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A Review of Image Denoising Techniques: Models, Learning Paradigms and Emerging Trends

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Abstract

Image denoising is a cornerstone problem in digital image processing and computer vision, aiming to remove noise while preserving essential image structures such as edges and textures. Over the years, denoising methods have evolved from classical spatial and transform-domain filters to sophisticated learning-based and deep neural network models. This paper presents a comprehensive and critical review of image denoising techniques, emphasizing methodological evolution, underlying assumptions and practical limitations. Unlike conventional surveys that focus primarily on algorithmic categorization, this review highlights geometric adaptivity, noise modelling realism and learning paradigms as key dimensions shaping modern denoising research. We analysed traditional, model-based and deep learning approaches, discussed their strengths, weaknesses and identified open challenges such as real-world noise generalization, edge preservation and interpretability. Finally, emerging trends and future research directions are outlined, positioning image denoising as a continually evolving field driven by both theoretical advances and real-world imaging demands.

Keywords: Image denoising, Noise modelling, Deep Learning, Edge preservation, Noise Filtering.

1. Introduction

Digital imaging systems face unavoidable noise problems which originate from their sensor flaws, environmental factors, transmission system failures and restrictions on light. Noise reduces the quality of images because it makes fine details impossible to see, it hinders both human viewers and computer vision systems in tasks like recognition, segmentation, tracking, medical diagnosis and remote sensing analysis [1]. The process of image denoising functions as an essential initial stage which removes noise from images while maintaining their vital structural details. The technology functions as an essential component for applications which include medical imaging, satellite monitoring, low-light photography and surveillance because it provides both visual clarity & efficient computational performance. Researchers have spent decades studying image denoising because the method requires balancing two conflicting needs, which are noise reduction and precise detail maintenance [2]. The aggressive denoising

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method successfully removes noise from images, but creates problems because it causes blurring of edges & textures. The early denoising methods used spatial filtering techniques, which included Gaussian filters and median filters [3], because they provided easy-to-use solutions, but these filters resulted in excessive image smoothing. Edge-preserving filters such as bilateral filtering and anisotropic diffusion, which maintain structural integrity, require users to adjust their settings for optimal results. Transform-domain methods used sparse representations found in wavelet & related domains, while non-local techniques, including NL-means and BM3D, depended on image self-similarity to improve their performance at the expense of increased computational requirements. The development of deep learning through machine learning advancement has established convolutional neural networks (CNNs) as the leading method for image denoising tasks [3]–[5]. The hierarchical feature representations which CNN-based models acquire enable them to perform better than traditional methods [6]. The restoration quality improved through the introduction of residual learning, multi-scale processing and attention mechanisms as innovative techniques. The usage of fixed convolutional grids by standard CNNs creates a restriction that prevents them from handling complex geometries and sharp edge patterns. The majority of models use synthetic Gaussian noise for training, which leads to difficulties when they need to process actual environmental noise situations. The system faces three main challenges, which involve limited ability to interpret its functions and high demands for computing power and problems with using it in systems that handle real-time tasks or operate under resource restrictions [2].

Current research studies investigate adaptive architecture solutions which utilize geometry-based methods together with deformable convolution, edge-aware filtering and directional sampling techniques to achieve improved structural detail retention. Self-supervised and unsupervised learning approaches reduce reliance on paired datasets, while generative models, which include diffusion-based frameworks, enable uncertainty-aware restoration through perceptual guidance [7]. The fast development of denoising methods together with various application needs makes it necessary to assess both traditional, model-based and deep learning techniques through comprehensive evaluation. This review analyses their underlying principles, strengths, limitations, and emerging research directions to provide a structured understanding of the field [3].

2. **Noise Models and Problem Formulation**

The process of image denoising usually operates through an inverse problem framework which requires the extraction of a pristine image from a noisy observation. The observed image in this model functions as a degraded representation of a hidden base image which suffers from noise that was introduced during the process of image acquisition, transmission and storage [8]. The relationship is mathematically expressed through the clean image which combines with a noise element that exists in either additive or multiplicative forms. Denoising becomes an ill-posed problem because the clean image remains hidden, thus requiring researchers to use learned models or prior knowledge for differentiating between noise and actual image features [2]. The statistical identification of noise types serves as a central component in image denoising because different types of noise produce unique probability distributions, which result in different patterns of noise across multiple spatial and signal-dependent contexts. The selection process and the algorithm development for denoising methods base their decisions on these features. The use of incorrect noise assumptions results in two problems, which include insufficient noise reduction and unwanted alterations to visible image components [9].

