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Using deep neural networks for image denoising in hardware-limited environments

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ABSTRACT

Image denoising remains a vital topic in digital image processing, as it aims to recover visually clear content from observations compromised by random fluctuations. This article provides an overview of advanced deep neural network methods for image denoising and compares their performance with classical techniques. Emphasis is placed on the capacity of modern deep architectures to learn data-driven relationships that preserve structural details more effectively than traditional strategies. Implementation is conducted in a programming environment using open-source libraries, and the research is carried out in a cloud-based platform with Google Colab to facilitate reproducible and scalable experimentation. Both classical and deep learning-based solutions undergo quantitative and visual assessment, measured through standardized quality indices such as signal-to-noise ratio and a measure of structural similarity, alongside processing speed analysis. Results indicate that neural network-based approaches deliver superior restoration accuracy and detail preservation, although they typically require more computational resources. Classical methods, while simpler to implement and often feasible on hardware with minimal capabilities, frequently struggle when noise levels are high or exhibit complex characteristics. Methods based on block matching and three-dimensional filtering achieve competitive outcomes but impose higher computational overhead, limiting their practicality for time-sensitive applications. Potential future directions include hybrid techniques that merge the benefits of convolutional and transformer-inspired frameworks, along with refined training methodologies that extend applicability to scenarios lacking large volumes of clean reference data. By addressing these challenges, the evolving field of image denoising stands to offer more efficient and robust solutions for diverse real-world tasks.

Keywords: Image denoising; deep neural networks; residual learning; transformer-inspired models; denoising quality; inference time

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INTRODUCTION

Image denoising is a fundamental challenge in digital image processing, aimed at restoring clear, noise-free images from degraded observations. Noise often appears as random fluctuations in pixel intensities and arises during image acquisition under adverse conditions. Consequently, images captured under these conditions frequently suffer from compromised clarity, diminished detail visibility, and reduced overall interpretability, which can adversely affect further processing tasks such as object recognition, scene analysis, and automated decision-making.

The task of effectively suppressing noise and simultaneously preserving crucial image features, including fine textures, edges, and structural content, is very important across diverse application areas.

These areas encompass digital photography, medical image diagnostics, satellite and aerial remote sensing, astronomical imaging, surveillance systems, industrial inspection, and various computer vision applications, where image quality significantly affects the accuracy and reliability of subsequent processing tasks.

Historically, researchers have approached the denoising task using classical filtering and algorithmic strategies. Such traditional approaches include linear filtering methods, such as Gaussian smoothing and Wiener filtering, as well as nonlinear techniques, such as median filters and bilateral filters. Transform-domain methods, particularly those employing wavelets or Fourier transforms, have been widely utilized as well, benefiting from

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their ability to isolate and suppress noise in specific frequency bands. Additionally, variational techniques and algorithms based on partial differential equations (PDE) have been explored extensively, as they provide strong theoretical foundations and intuitive geometric interpretations. Nevertheless, despite their theoretical advantages and computational efficiency, these classical methods frequently encounter practical limitations. They commonly assume simplistic noise models – most notably Additive White Gaussian Noise (AWGN) – and often prove insufficiently robust when dealing with realistic noise types characterized by complex statistical distributions and spatial correlations. Furthermore, classical filtering methods can unintentionally introduce artifacts or overly smooth images, thereby degrading important visual structures and textures, diminishing image interpretability, and negatively affecting downstream image analysis tasks.

In recent years, significant advances in machine learning, and particularly deep learning techniques, have profoundly reshaped the field of image denoising. Deep neural network methods, such as Convolutional Neural Networks (CNNs), have demonstrated remarkable effectiveness by automatically learning sophisticated, non-linear mappings from noisy inputs to their clean counterparts. Unlike traditional approaches, neural network-based denoising does not rely on explicit modeling of noise distributions or manual parameter tuning, but instead derives optimal filtering and restoration strategies directly from large-scale datasets comprising paired noisy and noise-free images. Through training on diverse examples, deep learning models can implicitly capture complex statistical properties of real noise patterns, allowing for superior denoising quality, especially under challenging real-world conditions. Modern deep neural network architectures, such as residual networks, dense convolutional networks, attention-based mechanisms, transformer-based models, and methods using self-supervised and unsupervised learning schemes, have progressively elevated image denoising performance to state-of-the-art (SOTA) levels. These neural architectures typically achieve higher values in standard quality metrics, such as Peak Signal-to-Noise Ratio (PSNR) [1], measured in decibels, and Structural Similarity Index Measure (SSIM) [1], a perceptually-motivated measure designed to evaluate structural preservation in images.

