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Attention-Enhanced Generative Adversarial Network for Image Denoising

S Sathish Kumar[1], Karnatham Rakesh[2*], Ponugumati Gowtham[3], Biyyala Akshith Kumar[4], Yedla Praveen[5]

[1]Assistant Professor, [2,3,4,5]UG Student, [1,2,3,4,5]Department Artificial Intelligence and Machine Learning[1]

[1,2,3,4,5]J.B. Institute of Engineering and Technology (UGC-Autonomous), Yenkapally, Hyderabad, 500075, Telangana.

*Corresponding author: Karnatham Rakesh (karnathamrakesh@gmail.com)

ABSTRACT

With the increasing use of digital imaging systems across domains such as surveillance, medical diagnostics, and multimedia applications, the presence of noise in captured images has become a critical issue affecting visual quality and subsequent analysis. This paper presents a robust and efficient framework for image denoising using an Attention-Enhanced Generative Adversarial Network (GAN), aimed at restoring clean images while preserving fine structural and textural details. Unlike conventional filtering and basic convolutional techniques that often lead to excessive smoothing and loss of important features, the proposed approach leverages the capability of deep learning to model complex noise distributions and underlying image patterns. A key aspect of this work is the incorporation of an attention mechanism within the generator network, which enables the model to selectively concentrate on highly degraded regions of the image while maintaining essential edges and textures. The system is trained using a combination of pixel-level and adversarial objectives, ensuring both reconstruction accuracy and visual realism. The overall architecture is designed in a modular manner, supporting efficient preprocessing, seamless model inference, and real-time visualization of results through a user-friendly interface. Experimental analysis demonstrates that the proposed method achieves significant noise reduction while retaining perceptual quality, as reflected in improved PSNR and SSIM metrics. The developed system offers a scalable and practical solution for real-world image denoising applications, addressing both performance and usability requirements.

Key Words: Image Denoising, Generative Adversarial Networks (GAN), U-Net, PatchGAN Real-World Noise.

1. INTRODUCTION

With the rapid advancement of digital imaging technologies and their widespread application in domains such as medical imaging, surveillance systems, remote sensing, and multimedia processing, the quality of captured images has become increasingly important. However, images acquired through sensors and transmission channels are often degraded by various types of noise, including Gaussian noise, salt-and-pepper noise, and environmental disturbances. Such noise not only reduces visual quality but also negatively impacts subsequent image analysis tasks such as object detection, segmentation, and recognition. Therefore, image denoising has emerged as a fundamental problem in the field of computer vision and image processing.

Traditional image denoising techniques, such as median filtering, Gaussian smoothing, and wavelet-based methods, have been widely used to suppress noise. While these methods are computationally efficient, they often fail to preserve fine details and textures, leading to over-smoothing and loss of important structural information. In recent years, deep learning-based approaches have shown significant improvements by learning complex mappings between noisy and clean images. Convolutional Neural Networks (CNNs), in particular, have demonstrated strong capabilities in capturing spatial features and restoring image quality. However, many CNN-based models still struggle to maintain a balance between effective noise removal and preservation of high-frequency details.

To address these challenges, generative models, especially Generative Adversarial Networks (GANs), have been explored for image restoration tasks. GANs consist of a generator and a discriminator network that are trained in an adversarial manner, enabling the generation of visually realistic outputs. This adversarial learning framework allows the model to better capture the underlying distribution of clean images and produce more natural-looking results compared to traditional methods. By leveraging this capability, GAN-based approaches provide an effective solution for reducing noise while maintaining perceptual quality.

In practical scenarios, image denoising systems must also be efficient, scalable, and capable of handling real-time inputs. Therefore, it is essential to design a system that integrates preprocessing, model inference, and output visualization in a streamlined manner. Such systems can be deployed in various real-world applications where image quality is critical, including medical diagnostics, autonomous systems, and security monitoring.

Overall, this paper focuses on developing an efficient deep learning-based framework for image denoising that enhances visual quality while preserving important image details. The proposed approach aims to overcome the limitations of conventional methods and provide a reliable solution for modern image restoration requirements.

