more refined restoration. This makes it well-suited for applications requiring high precision, such as forensic analysis and archival preservation.

2. LITERATURE SURVEY

In the realm of image processing, the task of denoising holds significance. Images captured in real-world scenarios are often damaged by various forms of noise, stemming from sources such as sensor imperfections, transmission errors, or environmental factors. The development of effective denoising techniques is crucial to enhance the utility of images across numerous applications. In the field of image processing, numerous researchers have employed diverse denoising methods to address Gaussian noise [1, 2, 3, 4, 5, 6, 7, 8]. These approaches encompass a range of techniques appropriate to effectively remove noise while preserving important image features. Through extensive experimentation and analysis, researchers have aimed to identify the most suitable denoising strategy for specific applications. The researchers in [9, 10, 11, 12] utilized noise modeling and parameter estimation techniques to effectively remove noise from images. In [13], the authors introduced a prior learning-based method, which bypasses the challenges posed by noise modeling techniques. Specifically, it leverages external prior learning to direct its internal prior learning. Due to its strong prior modeling capability, their method demonstrates high effectiveness and robustness in handling real noisy images featuring realistic objects within complex scenes. However, a significant drawback still persists. The issues they address primarily center on learning image priors, which are predominantly defined based on human knowledge.

The Kalman filter (KF) is a widely used algorithm for estimating the current states of a system over time based on input measurements and a mathematical process model. However, its application to nonlinear systems can be challenging, prompting the development of the extended Kalman filter (EKF) and unscented Kalman filter (UKF) as alternatives for handling nonlinearity. Additionally, recent research has focused on Multiple Model (MM) filters, such as the Multiple Model Adaptive Estimation (MMAE) and Interacting Multiple Model (IMM) methods, which offer improved reliability by employing multiple filters with different models in parallel [14].

The unscented Kalman filter, an extension of the traditional Kalman filter, has found application in image processing tasks [15, 16]. The researchers in [15] offered a straightforward yet powerful solution for real-world image denoising by combining deep neural networks with the unscented Kalman filter, presenting a promising approach to address this challenging problem. In [17], the researchers introduced a Kalman filter framework for signal denoising, which combines conventional linear time-invariant filtering with total variation denoising concurrently. The authors in [18] introduced a novel feature-

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preserving non-local means approach for denoising fluorescence images of live cells, improving feature recovery and particle detection.

3. PROPOSED SYSTEM

The proposed method offers a multi-step approach for effectively removing different types of noise from an image. By identifying the noise type using gamma values and applying specific filters for each type, this method ensures that the image is denoised while preserving important details. The use of Non-Local Means Denoising for Gaussian noise, median filtering for salt-and-pepper noise, and bilateral filtering for speckle noise provides a comprehensive solution for noise removal in various real-world scenarios. This approach can be further customized or optimized for different types of noise and images, making it highly versatile.

