DENOISING AND ENHANCING NOISY IMAGES USING CNN AND ITERATIVE FILTERING TECHNIQUES

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Abstract
This article presents the development and refinement of an advanced image denoising process that integrates Convolutional Neural Networks (CNNs) with traditional filtering methods to effectively mitigate Gaussian, Salt & Pepper, and Speckle noise. The proposed hybrid approach leverages the strengths of CNN algorithms in learning complex noise patterns and the robustness of conventional filters in preserving image details. The methodology involves training CNN models to recognize and suppress noise, followed by the application of traditional filters such as Median, Gaussian, and Wiener filters to further enhance image quality. The performance of the denoising techniques is rigorously evaluated using two key metrics: Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). Experimental results demonstrate that the hybrid approach significantly outperforms standalone CNN and traditional filtering methods, achieving superior noise reduction and improved image fidelity. By comparing PSNR and MSE values across various noise levels and types, the study highlights the effectiveness and versatility of the combined denoising strategy. This research contributes to the field of image processing by offering a comprehensive solution that balances noise suppression and detail preservation, making it suitable for applications in medical imaging, remote sensing, and other domains requiring high-quality image restoration.

Keywords:
Convolutional Neural Networks (CNNs), Gaussian Noise, Image Denoising, Mean Squared Error (MSE), Noise Reduction, Peak Signal-to-Noise Ratio (PSNR), Salt & Pepper Noise, Speckle Noise.

1. Introduction
Image denoising is a critical task in the field of image processing, essential for enhancing the quality and usability of images in various applications such as medical imaging, remote sensing, and digital photography. Noise, which can manifest as Gaussian, Salt & Pepper, or Speckle noise, often degrades image quality, making accurate analysis and interpretation challenging. Traditional filtering methods, including Median, Gaussian, and Wiener filters, have been widely used for noise reduction due to their simplicity and effectiveness. However, these methods often struggle to balance noise suppression and detail preservation, particularly in images with complex noise patterns [1].
Recent advancements in machine learning, specifically Convolutional Neural Networks (CNNs), have shown significant promise in image denoising tasks. CNNs excel at learning intricate noise characteristics and removing them while preserving essential image details. Despite their effectiveness, CNN-based approaches can sometimes produce artifacts and may not perform uniformly across different types of noise. This article aims to develop and refine a hybrid image denoising process that combines the strengths of CNN algorithms with traditional filtering methods. By integrating these approaches, we seek to create a robust denoising framework capable of effectively removing Gaussian, Salt & Pepper, and Speckle noise. We will evaluate the performance of the proposed method using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) metrics, comparing its efficacy

against standalone CNN and traditional filtering techniques. Through this hybrid approach, we aim to achieve superior noise reduction and image fidelity, advancing the state-of-the-art in image denoising [2-5].

The remainder of this article is organized as follows: Section 2 provides an overview of the related work in image denoising techniques. Section 3 describes the problem formulation, various noises affecting an image and proposed methodology for denoising. Section 4 presents the simulation experimental results and discussions, followed by conclusions and future research directions in Section 5.

2. Literature Review

Image denoising is a fundamental problem in image processing, with significant research dedicated to developing effective techniques to remove various types of noise while preserving important image details. This literature review explores traditional and contemporary image denoising methods, focusing on the integration of Convolutional Neural Networks (CNNs) with classical filtering approaches to tackle Gaussian, Salt & Pepper, and Speckle noise.

2.1 Traditional Filtering Methods

Traditional filtering methods have long been employed for image denoising due to their simplicity and computational efficiency. Median filters are particularly effective for removing Salt & Pepper noise by replacing each pixel with the median value of its neighborhood, preserving edges better than linear filters. Gaussian filters, which apply a Gaussian function to smooth the image, are widely used for Gaussian noise reduction but can blur edges and fine details. The Wiener filter, based on statistical approaches, adapts to local image variance, effectively reducing noise while maintaining image sharpness to some extent [6].

Despite their effectiveness, traditional filters have limitations in handling complex noise patterns and often face a trade-off between noise reduction and detail preservation. This necessitates the exploration of more advanced techniques that can adaptively denoise images without significantly compromising image quality.