2. LITERATURE SURVEY

Recent studies have explored various techniques for image denoising using both traditional and deep learning approaches. Early methods such as mean filtering, Gaussian filtering, and median filtering were widely used due to their simplicity and low computational cost; however, these methods often resulted in excessive smoothing and loss of fine image details, especially around edges and textured regions [1]. To overcome these limitations, advanced approaches such as wavelet-based denoising and non-local means were introduced, which consider global similarities within the image to better preserve structural information, although they still struggle with complex noise patterns and require careful parameter tuning [2]. With the advancement of machine learning, data-driven approaches have been applied to image denoising tasks, where initial methods relied on handcrafted features and statistical representations of image characteristics, but their performance was limited due to poor generalization across varying noise conditions [3]. The emergence of deep learning significantly improved denoising performance, particularly through Convolutional Neural Networks (CNNs), which are capable of learning hierarchical representations directly from data and have demonstrated superior performance in terms of Peak Signal-to-Noise Ratio (PSNR) and visual quality when compared to traditional techniques [4]. However, many CNN-based methods tend to produce over-smoothed outputs, leading to the loss of important high-frequency details and textures [5]. To address these challenges, Generative Adversarial Networks (GANs) have been introduced for image restoration tasks, where the generator and discriminator are trained in an adversarial manner to produce visually realistic outputs [6]. This adversarial learning process enables the model to generate high-quality denoised images by learning the underlying distribution of clean images rather than relying solely on pixel-wise reconstruction, thereby improving perceptual quality and structural preservation [7]. Several improvements to GAN architectures, including residual learning and optimization strategies, have been proposed to enhance training stability and performance [8], [9]. Recent research has also focused on applying GAN-based approaches to specialized domains such as medical imaging, where accurate noise removal is critical, achieving improved clarity and diagnostic quality [10], [11]. In addition, hybrid models that combine GANs with CNNs and other deep learning techniques have shown promising results by leveraging complementary strengths of different architectures [12]. Alternative approaches such as diffusion-based models have also emerged as effective solutions for image denoising, providing competitive performance and improved generalization capabilities [13]. Furthermore, comprehensive review studies highlight that deep learning-based methods consistently outperform traditional techniques in handling complex noise patterns and real-world scenarios [14], [15]. In addition to model architecture, preprocessing techniques such as resizing, normalization, and noise modeling play a crucial role in improving model performance by ensuring consistent input data and enhancing learning efficiency [16]. The effectiveness of denoising methods is commonly evaluated using metrics such as PSNR and Structural Similarity Index (SSIM), which measure reconstruction accuracy and perceptual similarity. Recent developments focus on designing efficient and scalable denoising systems capable of real-time processing by integrating preprocessing, model inference, and visualization into a unified framework. Despite significant advancements, achieving an optimal balance between noise removal and detail preservation remains a challenging problem, motivating further research in advanced deep learning-based image denoising techniques.

3. PROPOSED SYSTEM

The proposed system presents an end-to-end image denoising framework designed to process noisy input images and generate high-quality clean images using deep learning techniques. The system architecture integrates data preprocessing, deep learning-based image restoration, model inference, and an interactive user interface within a modular structure, enabling efficient image processing, scalable deployment, and real-time denoising. The architecture is organized into three primary components: the Data Processing Layer, the Deep Learning Pipeline, and the Application Interface Layer, each responsible for a specific stage of the overall workflow.

The Data Processing Layer is responsible for preparing input images before they are passed to the model. In this stage, the system processes raw noisy images obtained from user uploads and converts them into a suitable format for model input. The process begins with image normalization, where pixel values are scaled to a standard range to ensure consistency across different inputs. This is followed by resizing operations to match the input dimensions required by the model. Additionally, the system performs noise handling and format conversion, ensuring that images are transformed into tensor representations compatible with deep learning frameworks. This preprocessing stage plays a crucial role in improving model performance by eliminating inconsistencies and standardizing input data.

The Deep Learning Pipeline forms the core component of the proposed system and is responsible for image denoising and model training. The pipeline is based on a Generative Adversarial Network architecture consisting of a generator and a discriminator. The generator is designed to learn the mapping between noisy and clean images, producing denoised outputs that preserve important structural details. The discriminator evaluates the authenticity of generated images by distinguishing them from real clean images, thereby guiding the generator to improve its output quality through adversarial learning. During training, the model is optimized using a combination of pixel-level loss and adversarial loss, ensuring both reconstruction accuracy and visual realism.

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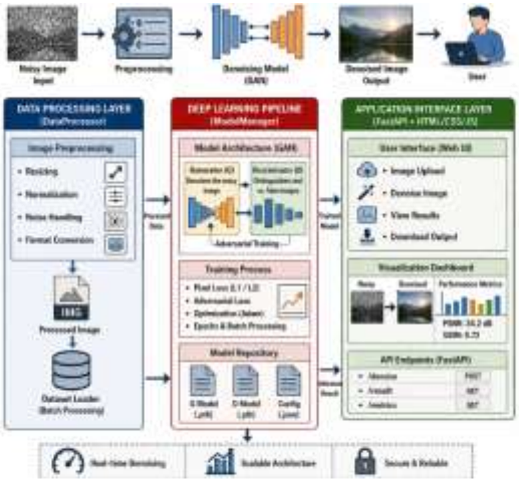

Figure 1. Proposed system architecture of Attention-Enhanced Generative Adversarial Network for Image Denoising

The training process utilizes a dataset of images, where noisy inputs and corresponding clean targets are used to train the model. The system employs batch processing to efficiently handle large datasets and iteratively updates model parameters through forward and backward propagation. The training pipeline also includes model optimization and convergence monitoring to ensure stable learning. Once the model achieves satisfactory performance, the trained generator is stored for future use, allowing the system to perform inference without retraining.