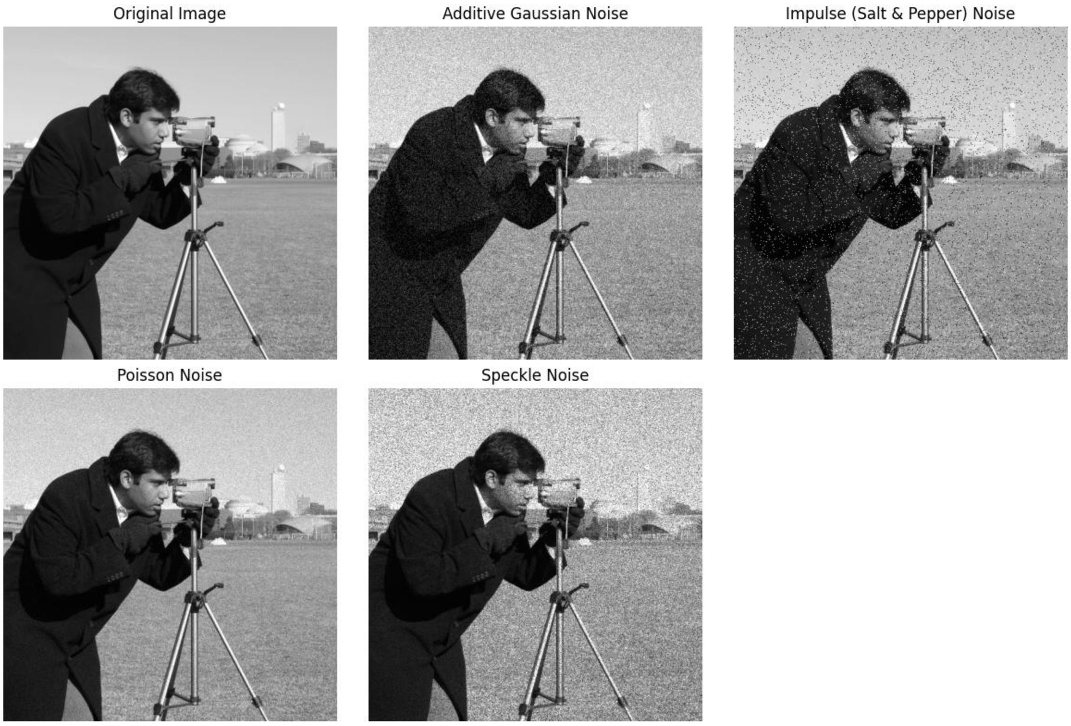

Fig.1: Comparative visualization of diff. noises applied to the same original grayscale image.

The figure displays a comparison between various noise models which were tested on an original grayscale image. The top row shows the original image alongside versions corrupted with additive Gaussian noise and impulse (salt & pepper) noise, highlighting their distinct noise distributions [2], [10]. The bottom row demonstrates how Poisson and speckle noise affect image quality through intensity-dependent and multiplicative noise effects on structural details.

- **Additive Gaussian Noise** serves as the most frequently researched noise model for image denoising studies. The distribution of the data points in the image exhibits independent and identical distribution properties which result in zero mean values and constant variance throughout the entire image. The mathematical framework of this model allows researchers to create mathematical solutions for denoising problems. Electronic thermal noise in imaging sensors is usually gets modelled as Gaussian noise. The actual noise produced by sensors in the field contains more complex elements, which include both signal-dependent and spatially varying noise components. The performance of algorithms which operate based on Gaussian noise becomes ineffective when applied to actual images from the real world [8], [11].
- **Impulse (Salt and Pepper) Noise** functions as salt and pepper noise through its appearance of randomly occurring pixels that show extreme intensity values which reach either the minimum or maximum grey level. This type of noise arises through three different causes, which include faulty sensor elements, bit errors during transmission and malfunctioning memory locations. The sparse and non-continuous nature of impulse noise makes it difficult

for linear smoothing filters to handle this type of noise because it differs from Gaussian noise. Traditional averaging-based methods spread noise while they distort nearby pixels, which requires specialized filtering techniques that use nonlinear or adaptive methods to identify and correct damaged pixels [12], [13].

- **Poisson Noise,** which scientists refer to as photon shot noise, has an inherent nature that depends on the signal strength, occurs frequently in low-light conditions of medical imaging, fluorescence microscopy and astronomical imaging. The noise model shows that noise variance increases with higher signal intensity which causes elevated noise levels in brighter areas. The spatial distribution of noise characteristics throughout the image violates the additive noise model assumptions which makes denoising process more difficult. Poisson denoising methods typically need two components: variance-stabilizing transformations and special modelling methods based on probability distribution [3], [12].
- **Speckle Noise** operates as a multiplicative noise which occurs in all coherent imaging systems that include synthetic aperture radar (SAR), ultrasound imaging and laser-based imaging. Speckle noise creates a granular distortion pattern which decreases image contrast while hiding structural details because it scales with the original signal strength. The multiplicative properties of speckle noise make it difficult to control because standard methods for removing additive noise fail to work effectively. Denoising methods for speckle noise usually use three techniques, which include logarithmic transformations, adaptive filters and statistical models designed for handling multiplicative noise [14].