Quantitative evaluation of denoising algorithms typically involves metrics like PSNR and SSIM, where higher values indicate superior restoration performance. While PSNR remains a widely-adopted measure due to its simplicity and ease of computation, it assesses quality based solely on pixel-wise error and often correlates weakly with human perceptual assessments. Conversely, SSIM provides a more perceptually aligned measure by explicitly considering luminance, contrast, and structural similarities. Due to the complementary nature of these metrics, modern studies commonly employ both PSNR and SSIM when evaluating denoising methods. Additionally, inference speed and computational complexity represent crucial practical considerations, as rapid image restoration is essential in many real-time or resource-constrained scenarios, such as mobile photography or embedded vision systems.

THE PURPOSE OF THE ARTICLE

The main goal of this article is to provide a concise review of modern image denoising approaches, emphasizing SOTA neural network solutions, and to experimentally compare their restoration performance.

Specifically, the objectives are to.

– Summarize key developments in both classical and deep neural network-based image denoising techniques, highlighting architectures such as convolutional networks and transformer-inspired models.

– Compare a selection of methods (including linear, non-linear, and deep CNN-based denoisers) under controlled experiments, focusing on restoration quality (PSNR, SSIM) and computational effort (inference time).

– Discuss practical considerations such as resource constraints and hardware requirements, given that efficient denoising is often desirable in mobile or industrial applications.

– Provide direction for future research, including investigations into more advanced transformer-based approaches and optimization techniques (e.g., pruning or quantization) to balance speed and quality.

By focusing on these aspects, the article offers both a theoretical overview and an empirical demonstration of how modern deep learning methods can significantly improve image denoising outcomes over classical algorithms, while acknowledging the trade-offs related to computational complexity.

The scientific novelty of the research lies in the integrated approach for experimental evaluation, which employs a real-world collection of architectural photographs to explicitly compare denoising quality and inference time between classical filters and a deep CNN model under constrained hardware conditions.

LITERATURE REVIEW

Image denoising has been extensively studied due to its significance in various applications requiring high image quality. Classical denoising methods predominantly rely on mathematical models and heuristics, which offer fast computation and interpretability but exhibit limitations in preserving essential image details.

Linear filters represent some of the simplest classical denoising approaches, including averaging and Gaussian smoothing. These methods reduce noise by averaging pixel values within local neighborhoods, which inevitably leads to undesirable blurring of edges and loss of fine textures, particularly under conditions of substantial noise [2]. Wiener filtering improves upon this by adaptively adjusting smoothing strength based on local variance estimates, thereby better preserving high-frequency image content; however, it still struggles to maintain sharp edges and fine details at higher noise levels [3].

Non-linear filters provide a more effective alternative to linear methods. Median filtering, for example, effectively handles impulse (salt-and-pepper) noise by replacing each pixel with the median intensity of its neighborhood, thus preserving edges better than averaging methods [4]. Bilateral filtering advances this approach further by combining spatial proximity and intensity similarity, significantly reducing noise while effectively preserving edges and structural details [5].

Variational and PDE-based methods, such as anisotropic diffusion and total variation (TV) denoising, significantly advanced denoising theory. Anisotropic diffusion reduces noise by iteratively smoothing images while selectively restricting diffusion across edges; however, it requires careful parameter tuning and can produce oversmoothing artifacts [6]. TV denoising employs an L1 regularization penalty on image gradients to preserve sharp edges, yet it may introduce characteristic staircase artifacts, leading to unnatural block-like effects and loss of fine textures [7].

Transform-domain and sparsity-based methods marked another significant development in classical denoising. Wavelet thresholding techniques selectively suppress insignificant wavelet coefficients, exploiting sparse representations, though their performance heavily depends on appropriate basis selection and thresholding rules [8]. Dictionary learning approaches, such as K-SVD, improved adaptability by learning image-specific sparse representations. Weighted Nuclear Norm Minimization (WNNM) further enhanced quality using low-rank approximations of similar patch groups but required extensive computational resources due to iterative optimization [9].