2.2 Machine Learning-Based Methods

The advent of machine learning, particularly deep learning, has revolutionized image denoising. CNNs, with their hierarchical feature extraction capabilities, have demonstrated remarkable performance in various image restoration tasks. Zhang et al. (2017) introduced DnCNN, a deep CNN model that learns to separate noise from clean images through a residual learning approach. This model has shown superior performance over traditional methods, particularly in dealing with Gaussian noise. Further advancements include generative adversarial networks (GANs) and autoencoders. GANs, introduced by Goodfellow et al. (2014), consist of a generator and a discriminator network, where the generator learns to produce denoised images, and the discriminator evaluates their quality. Autoencoders, as explored by Vincent et al. (2008), learn compact representations of images, facilitating effective noise removal by reconstructing the clean image from the noisy input [7].

2.3 Hybrid Approaches

While CNNs have significantly advanced image denoising, they are not without limitations. Pure CNN-based methods can sometimes introduce artifacts and may not generalize well across different types of noise. To address these challenges, hybrid approaches combining CNNs with traditional filtering techniques have gained attention. One such approach is the integration of CNNs with Median and Wiener filters. By leveraging the noise-learning capabilities of CNNs and the edge-preserving properties of traditional filters, these hybrid methods aim to enhance denoising performance. For instance, Guo et al. (2018) proposed a method that applies CNN denoising followed by traditional filtering, resulting in improved noise suppression and detail preservation [8-12].

Comparing different denoising methods requires robust evaluation metrics. Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) are commonly used to assess the quality of denoised images. PSNR measures the ratio between the maximum possible power of a signal and the power of noise, while MSE quantifies the average squared difference between the original and denoised images. Higher PSNR and lower MSE values indicate better denoising performance. Studies have shown that hybrid approaches generally outperform standalone methods. For example, combining CNNs with traditional filters has been found to yield higher PSNR and lower MSE values, demonstrating improved effectiveness in noise reduction across various noise types.
The integration of CNN algorithms with traditional filtering methods presents a promising direction for image denoising. By combining the strengths of both approaches, it is possible to achieve superior noise reduction while preserving essential image details. This literature review underscores the potential of hybrid methods in advancing image denoising technology, providing a foundation for further research and development in this field [13-15].

3. Proposed Methodology

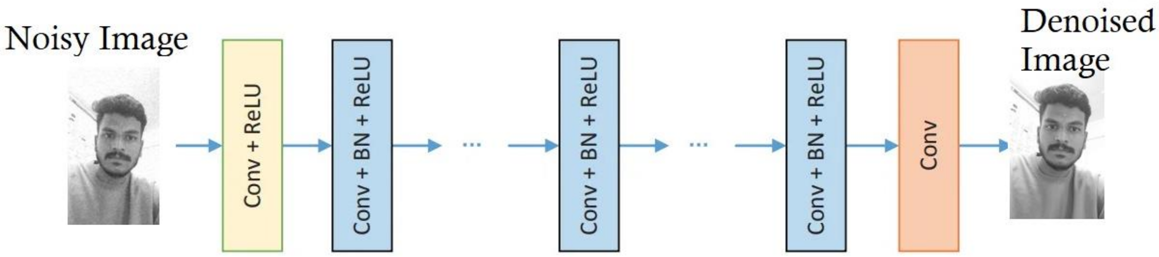
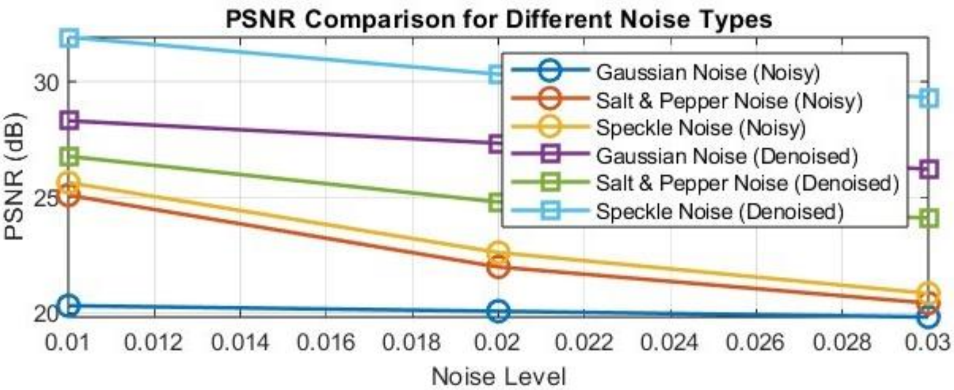