The process of accurately modelling noise serves as the essential need for successful image denoising operations. Denoising algorithms fail to achieve effective noise removal when the applied noise model fails to match the actual noise pattern present in the image. The existence of such mismatches results in the creation of residual artifacts which produce blurred edges and result in the disappearance of critical diagnostic details. Denoising research at present focuses on developing methods which can handle actual environmental noise patterns without making assumptions about their specific properties [9].

3. Classical Image Denoising Techniques

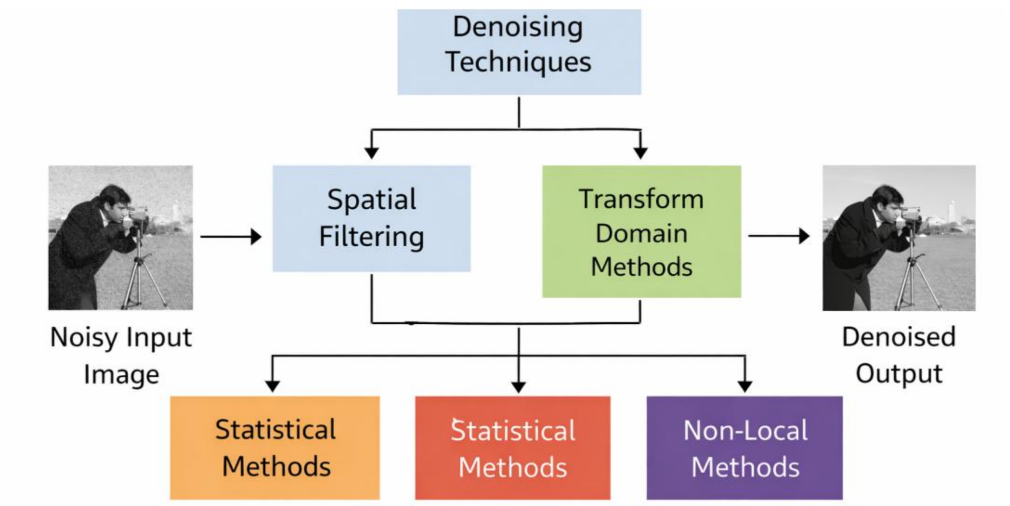

Fig. 2: Block Diagram of Classical Image Denoising Techniques

This block diagram demonstrates how traditional image denoising methods operate from their initial stage to their final stage. The system processes a noisy input image through its main methods which include spatial filtering and transform domain techniques. The methods utilize statistical methods and non-local techniques to achieve better noise reduction results. The final output results in a denoised image, which shows improved visual quality and decreased noise artifacts [12].

3.1 Spatial-Domain Filtering

The fundamental technique of spatial-domain filtering serves as the first method which scientists use for removing noise from images. The techniques process images by working on their pixel intensity values to change each pixel based on data from its surrounding area. The method assumes that neighbouring pixels share similar brightness levels, which allows them to decrease noise through either local averaging or specific smoothing techniques [15].