A significant advancement in classical denoising was achieved through non-local self-similarity, recognizing repetitive patterns across images. Non-Local Means (NLM) improved texture preservation by averaging pixels based on structural similarity rather than spatial proximity alone [10]. Block-Matching and 3D (BM3D) filtering extended this idea by grouping similar patches into stacks and applying collaborative transform-domain filtering, achieving SOTA results for many years but at the cost of higher computational complexity and occasional block artifacts at high noise levels [11].

Despite these successes, classical methods inherently face trade-offs between noise suppression and detail preservation, requiring careful manual tuning and often struggling with real-world noise complexities. These limitations motivated the transition to deep learning approaches, which implicitly learn denoising strategies from data.

Early neural network approaches, like the Multi-Layer Perceptron based method demonstrated competitive performance compared to BM3D but at substantial computational cost [12]. The Trainable Nonlinear Reaction-Diffusion (TNRD) method bridged classical models with neural networks, achieving competitive results through learned diffusion filters in shallow convolutional networks [13]. The limitations of classical methods and promising initial results from early neural network-based approaches motivated intensive research towards more advanced deep learning solutions.

Among these, convolutional neural networks (CNNs) rapidly emerged as the leading technique due to their powerful feature extraction capabilities, flexible architectures, and ability to learn directly from large-scale data.

IMAGE DENOISING WITH DEEP LEARNING

Advanced convolutional neural networks (CNNs), such as Denoising CNN (DnCNN), significantly improved denoising performance by introducing residual learning and batch normalization techniques [14, 15]. Building upon this, fast and Flexible Denoising CNN (FFDNet) enhanced robustness and efficiency by explicitly integrating noise-level information and processing downscaled image inputs [16, 17].

Deep learning approaches have transformed image denoising by learning rich models of images and noise directly from data. Instead of manually designing filters or priors, neural networks can learn how to remove noise by training on large datasets of noisy and clean image pairs. This section details the most widespread and interesting neural network architectures for denoising, from early attempts to current SOTA designs.

The watershed moment for deep learning in denoising came with the introduction of DnCNN [18]. DnCNN is a deep CNN (17 layers) that introduced two key ideas: residual learning and batch normalization for denoising. Instead of directly predicting the clean image, DnCNN is trained to predict the residual noise (the difference between noisy and clean image). This residual learning formulation makes the job easier, since the residual is often a simpler pattern (mostly high-frequency noise) and the network doesn't have to learn to reproduce the entire image content. After predicting the noise, the clean output is obtained by subtracting the noise from the input. DnCNN also used batch normalization layers to stabilize and accelerate training, which was novel in the context of low-level vision at the time (Fig. 1). With these innovations and a sufficiently deep architecture, DnCNN was able to significantly surpass BM3D in denoising performance for additive white Gaussian noise across a range of noise levels (about 0.5-0.7 dB higher PSNR than BM3D).

One limitation of DnCNN was that it was trained for a specific noise level (or had separate models for several discrete noise levels). If the noise variance changed, one would need to know it and possibly switch models. To address this, FFDNet was proposed as a fast and flexible denoising CNN [19]. FFDNet accepts an additional noise level map as input – essentially a constant channel indicating the estimated noise sigma.

This allows a single network to handle variable noise levels by adjusting its output based on the provided sigma. FFDNet also employs an architectural tweak: it operates on downsampled sub-images (e.g. splitting the image into four sub-images of half resolution) for efficiency. Operating on a smaller spatial size both speeds up processing and increases the effective receptive field of the filters on the original image. Thanks to these ideas, FFDNet is flexible (one model works for a range of noise) and fast in practice, while delivering denoising quality on par with DnCNN. In fact, for higher noise ($\sigma > 25$), FFDNet was reported to slightly outperform DnCNN in PSNR [20] (Table 1). As shown, the CNN-based methods (DnCNN and FFDNet) generally achieve higher PSNR values compared to classical methods (BM3D and WNNM), especially at moderate noise levels ($\sigma = 25$ and 50).