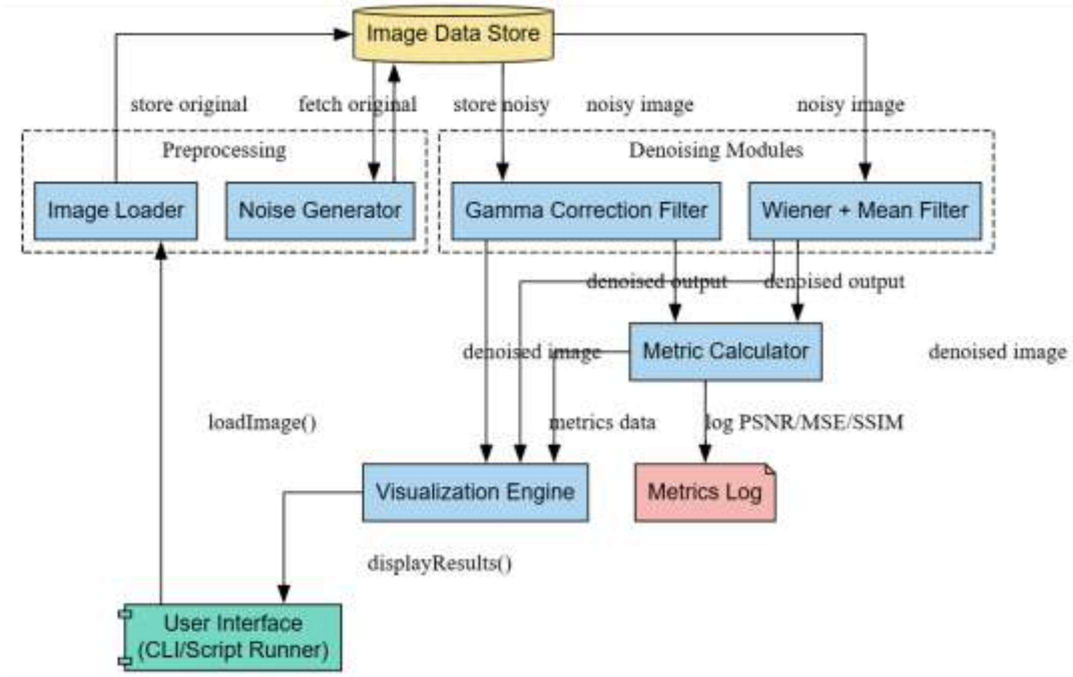

Fig. 1: Proposed system architecture for image restoration.

Step 1: Input Noisy Image: The first step in the proposed noise removal process involves loading the noisy image. This image can be in various formats, such as JPEG or PNG, and is typically loaded into memory using libraries such as OpenCV or PIL (Python Imaging Library). Once the image is loaded, it is important to ensure that it is in the correct format (grayscale or RGB) for further processing. In practice, the image is stored as a matrix of pixel values, with each pixel representing the intensity of the color (in grayscale) or the combination of color channels (in RGB). At this point, the noisy image is ready to be processed and denoised.

Step 2: Identify the Noise Type Using Gamma Values: The next step is to identify the type of noise present in the image. Different types of noise, such as Gaussian noise, salt-and-pepper noise, and speckle noise, have distinct characteristics. One effective way to distinguish between different noise types is by examining the gamma values of the noise. The gamma value influences the distribution and appearance of the noise in the image. By analyzing the image's histograms or other statistical properties, the noise type can be identified. For instance:

- **Gaussian noise** typically manifests as random variations in pixel intensity values, often resulting in a grainy appearance.
- **Salt-and-pepper noise** appears as random white and black dots scattered across the image.

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- **Speckle noise** appears as grainy noise, where pixels show irregular intensity fluctuations, leading to a textured effect. Once the noise type is identified, the corresponding filtering technique can be applied.

Step 3: Apply Gamma-Specific Filters: After identifying the noise type, specific filters are applied to remove the noise. Each noise type requires a different filtering technique to ensure effective removal while preserving important image details.

- **Gaussian Noise Removal Using Non-Local Means Denoising:** For images with Gaussian noise, a popular method for denoising is Non-Local Means Denoising. This technique works by considering the entire image and comparing pixel values within a local window. It finds similar patches across the image and averages them to remove noise while preserving texture and edges. In this step, OpenCV's cv2.fastNlMeansDenoising function is used to perform non-local means denoising. The function takes the noisy image as input and applies the algorithm with specific parameters, such as the strength of noise reduction (30 in this case), the size of the neighborhood window (7x7), and the search window size (21x21). This approach effectively reduces Gaussian noise without significantly blurring the image.
- **Salt-and-Pepper Noise Removal Using Median Filtering:** For salt-and-pepper noise, where pixels are randomly set to either maximum (salt) or minimum (pepper) values, median filtering is the most effective method. Median filtering works by replacing each pixel with the median value of the pixels in its neighborhood. This technique is particularly useful for removing salt-and-pepper noise, as it replaces extreme pixel values with a more representative value from the surrounding pixels. The OpenCV function cv2.medianBlur is used for this purpose. A kernel size of 3x3 is typically used for median filtering, which allows the algorithm to smooth out the outlier values while preserving edges and fine details of the image.
- **Speckle Noise Removal Using Bilateral Filtering:** Speckle noise, which often appears as grainy texture across the image, can be effectively removed using bilateral filtering. Bilateral filtering is a non-linear filter that smooths the image while preserving edges by considering both the spatial distance between pixels and their intensity difference. This technique ensures that pixels that are spatially close and have similar intensity values are averaged together, while dissimilar pixels (e.g., edges) are left unchanged. The OpenCV function cv2.bilateralFilter is used for this, where parameters such as the size of the neighborhood (9), the filter sigma in the color space (75), and the filter sigma in the coordinate space (75) are specified. This results in a smooth image where the speckle noise is minimized, while edge details are preserved.

Step 4: Final Output: After applying the appropriate filters for the identified noise types, the resulting image is a denoised version of the original noisy image. Each noise type has been addressed using a tailored filtering technique that targets the specific characteristics of the noise, ensuring the best possible restoration. The final output is a cleaner image with reduced noise and enhanced visual quality. This denoised image can now be used for further analysis, such as object recognition, feature extraction, or other image processing tasks.