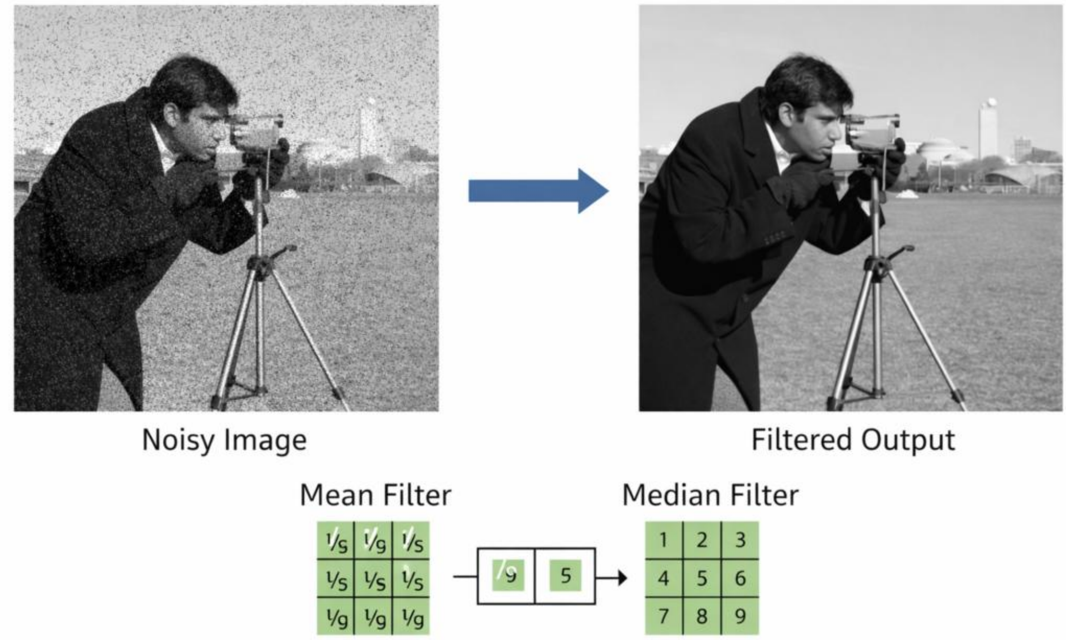

Fig. 3: Spatial-Domain Filtering on a Noisy Image

This figure shows how spatial-domain filtering works to process a noisy image. The left image shows the input corrupted with noise, while the right image shows the improved filtered output. Mean filtering reduces noise by averaging neighbouring pixel values within a kernel window. Median filtering replaces each pixel with the median of its neighbourhood, which removes impulse noise and keeps edge details intact.

Limitations of Spatial-Domain Filtering

Despite being uncomplicated and having good computational efficiency, spatial-domain filters are afflicted with a number of inherent limitations [12], [16].

- **Fixed Window Assumption** – Most spatial filters operate with fixed window parameters because they require specific kernel dimensions and shape specifications.

The established neighbourhood pattern of the filter prevents it from adjusting to different image characteristics which include textures, fine details and sharp edges.

- **Limited Contextual Awareness** – They rely solely on local pixel information and do unsatisfactorily by not taking advantage of non-local similarities or global structural patterns in the image.
- **Edge Blurring** – Smoothing operations decrease edge visibility because edges represent high-frequency image components. The inability of linear filters to differentiate between actual high-frequency image details and background noise results in image sharpness reduction.
- **Noise Model Dependency** – Some spatial filters operate under specific noise assumptions because their design requires Gaussian noise. The filters lose their ability to function when they face actual noise conditions which exceed their particular noise assumption requirements [17].

Spatial-domain filtering established the foundation for modern image denoising methods, but lacks the adaptability required for complex real-world scenarios. The method fails to separate noise from structural information because it struggles with edge region detection. The development of transform-domain non-local methods together with learning-based techniques became necessary due to existing limitations, which required advanced contextual and statistical modelling methods [18]. The spatial-domain methods serve low-complexity applications which require real-time processing but they fail to deliver high-quality image restoration results under severe noise conditions

3.2 Transform-Domain Methods

Transform-domain methods were created to solve spatial-domain filtering problems by enabling image analysis through different representational methods. The methods begin by converting an image into a different domain which allows them to separate signal components from noise elements instead of processing pixel brightness values. The process of denoising begins with the alteration of transform coefficients which leads to the creation of an image through inverse transform reconstruction [12]. The basic rule of transform-domain denoising depends on the fact that natural images produce their best compressed form through specific transform bases. The image contains important visual elements which exist in a limited set of major coefficients, while the background noise spreads throughout most of the minor coefficients. The method of reducing small coefficients through either attenuation or thresholding enables noise removal while maintaining vital visual details of the image. The basic element of transform-domain methods consists of frequency-based transformations which operate through the Fourier transform together with multi-resolution methods that use wavelet transformations. The widespread use of wavelet-based denoising methods exists because they provide spatial, frequency localization abilities which enable better edge and fine detail preservation than spatial filtering techniques [16].

Limitations of Transform-Domain Methods

Transform-domain techniques, despite offering an improvement in performance compared to classical spatial filters, have their own set of limitations [2], [19].

- **Global Basis Limitation** – Some transforms are based on fixed global basis functions which might not ideally represent a broad diversity of image structures, especially over highly textured or complex regions.
- **Threshold Selection Sensitivity** – The effectiveness of coefficient thresholding requires specific threshold parameter selection as its primary factor of performance. The incorrect threshold selection will create two problems which include residual noise and excessive smoothing.
- **Artifact Introduction** – The introduction of artifacts occurs because aggressive coefficient suppression creates visual artifacts that display ringing effects and pseudo-Gibbs phenomena, especially in edge regions.
- **Limited Adaptivity** – Traditional transform-domain methods, which exceed the capabilities of basic spatial filters, depend on pre-established transformation systems because they cannot adapt to the specific patterns found in images.

The spatial-domain filtering techniques receive their most substantial improvement through the development of transform-domain methods which use sparse representations together with frequency analysis. The method operates because it requires fixed transforms together with manual parameter adjustments which causes its performance to decrease whenever it deals with complex environments that have changing noise patterns. The researchers developed non-local denoising methods together with data-driven learning-based denoising approaches because they needed to solve existing challenges [12].

3.3 Non-Local and Patch-Based Methods

Non-local and patch-based methods were introduced to address the limitations of both spatial-domain and traditional transform-domain techniques. Natural images contain self-similarity which these methods use to their advantage since they operate beyond the limits of local filtering. The main finding shows that small image patches repeat at various distances across different parts of the image [14]. The system achieves better noise reduction through structure preservation by using non-local redundancy. Patch-based methods process image data through their system which uses small regions of overlapping image sections as processing units. The system searches for matching patches throughout the complete image with the exception of the reference patch area. The system processes these matching patches through weighted averaging or collaborative filtering methods to improve the signal quality while decreasing background noise [2].