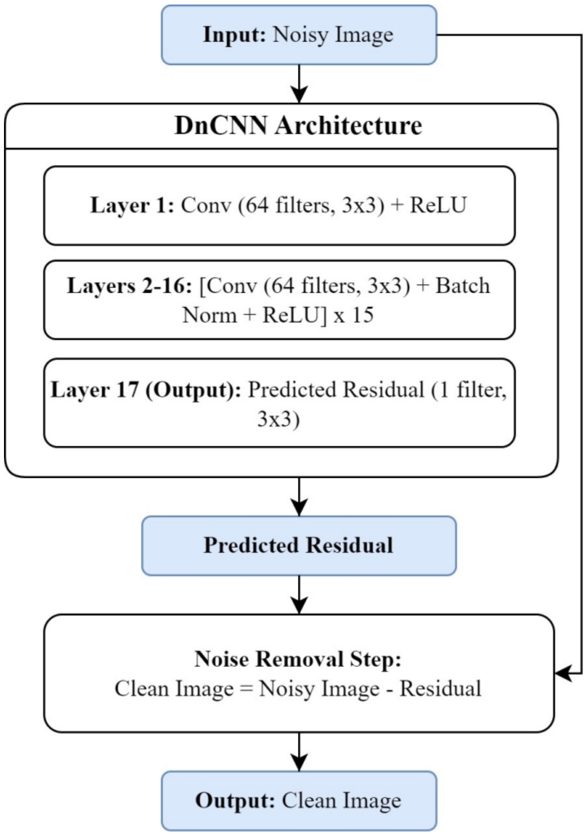

Fig. 1. **DnCNN architecture and residual-based denoising workflow**
Source: **compiled by the authors**

Table 1. **Comparison of PSNR for BM3D, WNNM, DnCNN, and FFDNetat different noise levels**

Method	$\sigma = 15$	$\sigma = 25$	$\sigma = 50$
BM3D	31.07	28.57	25.62
WNNM	31.37	28.83	25.87
DnCNN	31.72	29.23	26.23
FFDNet	31.62	29.19	26.30

Source: **compiled by the [20]**

Following the pioneering methods such as DnCNN and FFDNet, research has increasingly focused on pushing denoising performance further by deepening and widening network architectures while incorporating novel mechanisms. One prominent direction has been the integration of residual and dense connections inspired by high-level vision models like residual neural network (ResNet) [21] and densely connected networks (DenseNet) [22].

Recent methods incorporate attention mechanisms and non-local blocks to capture long-range dependencies by modeling similarities between distant image regions, echoing classical self-similarity approaches. For example, models such as N3Net [23] integrate learnable NLM-style filtering within a CNN; in N3Net, convolutional features are used to compute an affinity matrix that guides the weighted aggregation of information from spatially distant but similar patches.

Transformer-based models [24] have been recognized as the most modern and effective solution for image denoising since around 2021. These architectures use self-attention to capture long-range dependencies, which is essential for distinguishing noise from fine image details. For example, the Image Processing Transformer (IPT) leverages a large pretrained transformer originally developed for natural language processing to perform multiple restoration tasks – denoising, super-resolution, and inpainting – by effectively modeling global context. Building on this, SwinIR [25] partitions images into non-overlapping windows and applies self-attention locally, dramatically reducing computational complexity while still capturing long-range relationships through hierarchical merging [26].

For medium and small computing power, DnCNN is the most practical option. Transformer-based models require substantial resources. Their self-attention mechanism scales quadratically with image resolution, leading to high memory usage and slower inference, especially for high-resolution images [27]. Additionally, they demand large training datasets, increasing costs and making them less practical for resource-constrained environments [28].

IMAGE DENOISING EXPERIMENTS

In continuation of the theoretical framework presented earlier, a series of experiments were conducted to assess the performance of several image denoising methods under controlled conditions, with special attention to the practical viability of deep learning-based approaches in environments with limited computational resources.

Linear and basic nonlinear filters remain widely used in many image-processing pipelines due to their simplicity and low computational requirements. Evaluating these simpler methods provides a baseline for illustrating incremental improvements achieved by more advanced classical approaches such as BM3D, and subsequently demonstrates the additional benefits provided by deep learning techniques. Traditional filtering techniques – including Gaussian filtering, bilateral filtering, and BM3D – were implemented alongside a pretrained deep convolutional neural network (DnCNN) derived from the KAIR framework [29]. The objective was to quantitatively compare these methods using standard quality metrics (PSNR and SSIM) and to visually inspect the restoration results.

The experimental implementation was carried out in Python. The code begins by establishing the necessary environment and importing libraries such as OpenCV [30] for classical image processing, BM3D for advanced patch-based filtering, and PyTorch for deep learning inference. A set of helper functions was defined to simulate image degradation by adding synthetic Gaussian noise, compute image quality metrics, and facilitate visual comparisons by displaying the noisy, denoised, and reference images side by side. A test image is loaded, resized, and then corrupted with additive white Gaussian noise to generate the noisy observation.