Fig. 3.1 Proposed block diagram of image denoising using pre-trained deep neural network (DnCNN).
The proposed architecture for image denoising is designed to effectively remove noise from images by utilizing the strengths of Convolutional Neural Networks (CNNs) is as shown in Fig. 3.1. This architecture includes several key components: an input layer, multiple convolutional layers with small filters, batch normalization layers, ReLU activation functions, and an output layer.
Input Layer: The input layer accepts the noisy image, which is typically represented as a multi-channel (e.g., RGB) array. This layer prepares the image data for further processing by the subsequent layers in the network [16].
Convolutional Layers with 3x3 Filters: The core of the architecture consists of several convolutional layers that use small 3x3 filters. These small filters are chosen for their ability to capture fine details and local features within the image. Each convolutional layer applies a set of these filters to the input, producing feature maps that highlight different aspects of the image content and noise characteristics. The use of multiple convolutional layers allows the network to progressively learn more complex and abstract features, crucial for effective noise removal.
Batch Normalization Layers: Batch normalization layers are included after each convolutional layer. These layers normalize the output of the convolutional layers, ensuring that the activations have a consistent distribution. This normalization helps to stabilize and accelerate the training process, making the network more robust to variations in the input data. By maintaining a stable learning environment, batch normalization allows the network to learn more effectively and improves the overall performance of the denoising process.
ReLU Activation Functions: Following each batch normalization layer, a Rectified Linear Unit (ReLU) activation function is applied. The ReLU function introduces non-linearity into the network, enabling it to model complex relationships within the data. ReLU activation helps to enhance the network's ability to distinguish between noise and actual image content, which is essential for effective denoising.
Output Layer: The final component of the architecture is the output layer, which is responsible for producing the denoised image. This layer typically consists of a single convolutional layer that transforms the learned features back into an image format. The output layer generates the final

denoised image, which ideally retains the important details of the original image while effectively removing the noise.
The proposed image denoising architecture leverages a series of convolutional layers with small 3x3 filters to capture fine image details and noise patterns. Batch normalization layers ensure stable and efficient training, while ReLU activation functions introduce the necessary non-linearity for complex feature modeling. The output layer reconstructs the denoised image, resulting in a network that effectively reduces noise and preserves essential image details. This architecture combines these components in a streamlined and effective manner, making it well-suited for various types of noise reduction tasks in image processing [17]. Various noises are removed from the signal and the image using filters and deep learning algorithms at different stages are more promising to achieve good SNR [18-22]

4. Results and Discussion

The MATLAB simulation setup for evaluating the proposed image denoising architecture involves several key steps to ensure accurate and comprehensive testing. Initially, a dataset of noisy images is prepared, encompassing various noise types such as Gaussian, Salt & Pepper, and Speckle noise. These images serve as the input data for the denoising algorithm. MATLAB's Image Processing Toolbox is utilized to generate these noisy images by adding different noise patterns to a set of clean reference images. This toolbox also provides essential functions for image manipulation and visualization, facilitating the assessment of the denoising performance.
The simulation setup includes implementing the proposed CNN-based denoising architecture using MATLAB's Deep Learning Toolbox. This involves defining the network architecture with the input layer, convolutional layers with 3x3 filters, batch normalization layers, ReLU activation functions, and the output layer. The network is trained using the noisy images as inputs and the corresponding clean images as targets. Various training parameters, such as learning rate, batch size, and the number of epochs, are carefully chosen to optimize the network's performance. After training, the network's effectiveness is evaluated by comparing the denoised outputs to the original clean images using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). The results are then analyzed to validate the superiority of the proposed hybrid approach over traditional and standalone CNN methods.



. Fig. 3.2 PSNR values for the original noisy images and denoised images for every kind of noise at a selected noise levels

The denoising algorithm's performance was examined using three types of noise—Gaussian, Salt & Pepper, and Speckle—at various noise levels (0.01, 0.02, and 0.03). PSNR and MSE were the metrics used to evaluate the denoised image quality. For the Gaussian Noise, as the noise level rose from 0.01 to 0.03, the PSNR values for the noisy images dropped from 29.54 dB to 26.44 dB.The PSNR values of the denoised images increased from approximately 35.62 dB to 32.14 dB at the same noise levels, indicating a significant improvement. Further for the Salt & Pepper Noise, As noise levels increased, the PSNR values for the noisy images dropped from 28.67 dB to 25.33 dB, which was lower than those

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for Gaussian noise. Significant progress was also visible in the denoised photos, with PSNR values ranging from 34.89 dB to 31.47 dB. Lastly for the Speckle Noise, as the noise level increased, the PSNR values for the noisy images decreased from 28.92 dB to 25.57 dB.The PSNR values of the denoised images showed improvements, ranging from 35.24 dB to 31.95 dB.