The Non-Local Means (NLM) algorithm stands as the most important method which determines the basic principles of this category. The BM3D method uses its advanced techniques to group matching patches into three-dimensional stacks which it processes through joint filtering in the transform domain [16]. The methods enable superior detail retention which results in their success as the best current methods used in traditional non-learning approaches.

Limitations of Non-Local and Patch-Based Methods

In spite of the strong denoising capacity manifested by these non-local and patch-based techniques, substantial challenges were also encountered:

- **High Computational Complexity** - The process of finding matching patches throughout extensive image areas requires more computational resources, which results in slower performance compared to local filtering techniques.
- **Memory Requirements** - The storage and processing of multiple segmented patches present an increase in the memory requirement, specifically for a collection of highly illuminated images.
- **Dependence on Self-Similarity** - The performance of the system depends on its ability to repeat patterns. The system shows decreased performance when processing images that contain minimal repeated elements and their unpredictable texture patterns.
- Parameter Sensitivity – Proper and efficient tuning of similarity metrics, window sizes for searching, the parameter threshold are crucial to achieving outstanding performance.

Non-local and patch-based techniques established a new standard for traditional image denoising because they succeeded in using image self-similarity to improve their performance. The methods demonstrate better edge and texture preservation abilities than both spatial methods and conventional transform-domain techniques. The system required deep neural network methods because the existing approach had high computational expenses and depended on manually created similarity measurements which needed to be changed into automatic systems for complex image pattern recognition [20].

4. Deep Learning-Based Image Denoising

Deep learning-based image denoising has become the leading method for image restoration because it delivers better results than traditional model-based methods. Deep learning methods use a data-driven approach that learns how to convert noisy images into clean images through training processes, which distinguishes them from traditional methods that depend on pre-designed image transformations and manual image restoration methods[21]. The system allows researchers to create models which handle intricate image statistical data and various noise patterns without needing to depend on particular mathematical formulas for their work. Most deep learning-based denoising methods use Convolutional Neural Networks (CNNs) as their fundamental framework [4], [21], [22]. CNNs efficiently detect spatial patterns because their design allows local connections, weight sharing and their multi-level feature extraction method. The networks achieve their goal of distinguishing noise from important structural elements by using multiple stacked convolutional layers to learn higher-level abstract features. Automatic feature learning serves as the primary advantage of CNN-based models because it removes the requirement for manual feature development.

The implementation of residual learning led to better denoising results for CNN models because it changed the task from direct image reconstruction to predicting noise. The method achieves better results because it breaks down the task into simpler parts which results in faster completion times and better detail preservation through its noise separation process. The current architectural designs use encoder-decoder systems together with skip connections, multi-scale feature extraction, attention systems and transformer components to achieve both short-range and long-range connection tracking [4], [21], [22].

The advancements improve system flexibility which allows the models to manage different types of noise while operating under various imaging conditions. Deep learning-based methods provide their most significant benefit through their ability to perform complete system optimization which enables simultaneous training of the entire denoising process through a single objective function. The integrated learning method demonstrates superior quantitative results and enhanced visual quality when compared to traditional methods that use separate stages or manually created procedures. The system shows multiple benefits but it still encounters several obstacles [8], [23]. The ability of CNN-based denoising models to perform their tasks successfully depends on their access to extensive collections of high-quality training data which includes matched pairs of samples. The process of developing deep learning models necessitates extensive computational resources which include both processing capacity and memory storage.

The models that learn from synthetic noise patterns face difficulties when they try to operate in actual noise situations. Deep neural networks function as black-box systems because they provide users with less ability to understand their processes than traditional model-based methods. The development of image denoising technology has progressed through CNN-based methods and deep learning-driven techniques because these approaches enable dynamic feature extraction, maintain image structure and support direct system optimization. The field needs further study because researchers are still trying to solve present challenges that affect data usage, system performance, model effectiveness and research findings explanation [24], [25].