While well-known datasets such as the Smartphone Image Denoising Dataset (SIDD) or the Darmstadt Noise Dataset (DND) are frequently employed to benchmark image denoising methods, the experimental evaluation in this study utilized a set of multiple real-world photographs captured under varying lighting and environmental conditions. These photographs, which primarily depict architectural landmarks in large Ukrainian cities, serve not only to assess denoising performance on scenes featuring intricate structural details and diverse textures but also to demonstrate how such technologies may be integrated into industrial design workflows where maintaining high-quality visual information is essential. Moreover, the dataset was carefully curated to capture a broad spectrum of noise conditions and image qualities, thereby reflecting the challenges encountered in real-world scenarios and highlighting the impact of data variability on the performance of deep learning models. Although the dataset is comparatively smaller and more focused than standard benchmarks, it comprises several distinct images rather than a single photo, ensuring that the reported outcomes are not tied to an isolated case.

For the classical methods, Gaussian filtering, bilateral filtering, and BM3D were applied using parameters optimized to balance noise reduction with detail preservation. In parallel, the pretrained DnCNN model was implemented as a 20-layer network that mirrors the architecture specified by the KAIR framework. The model's weights were downloaded from an external repository [31]. An inference function converts the input image into the appropriate tensor format and processes it through the network to produce a denoised output.

Finally, the outputs from all denoising methods were aggregated into a single framework where PSNR and SSIM were computed against the original clean image, and the results were presented both numerically and visually. This experimental design enables a direct, quantitative comparison between classical filtering techniques and the deep learning-based DnCNN model (Fig. 2).

The performance was measured using PSNR and SSIM. The results of the experiments are shown in Table 2.

Gaussian Filtering produced the lowest quality, with a PSNR of 21.45 dB and an SSIM of 0.660. This low PSNR indicates that the uniform blur introduced by Gaussian filtering is too aggressive, leading to the loss of fine details and texture (Fig. 3b). The SSIM value further confirms that the structural information in the image is poorly preserved.

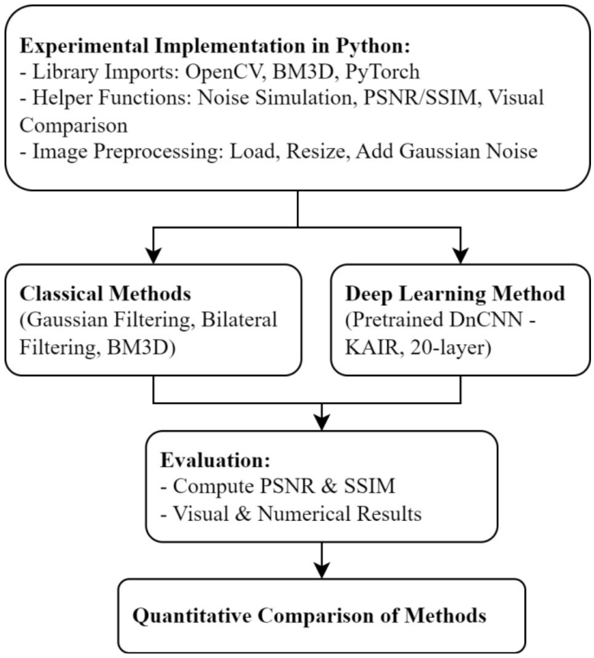

Fig. 2. **Flowchart of the denoising experiment**
Source: **compiled by the authors**