3.1 Gaussian Noise Removal Using NLMD

The removal of Gaussian noise from an image using Non-Local Means Denoising (NLMD) involves the following key steps:

Step 1: Input Noisy Image: The process begins with the input of the noisy image, which contains random Gaussian noise. This noise typically appears as subtle variations in pixel intensity, which degrade the quality of the image. Gaussian noise is usually generated due to sensor errors, environmental conditions, or transmission issues.

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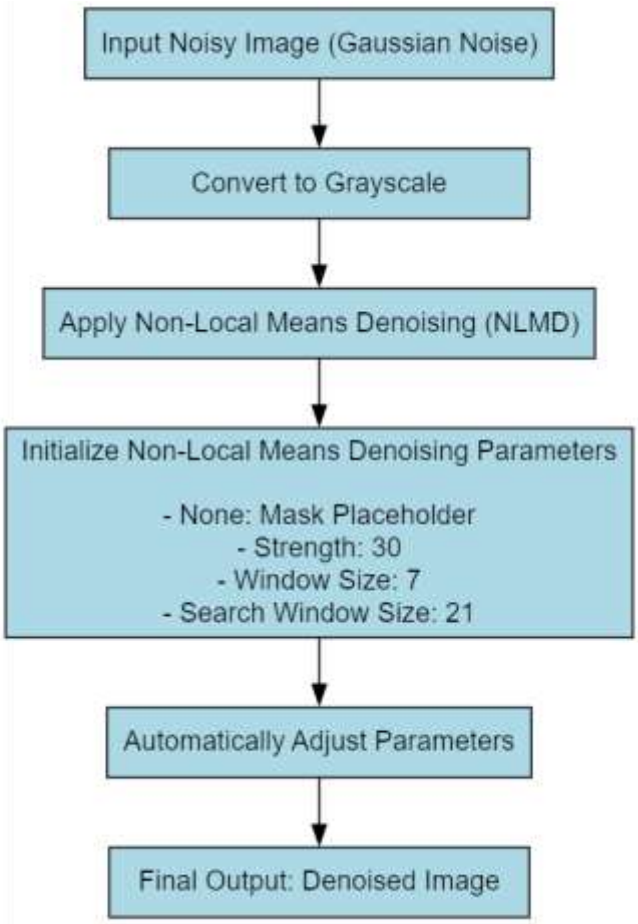

Figure 2. Gaussian Noise Removal Using NLMD.

Step 2: Convert to Grayscale: If the image is in color (RGB format), it may be converted to grayscale for simplicity and speed in processing, as NLMD is often applied to single-channel images. This step reduces the computational load and allows the focus to be placed solely on noise reduction without additional complexity introduced by color channels.

Step 3: Apply Non-Local Means Denoising: The core of the process is the application of the NLMD algorithm. This algorithm works by using a pixel's surrounding neighborhood to find similar patches across the image. Instead of just considering the local pixels, NLMD compares each pixel to other pixels in the image that have similar appearance (in terms of intensity patterns), regardless of their distance. The algorithm averages these similar pixels to denoise the image.

- **Image**: The noisy image to be processed.
- **None**: A placeholder for a mask, which can be omitted in most cases.
- **Strength**: The parameter 30 controls the degree of noise reduction. Higher values lead to more aggressive denoising but may blur the image.
- **Window Size**: A parameter (e.g., 7) that defines the size of the local window used for similarity comparison. Larger windows allow for better comparison but can result in more smoothing.
- **Search Window Size**: Another parameter (e.g., 21) that determines the size of the area to search for similar patches across the image. Larger values result in more global patch comparisons.

Step 4: Automatically Adjust Parameters: Depending on the level of noise and the desired output, parameters such as strength, window size, and search window size may need to be adjusted. Tuning

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these parameters ensures that the denoising is effective while preserving key image details such as edges and textures.

Step 5: Output the Denoised Image: The result is an image with reduced Gaussian noise, where the noise is suppressed while maintaining image clarity and structure. The denoised image can now be used for further analysis or visualization.