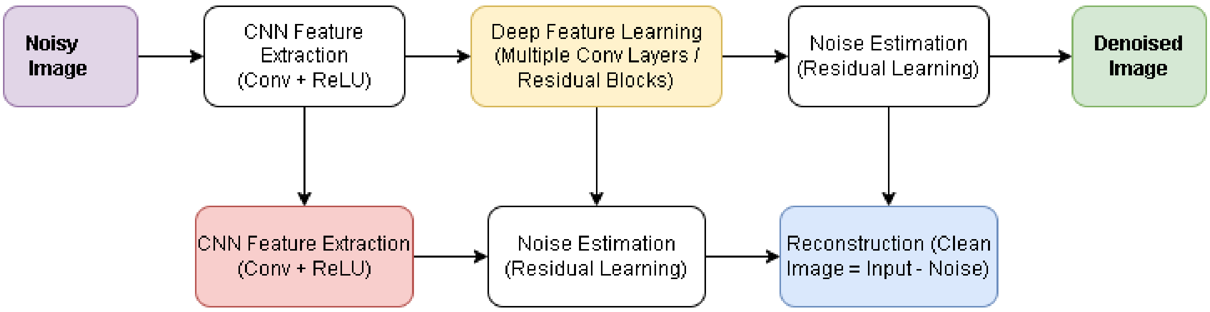

Fig. 4: Block Diagram of Image Denoising

The above diagram shows a deep learning image denoising system which starts with a noisy image, uses CNN-based feature extraction and deep feature learning to process the image. The system uses residual learning to determine the noise part of the input which gets removed to create the final denoised output.

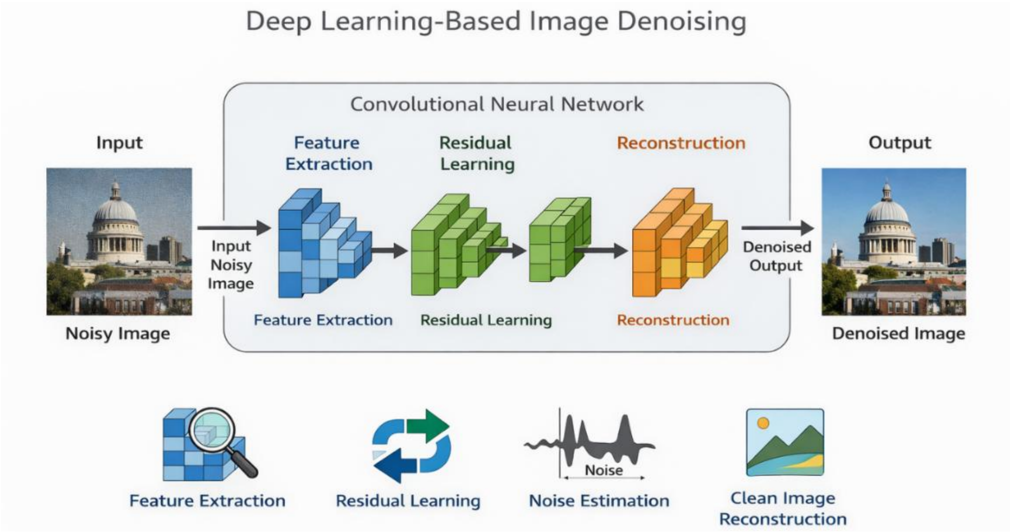

Fig. 5: Deep Learning-Based Image Denoising

This figure shows the process of deep learning-based image denoising which uses a Convolutional Neural Network (CNN) to perform its function. The network receives a noisy input image which it uses to extract features through its convolutional layers. The system uses residual learning to process extracted features to determine the noise component which exists in the captured image. The reconstruction stage uses the predicted noise which we try to remove from the input data to produce a clean image. The final output results in a denoised image which maintains its structural components while showing less noise. The diagram demonstrates how the complete CNN-based denoising system learns through its entire process [18], [26].

5. Geometry-Aware and Edge-Preserving Methods

The geometric-based and edge-keeping denoising techniques exist to solve their primary challenge which requires them to take away noise while maintaining all structural aspects of the image. Important visual elements of natural images are found mainly at the edges, contours and throughout the geometric patterns of the image. The traditional smoothing methods create blurring effects which produce high-frequency components as well as sharpness loss and structural damage [27]. The denoising process uses structural knowledge which geometry-aware methods use to perform their denoising function. Edge-preserving filtering methods smooth out uniform areas of an image while keeping the boundaries between different objects intact. The main techniques used for this purpose include anisotropic diffusion, bilateral filtering and guided filtering which adjust their smoothing effects according to the local brightness changes or edge detection results. The methods achieve noise reduction through their filtering process which depends on the strength of edges and the orientation of elements in the image [28]. The concept of geometry-aware methods extends its framework through the implementation of geometric priors and structure-sensitive models which restore functions through their restoration methods. Diffusion-based models use gradient magnitude as a control mechanism which directs smoothing processes to follow edges while preventing diffusion across those edges. The variational and partial differential equation (PDE) formulations use regularization terms which maintain edge discontinuities while reducing noise. The methods which stress structural coherence work best in situations that require precise boundary measurements. The latest research connects geometry-based principles with multi-scale methods and machine learning frameworks of multiple dimensions. Deep learning models may incorporate edge-aware loss functions, gradient-based regularization, or structural similarity constraints to enhance edge preservation during training [24], [29], [30]. The hybrid strategies enable better noise control, together with detailed visual results than methods that rely only on smoothing techniques. The geometry-aware edge-preserving methods contain advantages, yet they still face operational restrictions. The methods require precise edge detection and gradient estimation because their performance relies on these two elements which may become corrupted by noise. The process of selecting parameters requires special attention because it affects both the strength of smoothing and the ability to maintain edges which depends on the specific application. The process of edge preservation leads to excessive noise in regions that contain high levels of texture detail [10].

