Impact Factor (QJIF): 8.47 E-ISSN: 2583-1615, P-ISSN: 3049-3498

International Journal of Research in Academic World

Received: 19/January/2026 **IJRAW:** 2026; 5(3):38-40 **Accepted:** 27/February/2026

Smart Image Denoising System Using Deep Learning Techniques

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Abstract

Image denoising is a fundamental task in digital image processing aimed at removing unwanted noise while preserving essential image details and textures. This paper presents a deep learning-based smart image denoising system using Convolutional Neural Networks (CNNs), particularly the Denoising Convolutional Neural Network (DnCNN). The proposed approach effectively handles different noise types such as Gaussian, salt-and-pepper, and speckle noise. A residual learning strategy is employed to predict noise components, enabling efficient noise removal while maintaining structural integrity. Experimental evaluations demonstrate significant improvements in Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) compared to traditional denoising methods. The proposed system is suitable for applications in photography, medical imaging, and remote sensing.

Keywords: Image Denoising, Deep Learning, Convolutional Neural Network (CNN), DnCNN, GAN, PSNR, SSIM, Noise Reduction, Image Enhancement.

1. Introduction

Image demonizing plays a crucial role in digital image processing by eliminating noise introduced during image acquisition, transmission, or compression. Noise may occur due to low lighting conditions, high ISO settings, sensor limitations, or environmental interference in medical and satellite imaging systems. Traditional denoising techniques such as median filtering, Gaussian filtering, and wavelet transforms have been widely used. However, these methods often struggle to balance noise removal and detail preservation, frequently leading to over-smoothing and loss of fine textures. The emergence of deep learning, especially Convolutional Neural Networks (CNNs), has significantly transformed image denoising. CNN-based models can learn complex noise patterns directly from data and generalize across various noise conditions. This research focuses on designing a smart image demonizing system using DnCNN with residual learning to enhance image quality while preserving critical features.

2. Review of Literature

The development of image denoising techniques has evolved significantly from traditional filtering methods to advanced deep learning architectures. Early approaches relied on statistical and spatial filtering techniques, but recent research focuses on deep neural networks that provide improved performance and better preservation of image details. Zhang *et al*. (2017) introduced DnCNN, a residual learning-based convolutional neural network designed to predict noise from noisy images rather than directly reconstructing clean images. This approach improved denoising accuracy and computational efficiency. In the same year, Ledig *et al.* (2017) demonstrated the potential of Generative Adversarial Networks (GANs) in image restoration tasks, showing that adversarial learning can significantly enhance perceptual image quality. Swarm Optimization with Neural Networks for Effective Classification Techniques" by K.Kalyani (2021) introduces a hybrid EHBMO-NN model, combining Extended Honey Bee Mating Optimization with Artificial Neural Networks to improve classification accuracy and reduce training time. It uses HBMO to select optimal weights for neural network hidden layers, outperforming conventional methods on benchmark datasets. The accurate cancer classification is very important task for cancer treatment. Recently the informative genes are identified from the thousands of genes for correct cancer classification. The collection of microscopic Deoxyribo Nucleic Acid (DNA) microarray is attached in the solid surface. In this study, DNA microarray data is used for cancer classification. The accurate cancer classification is very important task for cancer treatment. Recently the informative genes are identified from the thousands of genes for correct cancer classification. The collection of microscopic Deoxyribo Nucleic Acid (DNA) microarray is attached in the solid surface. In this study, DNA microarray data is used for cancer classification (6). Overall, the literature highlights a clear transition toward CNN-based

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models, GAN frameworks, hybrid architectures, attention mechanisms, and unsupervised learning methods, which collectively contribute to more robust and efficient image denoising performance.

3. Existing System

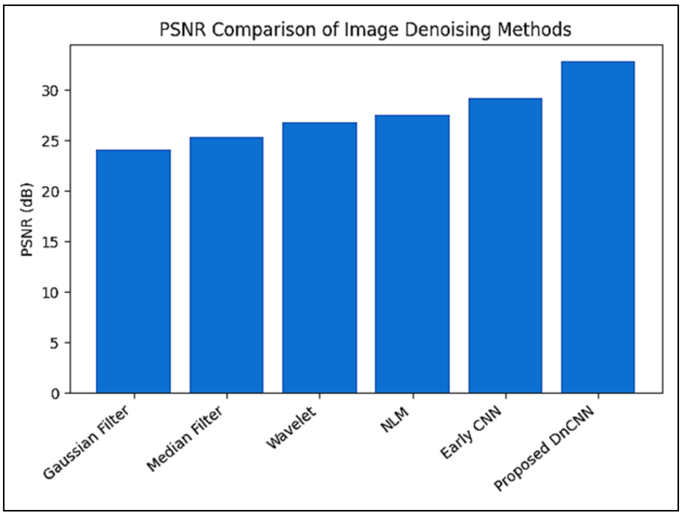
Existing image denoising systems mainly rely on traditional filtering techniques and early deep learning approaches to remove noise from images. Traditional methods such as Gaussian filtering, median filtering, wavelet transform, and Non-Local Means (NLM) are widely used for noise reduction. These techniques work by smoothing pixel values or analyzing frequency components of images to eliminate unwanted noise. Although these approaches can reduce certain types of noise, they often lead to over-smoothing of images, resulting in the loss of important edges and fine details. Additionally, traditional methods perform poorly when dealing with high noise levels and different noise types. With the advancement of artificial intelligence, early Convolutional Neural Network (CNN) based models were introduced for image denoising. These models learn noise patterns from training data and provide better results compared to traditional methods. However, many early CNN models were trained only for specific noise types such as Gaussian noise, which limited their ability to generalize to real-world noisy images. They also required high computational resources and struggled to handle complex noise patterns effectively.