To enhance system efficiency, the trained models are stored in a Model Repository, which maintains different versions of the generator model. This enables model versioning and allows the system to select the most reliable model for deployment. The repository supports quick loading of trained models, reducing computational overhead and improving response time during inference.

The Inference Engine is responsible for applying the trained model to new input images. During this phase, only the generator network is used to process the preprocessed noisy image and generate a clean output. The inference process is optimized for speed and efficiency, enabling real-time image denoising. The output image is further processed if necessary and passed to the next stage for evaluation and visualization.

The system also includes an Evaluation Module, which assesses the quality of the denoised image using standard performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). These metrics provide quantitative measures of reconstruction accuracy and perceptual similarity, allowing the system to validate model performance and ensure reliability.

The final component of the architecture is the Application Interface Layer, which enables user interaction through a web-based platform. This layer acts as the bridge between the user and the backend processing system, providing functionalities for image upload, result visualization, and performance evaluation. The interface allows users to upload images, view denoised outputs, and compare results in a user-friendly manner. Additionally, the system supports real-time processing, enabling users to obtain results instantly after submission.

The platform also provides a Prediction Interface, which supports both single-image and batch-image denoising. In single-image mode, users can upload an individual noisy image and receive an immediate denoised output. In batch mode, multiple images can be processed simultaneously, making the system suitable for large-scale applications. This flexibility enhances the usability of the system in practical scenarios.

Overall, the proposed system provides a comprehensive and scalable solution for image denoising by integrating preprocessing, deep learning-based restoration, model management, and user interaction within a unified framework. The modular design ensures flexibility, efficiency, and ease of deployment, making the system suitable for real-world applications where image quality is critical.

4. Results Description

The Figure 3 image presents a clean and modern Image Denoising System dashboard designed for processing and enhancing noisy images using a GAN-based deep learning model. The

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interface highlights the core functionality of the system by displaying two main sections: the original noisy image and the denoised result, allowing users to visually compare input and output images side by side. The layout is simple and user-friendly, with a dark-themed design that enhances visual clarity and focus on image quality.

The dashboard also includes interactive controls such as the “Start Over” button, which allows users to reset the application and upload a new image, and the “Download” button, which enables users to save the denoised output for further use. These features make the system practical for real-time applications.

Overall, the interface demonstrates an intuitive and efficient end-to-end image denoising platform that integrates deep learning inference with user interaction, providing seamless visualization and easy accessibility for image restoration tasks.

Figure 2. Web interface for proposed Attention-Enhanced Generative Adversarial Network for Image Denoising

The figure 3 illustrates the variation of Peak Signal-to-Noise Ratio (PSNR) over training epochs for the proposed image denoising model. Initially, the PSNR value is low, indicating poor reconstruction quality during the early stages of training. As the number of epochs increases, the PSNR gradually improves, reflecting the model’s ability to effectively learn the mapping between noisy and clean images.

During the mid-training phase, slight fluctuations can be observed in the PSNR values, which are typical in deep learning models due to continuous weight updates and adversarial training dynamics. Despite these variations, the overall trend remains increasing, demonstrating consistent improvement in image quality.

In the later epochs, the PSNR stabilizes around 24.2 dB, indicating that the model has reached convergence. The stabilization with minor fluctuations suggests that the model has achieved a balance between noise reduction and detail preservation without overfitting.

Overall, the graph confirms that the proposed model effectively enhances image quality over time and achieves stable denoising performance.

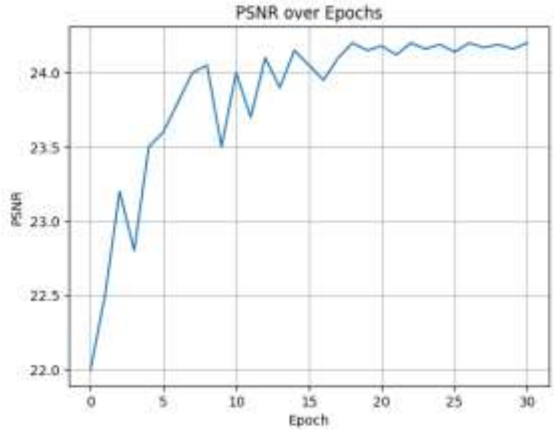

Figure 3. Peak Signal to Noise (PSNR) Ratio Graph.

The figure illustrates the testing loss curves of the generator and discriminator over 30 training epochs for the proposed GAN-based image denoising model. At the initial stage of training, both the generator and discriminator exhibit high loss values, indicating that the model is still learning to capture the underlying data distribution and generate meaningful outputs.