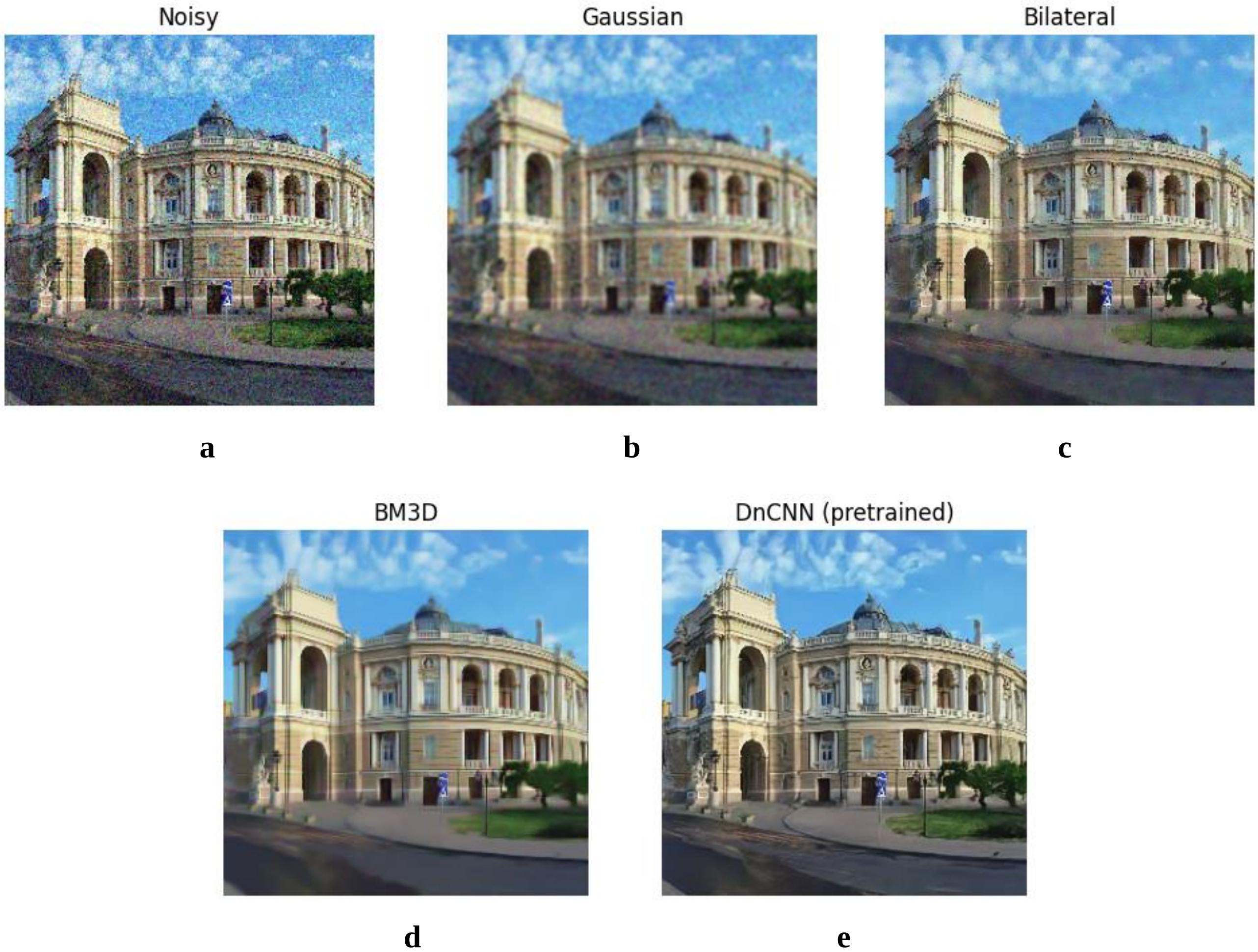

Fig. 3. **Comparison of image denoising results:**
a – original noisy image; b – Gaussian-filtered image; c – bilateral-filtered image;
d – BM3D-filtered image; e – pretrained DnCNN-denoised image
Source: **compiled by the authors**

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Table 2. **Experimental comparison of Gaussian, Bilateral filtering, BM3D, and DnCNN**

Method	PSNR (dB)	SSIM
Gaussian	21.45	0.660
Bilateral filtering	26.34	0.804
BM3D	25.03	0.807
DnCNN (pretrained)	27.96	0.894

Source: **compiled by the authors**

Bilateral filtering improved the quality, achieving a PSNR of 26.34 dB and an SSIM of 0.804. By considering both spatial and intensity information, bilateral filtering is able to reduce noise while better preserving edges compared to the Gaussian filter (Fig. 3c). However, its performance is still limited when handling complex textures and higher noise levels.

BM3D, which exploits non-local self-similarity, reached a PSNR of 25.03 dB and an SSIM of 0.807. Although its PSNR is slightly lower than that of bilateral filtering, its SSIM is comparable (Fig. 3d). BM3D typically excels in preserving structural details through collaborative filtering, but in this case, its overall performance is not as high as that of the deep learning method.