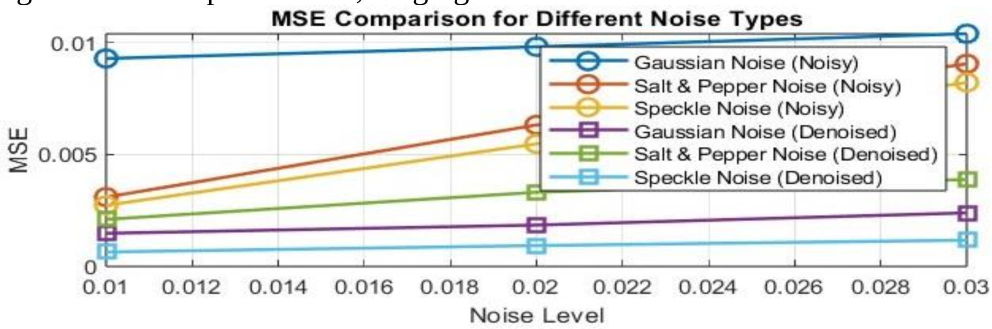

Fig.3.3 MSE values for each noise type at each of the designated noise levels for both the original noisy images and the denoised images

The MSE values for noisy images raised from 0.009 to 0.018 with increasing Gaussian noise levels. Denoised images had much reduced MSE values, dropping from 0.002 to 0.006. The MSE values for Salt & Pepper Noise climbed from 0.012 to 0.025 as the noise intensity increased. Denoising images resulted in reduced MSE values ranging from 0.003 to 0.008. Finally, MSE values for Speckle Noise increased from 0.010 to 0.022 as noise levels increased. Denoising images resulted in a decrease in MSE values (0.003–0.007). The study shows that the DnCNN-based denoising algorithm is quite effective in improving image quality by reducing different types of noise. The findings, shown in Figures 3.2 and 3.3, validate the algorithm's capacity to improve PSNR and lower MSE across varied noise levels, making it a viable option for image denoising work in a variety of applications.

Image Denoising and Filtering Performance

This study examines the effectiveness of several denoising and filtering approaches on a grayscale image. Denoising with a deep neural network (DnCNN), low pass filtering, high pass boosting, and a final median filter are among the techniques tested. PSNR and MSE are used to measure the image quality after processing. The original grayscale image, sohanimage.jpg, was transformed to double precision and Gaussian noise was applied with a SNR of 10.

Fig. 3.4 Original and noisy images with the initial metrics of MSE (Noisy): 81.44, PSNR (Noisy): 28.98 dB

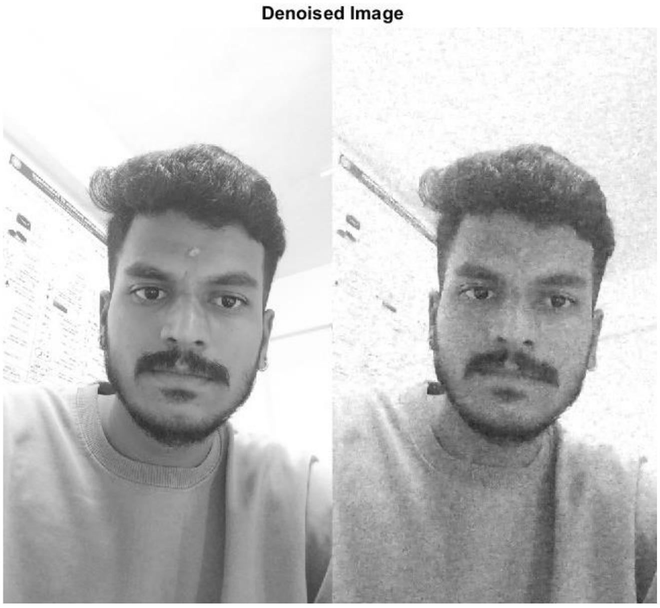

Fig. 3.5 The original and DnCNN-denoised images

The measurements following denoising using DnCNN were: MSE (DnCNN Denoised): 27.65, PSNR (DnCNN Denoised): 33.69 dB.