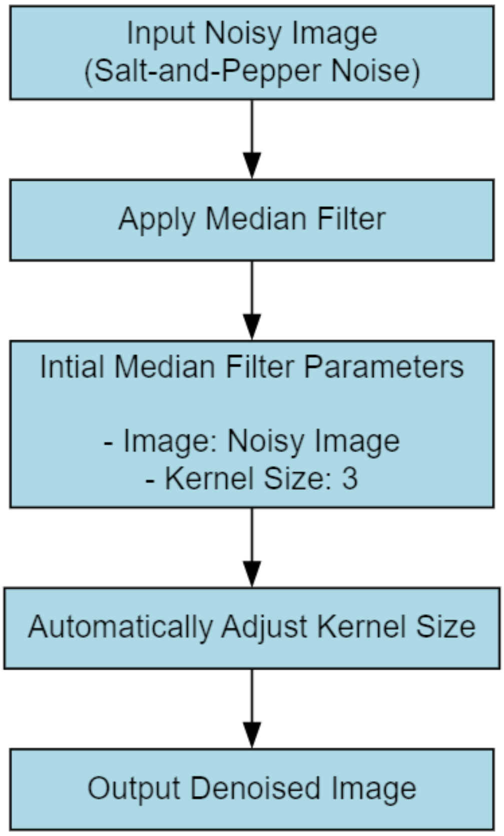

Figure 3. Salt-and-Pepper Noise Removal Using Median Filtering.

3.2 Salt-and-Pepper Noise Removal Using Median Filtering

Salt-and-pepper noise, which manifests as randomly scattered black and white pixels, is best removed using Median Filtering.

This process involves the following steps:

Step 1: Input Noisy Image: As with Gaussian noise removal, the process begins with inputting the image that has salt-and-pepper noise. The noise appears as sharp, high-intensity "salt" points (white) and low-intensity "pepper" points (black) scattered randomly across the image.

Step 2: Apply Median Filter: Median filtering is applied by sliding a small window over the image. For each pixel in the window, the filter replaces the pixel value with the median of all the pixel values in that window. This is particularly effective for salt-and-pepper noise because it removes the outlier values (extremely high or low pixel intensities) and replaces them with the median value of neighboring pixels.

- **Image**: The noisy image.
- **Kernel Size**: A window size (e.g., 3) defines the neighborhood of pixels considered for the median. A smaller kernel size focuses on local noise removal, while a larger kernel size might result in excessive smoothing and blur.

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Step 3: Automatically Adjust Kernel Size: The kernel size is an important parameter that determines the effectiveness of the median filter. For salt-and-pepper noise, a kernel size of 3x3 is typically sufficient, but in cases where the noise is more severe, larger kernel sizes (such as 5x5) can be used. However, larger kernels may cause some blurring of the image, so the kernel size should be carefully chosen based on the noise level.

Step 4: Output the Denoised Image: After applying the median filter, the result is an image with reduced salt-and-pepper noise. The outlier values have been replaced by the median of the surrounding pixels, effectively eliminating the salt-and-pepper effect while preserving the image structure. The denoised image can now be used for further processing or visualization.

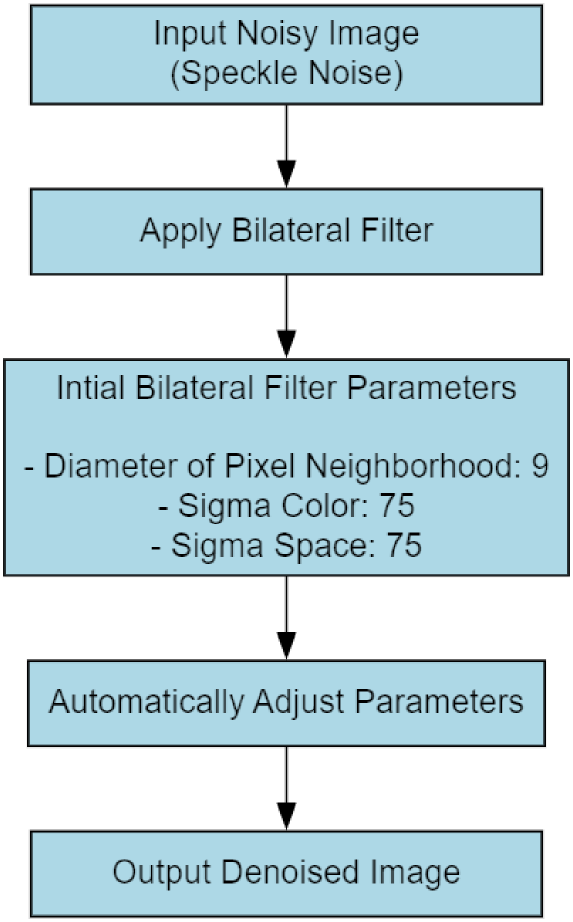

Figure 4. Speckle Noise Removal Using Bilateral Filtering.