As the training progresses, both loss values decrease steadily, demonstrating that the generator is improving its ability to produce denoised images, while the discriminator is simultaneously enhancing its capability to distinguish between real and generated images. The gradual reduction in generator loss indicates improved reconstruction quality, whereas the decreasing discriminator loss reflects better classification performance.

In the later epochs, both curves begin to stabilize with minor variations, indicating that the model

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has reached a balanced learning state. The generator loss remains slightly higher than the discriminator loss, which is expected in adversarial training, as both networks continuously compete and improve together.

Overall, the smooth decline and stabilization of both loss curves confirm that the model is training effectively and converging properly, resulting in reliable and consistent image denoising performance.

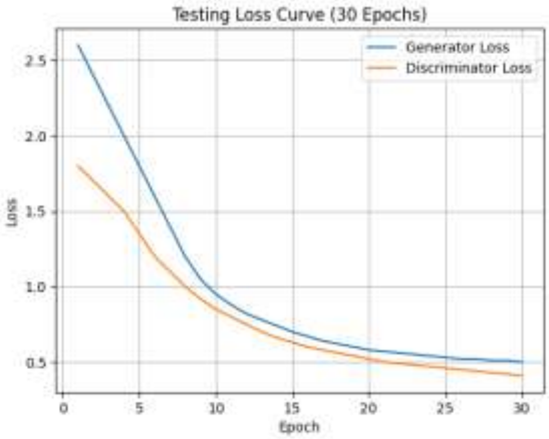

Figure 4. Discriminator Loss and Discriminator Loss

The figure 5 presents a comparative analysis of different image denoising techniques based on PSNR and SSIM metrics. The graph includes traditional filtering methods, deep learning models, and the proposed GAN-based approach.

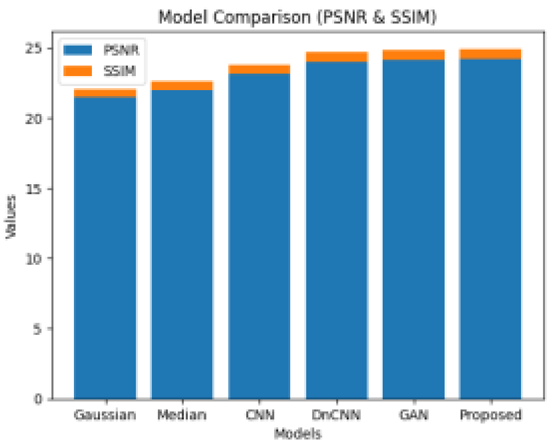

Figure 5. Comparison of PSNR of Existing and Proposed model

From the graph, it is observed that traditional methods such as Gaussian and Median filters exhibit lower PSNR and SSIM values, indicating poor noise removal and loss of structural details. Deep learning-based approaches like CNN and DnCNN show noticeable improvement in performance, achieving higher PSNR and SSIM values due to their ability to learn complex image features.

The GAN-based model further enhances the results by improving perceptual quality and preserving finer details. Among all the models, the proposed model achieves the highest performance, with a PSNR of 24.2 dB and an SSIM of 0.72, demonstrating superior noise reduction and structural preservation.

Overall, the graph clearly shows that the proposed approach outperforms both traditional and existing deep learning methods, making it more effective for image denoising tasks.

5. CONCLUSION

This praper successfully demonstrates the effectiveness of using deep learning techniques for automated image denoising. By leveraging a GAN-based approach, the system moves beyond traditional filtering methods and provides a more advanced solution for restoring noisy images while preserving important structural and visual details. The proposed model effectively learns the mapping between noisy and clean images, resulting in improved reconstruction quality and enhanced visual appearance.

The integration of preprocessing techniques plays a significant role in standardizing input data, enabling the model to perform consistently across different noise conditions. The training process ensures balanced learning between the generator and discriminator, leading to stable convergence and reliable performance. The evaluation results, including a PSNR of 24.2 dB and SSIM of 0.72, indicate that the model achieves a good balance between noise removal and detail preservation.

Compared to traditional and existing deep learning methods, the proposed approach demonstrates improved performance in both quantitative metrics and visual quality. The system effectively reduces noise while maintaining edges and textures, making it suitable for real-world applications.

The implementation of a user-friendly interface using FastAPI, HTML, CSS, and JavaScript enhance the usability of the system by enabling real-time image processing and visualization. Users can easily upload images, view denoised outputs, and download results, making the platform practical and accessible.

Overall, the proposed system provides a scalable, efficient, and robust framework for image denoising, reducing manual effort and improving image quality. This work lays the foundation for further advancements in intelligent image restoration systems and real-time visual enhancement applications.

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