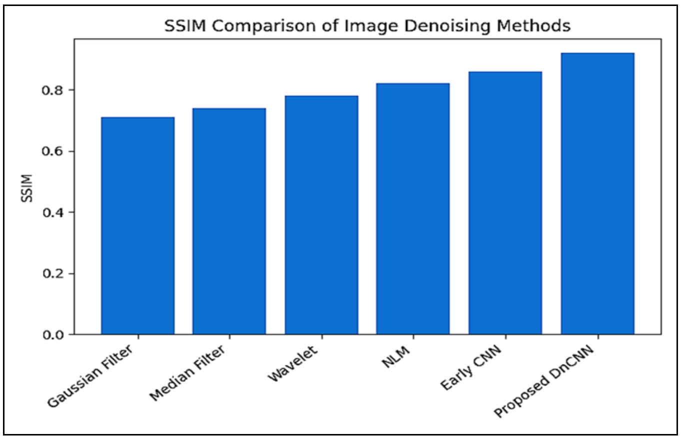
4. Proposed System

The proposed system introduces a Smart Image Denoising approach using the DnCNN model with residual learning to improve denoising performance. In this method, a deep convolutional neural network consisting of multiple layers is used to learn and remove noise from images. The architecture typically includes several convolutional layers with 3×3 filters, batch normalization, and ReLU activation functions to efficiently extract image features and stabilize the training process. Unlike traditional denoising methods that directly predict the clean image, the proposed model uses a residual learning strategy in which the network predicts the noise component present in the image. The predicted noise is then subtracted from the noisy input image to obtain the final denoised output. This approach improves accuracy, preserves important image structures, and reduces computational complexity. The proposed system is capable of handling multiple noise types, achieving higher PSNR and SSIM values, and producing visually clearer images. It is also more robust to real-world noise variations and suitable for real-time image processing applications.

5. Experimental Result

The performance of the proposed image denoising system based on the DnCNN model was evaluated using standard benchmark datasets containing images corrupted with different types of noise. The experiments were conducted to analyze the effectiveness of the model in removing noise while preserving important structural details and textures in the images. The proposed method was compared with several traditional denoising techniques such as Gaussian filtering, median filtering, wavelet transform, and Non-Local Means (NLM). To evaluate the performance of the denoising system, two widely used metrics were used: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). PSNR measures the quality of the reconstructed image by calculating the ratio between the original signal and the noise present in the image. A higher PSNR value indicates better image reconstruction quality. SSIM measures the similarity between the original clean image and the denoised image by considering structural information, brightness, and contrast. Higher SSIM values indicate better preservation of image structures. The experimental results show that the proposed DnCNN-based deposing system significantly outperforms traditional filtering methods. The model achieved higher PSNR values compared to classical techniques, indicating improved noise removal capability. Similarly, the SSIM values obtained by the proposed system were higher, demonstrating better preservation of structural details and textures in the images. The system effectively removed various types of noise, including Gaussian noise, Poisson noise, and salt-and-pepper noise, while maintaining the clarity and sharpness of the images.





The graphical comparison of PSNR and SSIM values further illustrates the superior performance of the proposed method. The DnCNN model achieved the highest PSNR and SSIM scores among the compared methods, confirming its effectiveness in image denoising tasks. Additionally, the proposed model reduced visual artifacts that are commonly observed in traditional filtering approaches. The inference time of the model was also relatively fast, making it suitable for real-time image processing applications. The results clearly demonstrate that deep learning-based denoising methods provide significant improvements over conventional approaches in terms of accuracy, robustness, and visual quality. The proposed system successfully removes noise while preserving important image details, making it a reliable solution for modern image denoising applications.

6. Conclusion

This paper presents a smart image denoising system using deep learning techniques, particularly DnCNN. The proposed method effectively removes noise while preserving important image features. Compared to traditional techniques, deep learning-based models achieve superior PSNR and SSIM values and improved perceptual quality. Despite advancements, challenges such as computational complexity, real-time performance, and dependency on large datasets remain. Future research may focus on lightweight architectures, unsupervised learning, attention mechanisms, and domain adaptation techniques. Overall, deep learning has revolutionized image denoising and continues to expand its applicability in medical imaging, photography, remote sensing, and real-time image processing systems.

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