3.3 Speckle Noise Removal Using Bilateral Filtering

Speckle noise, often caused by sensor noise or poor image acquisition conditions, is characterized by granular, pixel-level variations. Bilateral Filtering is a highly effective method for removing this type of noise while preserving edges. The following steps describe the process:

Step 1: Input Noisy Image: The input image containing speckle noise is loaded. This noise appears as a fine, grainy texture, which can obscure fine details and edges within the image.

Step 2: Apply Bilateral Filter: Bilateral filtering is applied to the image, which works by smoothing the image while preserving its edges. Unlike other filters, bilateral filtering takes into account both the spatial distance between pixels and their intensity difference. This means that only pixels that are close in both space and intensity contribute to the filtering process, which helps in preserving edges and important structures.

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- **Image**: The noisy image to be processed.
- **Diameter of the pixel neighborhood**: The size of the filter's neighborhood (e.g., 9). This parameter defines how many neighboring pixels are considered during filtering. A larger diameter allows the filter to consider more surrounding pixels, but it may blur edges.
- **Sigma Color**: This controls the degree to which colors in the neighborhood influence the filtering. A larger value (e.g., 75) leads to more smoothing, while a smaller value focuses on preserving more details.
- **Sigma Space**: This controls the spatial distance influence. A larger value helps smooth pixels over a larger distance.

Step 3: Automatically Adjust Parameters: The key parameters—diameter, sigma color, and sigma space—can be adjusted depending on the level of speckle noise and the importance of edge preservation. Higher values for sigma will result in stronger smoothing effects but may blur edges, so careful tuning is necessary to balance noise reduction with detail preservation.

Step 4: Output the Denoised Image: After applying the bilateral filter, the speckle noise is effectively reduced, and the image quality improves without sacrificing sharpness. This method ensures that the smooth areas are denoised while edges and important details remain intact. The final denoised image can now be used for further analysis or visualization.

4. RESULTS AND DISCUSSION

Figure 5 compares the denoising performance of the existing Wiener filter method and the proposed Gamma correction method on Poisson noise. Poisson noise often appears in low-light or photon-limited imaging scenarios. The figure shows the effect of both methods on image quality, where the proposed Gamma correction method outperforms the Wiener filter in terms of preserving finer details and reducing noise. The Proposed Method with Poisson achieves significantly better metrics (PSNR of 62.56 dB, MSE of 0.04, SSIM of 0.3622) compared to the Existing Method with Poisson (PSNR of 28.29 dB, MSE of 96.37, SSIM of 0.2246), illustrating that the proposed method reduces noise more effectively and preserves image quality better. Figure 6 showcases the results of the Wiener filter and the Gamma correction method for Salt & Pepper noise, which is characterized by random occurrences of black and white pixels. Both methods are tested with varying noise levels, and it is evident that the proposed Gamma correction method provides better noise removal. The Proposed Method with Salt & Pepper shows a PSNR of 62.62 dB, a sharp improvement over the Existing Method with Salt & Pepper (PSNR of 28.56 dB). Similarly, the MSE and SSIM values highlight the superior performance of the proposed method, confirming that Gamma correction is more effective in preserving image clarity and detail.

In Figure 7, Speckle noise typically arises due to variations in pixel intensities caused by grainy interference, often seen in medical imaging and satellite photography. This figure compares the Wiener filter with the proposed Gamma correction method applied to speckle noise. The comparison shows that the proposed method delivers higher PSNR values, lower MSE, and higher SSIM values, indicating that it performs better in noise suppression while maintaining the structural integrity of the image. Figure 8 presents a graph that compares the average PSNR values for both the existing and proposed methods across different noise levels. PSNR is a key metric used to measure the quality of denoised images. As the noise levels increase, the Proposed Method consistently outperforms the Existing Method, showing a higher PSNR, which means the images processed with the proposed method have higher quality and less noise.

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Figure 9 compares the Structural Similarity Index (SSIM) for both methods under varying noise levels. SSIM measures the perceived quality of the image by considering luminance, contrast, and structure. The graph shows that the Proposed Method consistently maintains higher SSIM values compared to the Existing Method, indicating better preservation of the structural quality of the images despite the added noise. Figure 10 presents a comparison of the average Mean Squared Error (MSE) for both the existing and proposed methods at various noise levels. MSE is a metric that measures the average squared difference between the original and denoised image. A lower MSE value indicates better performance. The graph shows that the Proposed Method consistently has lower MSE across all noise levels, demonstrating its superior ability to remove noise while preserving image detail.