The combination of geometry-aware approaches with edge-preserving techniques establishes crucial methods which help maintain structural integrity during the image denoising process. The methods achieve better performance in reducing noise while keeping image details intact through their use of geometric priors and edge-sensitive mechanisms which assist in restoring images across traditional and contemporary denoising methods [20].

6. Evaluation Metrics and Comparative Analysis

The assessment of image denoising performance requires objective and quantitative evaluation metrics to measure restoration quality and facilitate fair comparison among different methods. Denoising needs evaluation criteria that will assess both numerical accuracy and visual quality because its main goal is to eliminate noise while maintaining structural and perceptual fidelity. The Peak Signal-to-Noise Ratio (PSNR) stands as one of the most utilized objective measurement tools because it calculates the logarithmic ratio between maximum pixel brightness and the mean squared error (MSE) that exists between restored images and their original versions [31]. The PSNR measurement system establishes higher reconstruction quality standards through its automatic evaluation system. The PSNR measurement system evaluates image quality through pixel-level comparison which does not match human visual assessment. The Structural Similarity Index Measure (SSIM) serves as the standard solution to this specific constraint. SSIM evaluates image quality by comparing luminance, contrast and structural information between images. SSIM functions as a superior measurement tool because it provides better accuracy for assessing how things appear to human observers and how their internal structures are maintained, which makes this assessment method ideal for testing edge-aware and detail-preserving techniques. The assessment process uses PSNR and SSIM together with three additional evaluation metrics, which include Mean Absolute Error (MAE), Feature Similarity Index (FSIM) and deep feature-based perceptual metrics [32]. The introduction of learned perceptual metrics establishes a new system that assesses image quality through matching high-level features which pretrained neural networks extract. Researchers require these metrics to assess deep learning-based denoising techniques, which produce results that differ from actual pixel accuracy but still maintain perceptual realism. In comparative analysis researchers need to conduct tests which measure algorithm performance under different noise conditions by using both controlled additive Gaussian noise with different standard deviations and actual noise datasets [8]. The performance comparison requires assessment of both numerical measurements and the system's ability to handle different noise levels and its capacity to detect visual defects. The assessment of deployment feasibility depends on three main factors which are runtime requirements, memory usage and model complexity. The complete assessment of denoising results requires multiple metrics because no single metric can show every aspect of denoising performance [8], [11]. High PSNR methods create images with excessive smoothness, while methods that focus on visual quality research lose some measurement precision. The evaluation process needs complete assessment methods which combine various objective metrics with visual inspection methods to achieve dependable results. The complete assessment of image denoising methods requires standardized dataset testing and multiple measurement methods according to their requirements. The assessment process establishes impartial performance standards which help researchers create methods that achieve optimal results in noise reduction, structural maintenance, visual quality and processing speed.

Table 1: Comparative Summary of Image Denoising Techniques

Category	**Core Idea**	**Learning Paradigm**	**Key Advantages**	**Major Limitations**
Spatial-Domain Filtering	Local neighbourhood smoothing in pixel space	Model-based (non-learning)	Simple, fast, low computational cost	Edge blurring, limited adaptivity, poor performance under complex noise
Transform-Domain Methods	Sparse representation in frequency/multi-resolution domain	Model-based (non-learning)	Better detail preservation than spatial filters, effective noise suppression	Fixed basis functions, threshold sensitivity, possible artifacts
Non-Local / Patch-Based Methods	Exploiting image self-similarity across patches	Model-based (non-learning)	Strong texture preservation, high quantitative performance	High computational and memory cost
Variational / Optimization Models	Energy minimization with regularization priors	Model-based Optimization	Theoretically grounded, interpretable	Iterative and computationally intensive, parameter tuning required
CNN-Based Methods	Hierarchical feature learning via	Supervised Deep Learning	Automatic feature learning, strong detail preservation,	Large training data requirement, high computational cost

	convolutional layers		end-to-end optimization	
Transformer-Based Methods	Global self-attention for long-range dependency modelling	Supervised Deep Learning	Superior perceptual quality, effective for high-resolution images	Very high memory and computation demand
Self-Supervised Methods	Learning from noisy data without clean targets	Self-supervised Learning	Reduced dependency on paired datasets	May underperform fully supervised models
Hybrid / Plug-and-Play Methods	Integration of learned priors with model-based optimization	Hybrid (Model + Learning)	Balance between interpretability and performance	Complex design and integration