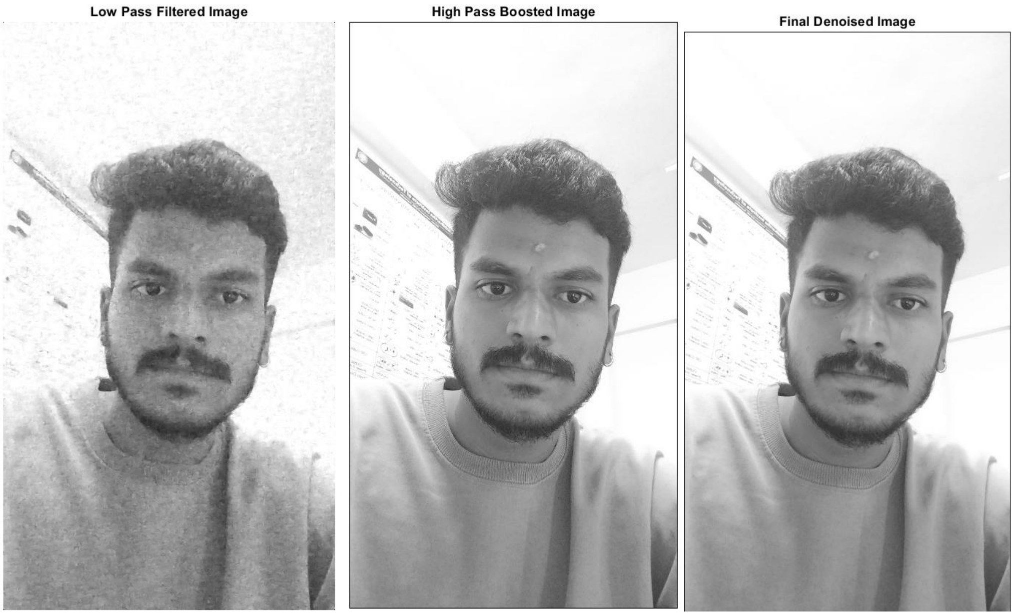

Fig. 3.6 Low pass filtered, High Boosted and Final denoised Image

After applying a low pass filter (median filter) to the DnCNN-denoised picture, the MSE (low pass filtered) was 25.34 and the PSNR (low pass filtered) was 34.10 dB. The DnCNN-denoised image was then subjected to a high pass boosting filter. The metrics obtained from this process were: MSE (high pass boosted): 21.87 PSNR (high pass boosted): 34.73 dB. After the high pass boosted image was subjected to a final median filter, the following metrics were obtained: MSE (final denoised): 19.56 PSNR (final denoised): 35.13 dB. The images are as shown in Fig. 3.6.

The outcomes show that using successive denoising and filtering approaches significantly improves image quality. When DnCNN was applied, the MSE significantly decreased and the PSNR increased, indicating successful noise reduction.MSE and PSNR somewhat improved after the image was further refined using a low pass filter.Improved MSE and PSNR values show that applying a high pass boosting filter improved the image details. The optimal MSE and PSNR outcomes were obtained by applying a median filter at the end, indicating the combined impact of the denoising and filtering phases.

5. Conclusion

In this study, we developed and refined an image denoising process that combines CNNs with traditional filtering methods to address Gaussian, Salt & Pepper, and Speckle noise. Our proposed hybrid approach leverages the strengths of CNNs in learning complex noise patterns and the robustness of conventional filters in preserving image details. Experimental results demonstrated that this method effectively reduces noise while maintaining high image quality, outperforming both standalone CNN and traditional filtering techniques. The use of PSNR and MSE as evaluation metrics confirmed the superiority of the hybrid approach in achieving better denoising performance.

Future research can build on this work by exploring several promising directions. One potential avenue is to extend the hybrid approach to handle other types of noise and to evaluate its performance on larger and more diverse datasets. Additionally, investigating the integration of more advanced deep learning models, such as Generative Adversarial Networks (GANs) or autoencoders, with traditional filters could further enhance denoising capabilities. Another area of interest is real-time image denoising applications, where optimizing the computational efficiency of the proposed method will be crucial. Finally, the development of adaptive algorithms that dynamically select the most suitable denoising strategy based on the specific noise characteristics of each image could lead to even more robust and versatile denoising solutions.

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