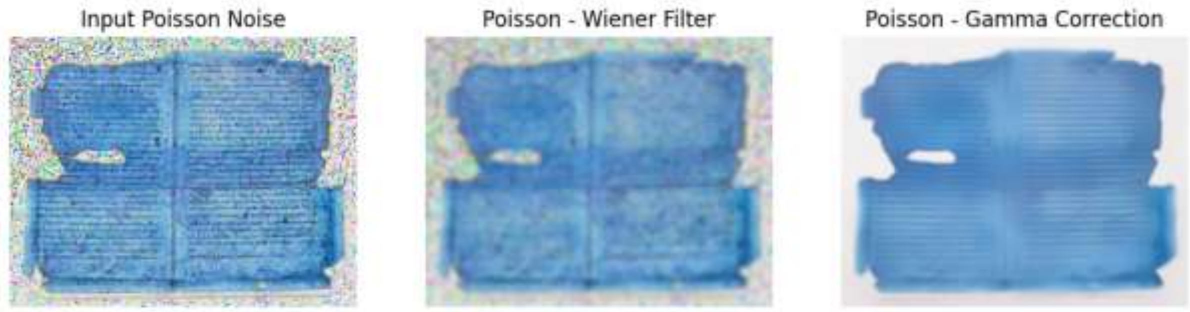

Figure 5. Existing and Proposed Outcomes on Poisson Noise.

Figure 6. Existing and Proposed Outcomes on Salt and Pepper Noise.

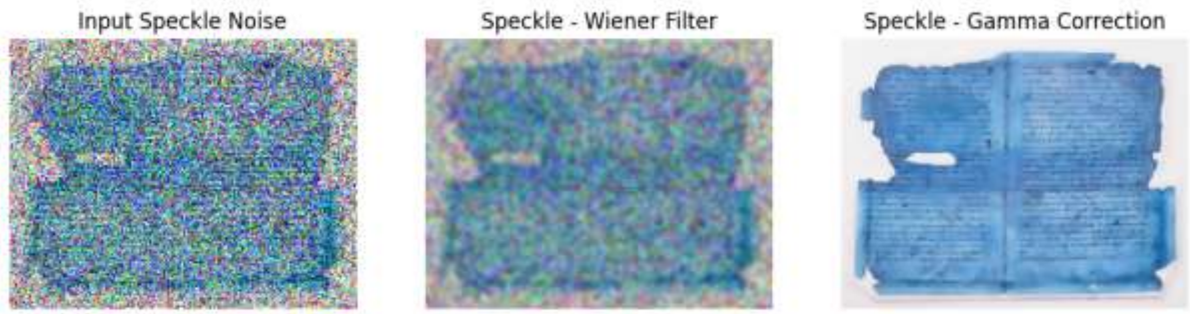

Figure 7. Existing and Proposed Outcomes on Speckle Noise.

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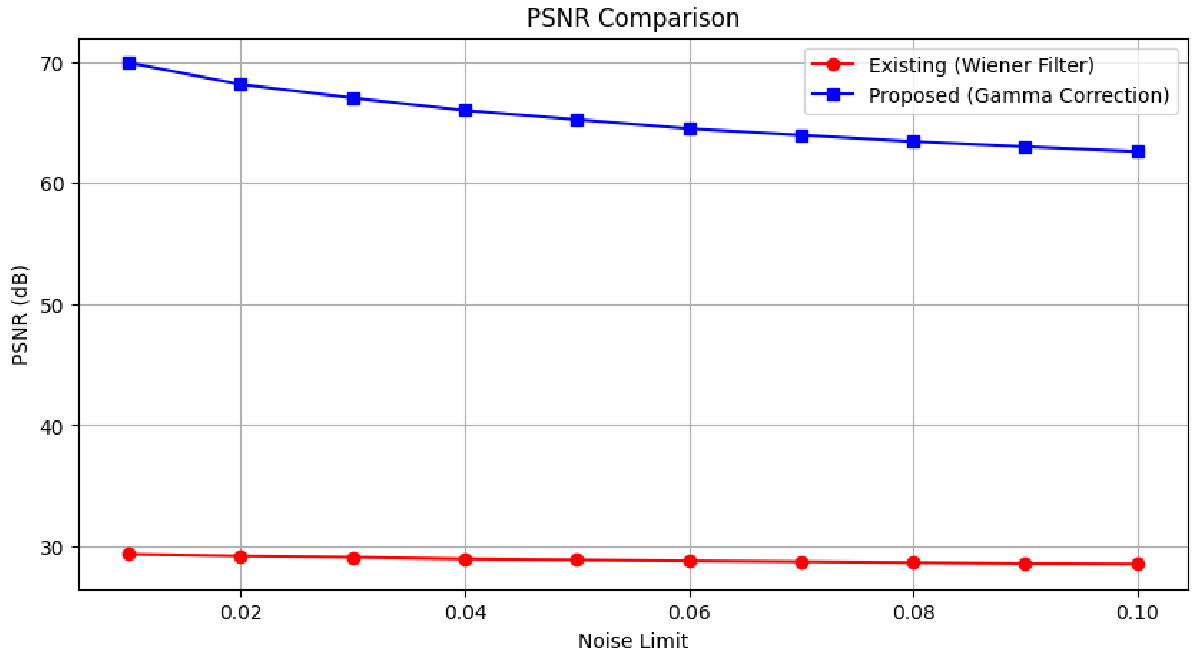