The pretrained DnCNN model achieved the highest performance, with a PSNR of 27.96 dB and an SSIM of 0.894 (Fig. 3e). This indicates that the deep learning approach is much more effective in removing noise while preserving the image's fine details and structural information. DnCNN benefits from being trained on large datasets, enabling it to learn a non-linear mapping from noisy images to clean images, which results in better quantitative and perceptual quality.

In summary, while classical methods such as Gaussian, bilateral filtering, and BM3D can reduce noise, they tend to sacrifice detail or fail to handle complex textures. The deep learning-based DnCNN significantly outperforms these methods by achieving higher PSNR and SSIM values, making it a more robust choice for applications that require high-quality image restoration.

METRICS AND INFERENCE TIME

While PSNR and SSIM remain the two most frequently employed quantitative indicators for evaluating denoising effectiveness, they capture somewhat different dimensions of image fidelity. PSNR, derived from the mean squared error between the predicted and ground-truth images, is easy to compute and widely recognized but can fail to reflect perceptual aspects. SSIM, in contrast, accounts for luminance, contrast, and structural information, often aligning better with the human visual system's sensitivity to edges and fine details. Consequently, an algorithm producing a relatively modest gain in PSNR but a marked improvement in SSIM can offer superior visual quality. It is, therefore, prudent to report both metrics to achieve a well-rounded assessment of denoising performance, as done in the experiments above.

In addition to these quality metrics, inference time is a crucial consideration, especially for real-world applications requiring rapid image restoration (e.g., mobile photography, surveillance, or industrial inspection on resource-constrained hardware). Traditional methods like bilateral filtering or BM3D can be computationally heavy for large images, yet they often remain CPU-friendly for moderate resolutions, eliminating the need for specialized hardware. Deep neural networks, however, may exhibit higher computational requirements: DnCNN, FFDNet, and other CNN-based approaches rely on GPU acceleration to achieve real-time or near real-time inference speeds at high resolutions. For applications where low-latency processing is essential, smaller architectures or optimization techniques (e.g., model pruning, quantization, and efficient blocks such as depthwise convolutions) can be employed to strike a balance between denoising accuracy and runtime constraints.

As a result of the experiment, the inference time was also estimated, demonstrating how the computational demands of each method vary significantly. The experiments were performed on a Google Colab Pro instance equipped with an NVIDIA A100 GPU, which is known for its high computational throughput (Table 3).

Table 3. **Inference time of Gaussian, Bilateral filtering, BM3D, and DnCNN denoising methods**

Method	Inference Time (ms)
Gaussian	0.90
Bilateral filtering	12.13
BM3D	3122.11
DnCNN (pretrained)	7.01

Source: **compiled by the authors**

Gaussian Filtering shows an exceptionally low inference time (0.90 ms) due to its simplicity – a fixed convolution operation that is highly optimized in many libraries. However, the lower PSNR and SSIM values suggest that while it is fast, its denoising capability is limited.

Bilateral filtering requires a longer inference time (12.13 ms) compared to Gaussian filtering. This is because bilateral filtering not only considers spatial proximity but also pixel intensity similarity, which adds computational overhead. The additional complexity results in better preservation of edges and improved denoising performance, as reflected in its PSNR and SSIM values.

BM3D demonstrates a significantly higher inference time (3122.11 ms). The algorithm involves block matching and collaborative filtering in a 3D transform domain, which are computationally intensive processes. The implementation, likely not optimized for GPU acceleration, leads to this substantial runtime even on a high-performance instance. This method is robust in terms of denoising quality but is less feasible for real-time applications.

DnCNN achieves a competitive balance between quality and speed. With an inference time of 7.01 ms, it benefits from GPU acceleration provided by the A100. The network's architecture, which comprises a series of convolutional layers, is efficiently executed on GPUs. This method attains the highest PSNR and SSIM, indicating superior denoising performance while maintaining low inference times.

Thus, while classical methods like Gaussian and bilateral filtering offer rapid inference, they compromise on denoising quality. BM3D, despite its effective noise reduction, suffers from a prohibitive inference time due to its complex processing steps. Conversely, the DnCNN model, optimized for GPU execution, delivers both high denoising quality and low inference latency, making it well-suited for real-time applications in high-performance computing environments like a Colab Pro instance with an NVIDIA A100 GPU.