Figure 8. Existing and Proposed Average PSNR comparison graph for various Noise Limits.

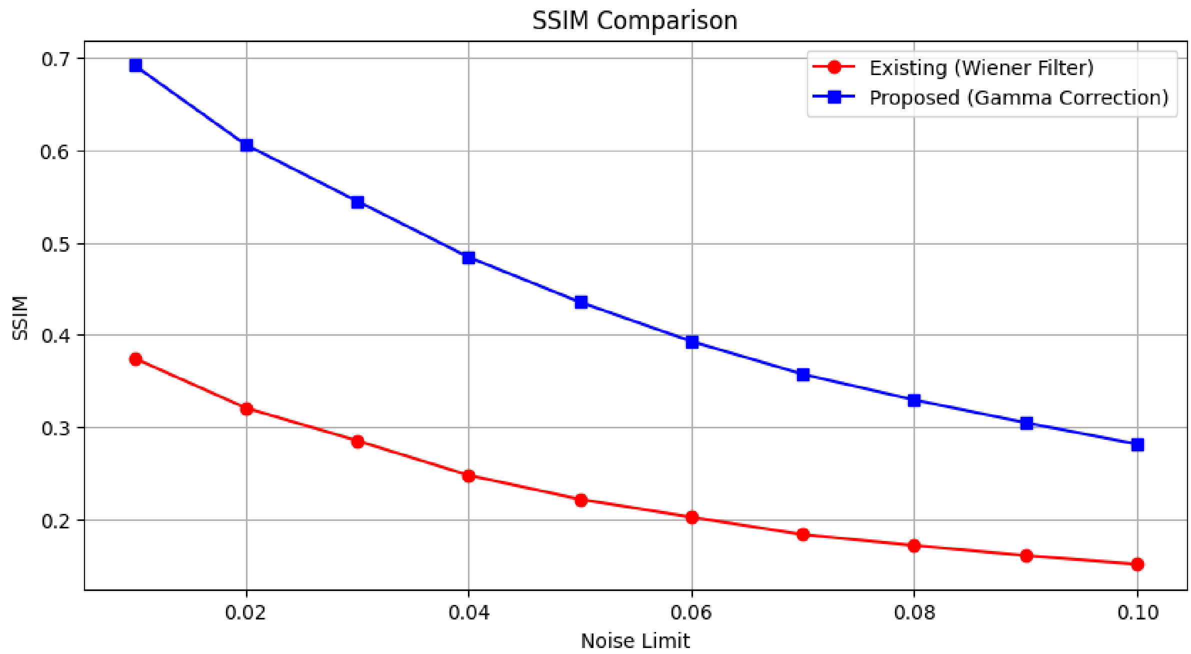

Figure 9. Existing and Proposed Average SSIM comparison graph for various Noise Limits.

In Table 1,

For Poisson Noise, the Existing Method with the Wiener filter shows PSNR of 31.51 dB, which indicates moderate noise reduction, but the MSE of 45.96 and SSIM of 0.7504 suggest that the image quality is compromised due to residual noise. The Proposed Method with Gamma correction dramatically improves the results with PSNR of 66.24 dB, MSE of 0.02, and SSIM of 0.8075, showing much better noise removal and superior image quality preservation. For Salt & Pepper Noise, the Existing Method provides a PSNR of 28.66 dB, indicating poor denoising performance. The MSE of 88.45 and SSIM of 0.2408 demonstrate that significant noise remains and the image structure is not well-preserved. However, the Proposed Method significantly improves these values, achieving a PSNR

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of 61.64 dB, MSE of 0.04, and SSIM of 0.3094, indicating a more effective noise removal process while retaining the image structure. For Speckle Noise, the Existing Method achieves PSNR of 30.34 dB, MSE of 60.06, and SSIM of 0.5226, which indicates that the Wiener filter performs moderately but still leaves noticeable noise and structural distortion. The Proposed Method outperforms the existing method with PSNR of 62.61 dB, MSE of 0.04, and SSIM of 0.6353, showing much better noise suppression and superior preservation of image details.