CONCLUSIONS

The results of this study underscore the transformative impact of deep learning on image denoising. Modern neural network architectures – particularly CNN-based models such as DnCNN – consistently demonstrate superiority over classical methods. These networks achieve higher PSNR and SSIM values while maintaining competitive inference speeds through efficient GPU utilization. Their capability to learn complex, non-linear mappings from noisy inputs to clean outputs, facilitated by mechanisms like residual learning and batch normalization, sets a new benchmark in the field.

Classical denoising techniques, including Gaussian, bilateral filtering, and BM3D, remain relevant in scenarios where computational resources are severely limited. However, these methods generally fall short in preserving fine details and structural information. For example, while Gaussian filtering offers extremely fast processing, its uniform smoothing often results in significant loss of essential details. BM3D, although effective at reducing noise by leveraging non-local self-similarity, incurs prohibitive inference times that hinder its applicability in real-time applications. The comparative experiments clearly illustrate that deep learning-based approaches offer a more balanced trade-off between denoising quality and runtime efficiency.

Transformer-based models, introduced around 2021, represent the frontier of denoising technology by capturing global contextual information through self-attention mechanisms. Despite their state-of-the-art performance in modeling long-range dependencies, these models demand substantial computational resources and large-scale training data. Their increased memory consumption and longer inference times make them less practical for resource-constrained environments, highlighting an important trade-off between performance gains and computational efficiency.

Looking ahead, further research is essential to bridge the gap between high-performance denoising and practical deployment. Hybrid architectures that combine the efficiency of CNNs with the global context modeling of transformers offer a promising avenue for future development. Additionally, techniques such as model pruning, quantization, and knowledge distillation may help to reduce the computational overhead of deep models without sacrificing denoising quality. Moreover, self-supervised and unsupervised learning methods present an exciting opportunity to further enhance the robustness of denoising models, particularly in scenarios where clean training data are scarce.

In conclusion, while modern deep learning methods have significantly advanced the state-of-the-art in image denoising, ongoing innovation is necessary to optimize these techniques for real-world applications. Achieving an optimal balance between denoising performance and computational efficiency will be crucial for the integration of these methods into practical imaging systems, ranging from mobile photography to high-throughput industrial inspection. The continued evolution of deep neural networks, combined with advancements in hardware and training strategies, is poised to further revolutionize the field of image restoration in the coming years [32, 33].

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Використання глибоких нейронних мереж для видалення шуму із зображень в умовах обмежених апаратних ресурсів

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АНОТАЦІЯ

Усунення шуму на зображеннях залишається важливою темою в цифровій обробці зображень, адже має на меті відновлення чіткого візуального вмісту з даних, пошкоджених випадковими коливаннями. У цій статті представлено огляд сучасних методів усунення шуму на основі глибоких нейронних мереж та порівняння їх ефективності з класичними техніками. Особливий акцент зроблено на здатності сучасних глибоких архітектур вивчати залежності в даних, що дозволяє більш ефективно зберігати структурні деталі, ніж традиційні методи. Реалізацію проведено в програмному середовищі з використанням бібліотек відкритого коду, а дослідження виконано на платформі Google Colab, що забезпечує відтворюваність і масштабованість експериментів. Класичні та нейромережеві методи оцінюються кількісно та візуально за допомогою стандартизованих показників якості, таких як співвідношення сигнал/шум і показник структурної подібності, а також аналізу швидкості обробки. Результати демонструють, що нейромережеві підходи забезпечують вищу точність відновлення і краще зберігають деталі, хоча зазвичай потребують більших обчислювальних ресурсів. Класичні методи, хоч і простіші в реалізації та доступні для обладнання з мінімальними можливостями, часто не справляються за високого рівня шуму або його складного характеру. Методи на основі зіставлення блоків та тривимірної фільтрації демонструють конкурентні результати, проте вимагають значних обчислювальних витрат, що обмежує їх застосування для завдань, чутливих до часу. Перспективні напрямки розвитку включають гібридні підходи, що поєднують переваги згорткових і трансформерних архітектур, а також удосконалення стратегій навчання, які дозволять використовувати методи за відсутності великих обсягів чистих еталонних даних. Вирішення цих викликів забезпечить розвиток методів усунення шуму на зображеннях, що дозволить отримати більш ефективні та надійні рішення для широкого спектру практичних задач.

Ключові слова: усунення шумів із зображення; глибокі нейронні мережі; залишкове навчання; моделі на основі трансформерів; якість шумозаглушення; час висновку

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