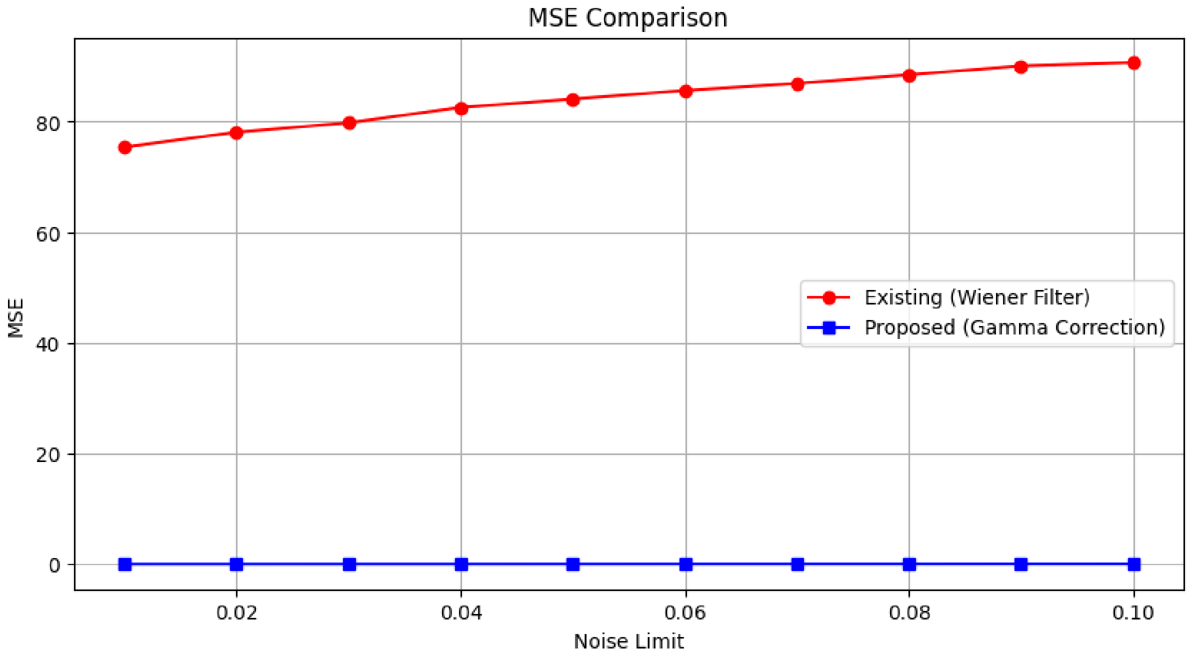

Figure 10. Existing and Proposed Average MSE comparison graph for various Noise Limits.

Table 1: Comparison of existing and proposed methods on poison, salt & pepper, and speckle noise

Noise Type	Method	PSNR (dB)	MSE	SSIM
Poisson Noise	Existing Method	31.51	45.96	0.7504
	Proposed Method	66.24	0.02	0.8075
Salt & Pepper	Existing Method	28.66	88.45	0.2408
	Proposed Method	61.64	0.04	0.3094
Speckle Noise	Existing Method	30.34	60.06	0.5226
	Proposed Method	62.61	0.04	0.6353

5. CONCLUSION

The proposed method leveraging Gamma correction significantly outperforms the existing Wiener filter in denoising images affected by Poisson, Salt & Pepper, and Speckle noise. Through a detailed comparison of performance metrics such as PSNR, MSE, and SSIM, it is evident that the proposed approach provides a more effective noise reduction capability, enhancing image quality while preserving structural integrity. Specifically, the PSNR values for the proposed method are notably higher across all noise types, and the MSE is dramatically reduced, showcasing the method's superiority in suppressing noise. Additionally, the SSIM scores demonstrate that the proposed method retains more

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of the original image's structural features, making it a promising alternative for high-fidelity image processing applications. The results emphasize that Gamma correction is a highly effective tool for image denoising, offering improvements in both subjective image quality and objective evaluation metrics, marking a significant advancement over traditional Wiener filter techniques.

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