The above table presents a comparative analysis of major image denoising techniques through their fundamental principles, educational methods, their respective advantages and disadvantages. The mathematical framework of spatial, transform-domain and non-local approaches enables classical model-based methods to use predefined mathematical rules which obtain fundamental results but fail to handle complex noise patterns. Theoretical precision of optimization-based models improves through their mathematical foundation, yet these models consume substantial processing power and need automatic system configuration [27]. Deep learning methods achieve better results and visual quality through their CNN and transformer models, which process information at both local and global levels, but these techniques require extensive training data and powerful processing systems. Self-supervised methods enable training without the need for clean data, while hybrid approaches use model-based interpretability together with learning-based performance to operate. The table demonstrates how filtering methods evolved from their traditional methods into modern data-driven techniques and integrated systems [29].

7. Challenges and Open Issues

Image denoising techniques have reached advanced development stages, yet they still face persistent research challenges which remain to be solved. The current state of modern methods, particularly those based on deep learning technology has delivered substantial enhancements to both quantitative measurements and visual performance. Nevertheless, the current methods face ongoing challenges related to their deployment in real-world situations and their capability to handle various environmental conditions [11]. The generalization problem stands as a primary obstacle that researchers must overcome. Many denoising models are trained on synthetic noise distributions which include additive white Gaussian noise, but these synthetic noise patterns fail to capture the complete range of actual environmental noise. Imaging systems face multiple types of noise which include signal-dependent noise, spatially variant noise and noise that arises from specific sensor characteristics and environmental factors [33]. The performance of models which were developed based on basic noise patterns drops when these models face actual data from real-world scenarios. The second important problem that needs resolution involves obtaining available data. Supervised deep learning approaches require large-scale paired datasets consisting of noisy and corresponding clean images [34]. The process of obtaining suitable ground-truth data becomes challenging, costly and unfeasible in actual imaging settings. Unsupervised and self-supervised learning strategies have been developed to reduce this dependency, yet they still exhibit performance deficiencies when compared to fully supervised methods under specific conditions. The two factors of computational complexity and resource needs continue to be vital issues. The advanced deep learning systems of today use multiple millions of parameters which result in substantial memory requirements and processing expenses throughout both their training and inference phases. The system's resource requirements prevent it from running on mobile devices, embedded systems, and real-time imaging systems which need to function in low-resource environments [20].

The fundamental challenge of achieving noise suppression while maintaining detailed visuals remains a persistent problem. Excessive smoothing can remove fine textures and subtle structures, whereas insufficient denoising leaves residual noise. The research field still needs to solve the problem of creating models that can achieve perfect performance across different types of images and their associated noise conditions [10].

The research problem involves measuring the interpretability and theoretical comprehension of deep denoising models. Deep neural networks operate as black-box systems even though model-based methods provide straightforward mathematical descriptions [26]. Researchers focus their work on two main objectives which involve creating interpretable architectural designs and developing theoretical frameworks that ensure system stability and convergence. Researchers continue their work to address two main challenges which involve developing systems that maintain functionality in new situations that use different types of noise and operate at extreme noise levels and different domain conditions. The researchers plan to study domain adaptation methods, create lightweight models, develop hybrid frameworks and enhance methods for perceptual evaluation [35]. Denoising research has made considerable progress, yet researchers still need to solve problems that impact system performance through generalization, data dependency, computational efficiency, interpretability and robustness. The existing open problems need resolution to enable the creation of dependable and effective denoising systems which can function in various situations.

8. Future Research Directions and Conclusion

8.1 Future Research Directions

Although image denoising methods have reached a high level of development, researchers still need to investigate multiple research paths that show potential for further study. Researchers need to focus their efforts on developing methods which will enable systems to function correctly with all types of real-world noise patterns [9]. Future models should aim to handle signal-dependent, spatially varying and mixed noise without relying heavily on synthetic training assumptions. The use of domain adaptation together with transfer learning methods will improve the ability to handle different datasets. The creation of efficient lightweight architectural systems stands as an important research path [35]. Denoising techniques now find widespread application across real-time systems, mobile devices and edge-computing platforms, which creates a need for models that possess fewer parameters and lower memory usage while delivering faster inference times and maintaining restoration quality. The field of research active today investigates self-supervised learning methods together with unsupervised learning techniques. The methods enable learning from noisy observations because they decrease the requirement for large, paired datasets. The main goal for them involves achieving better stability and convergence results while matching supervised model performance [26].

The research area of model-based prior integration with deep learning systems continues to receive research interest. The mathematical interpretability of hybrid approaches which combine data-driven knowledge creation and data-driven feature extraction will enhance system strength and confirm theoretical boundaries. The research field needs to achieve two main goals which involve developing better methods to explain deep denoising networks and establishing more solid theoretical foundations. The upcoming research work will investigate three areas which include perceptually driven optimization objectives and multi-task learning frameworks and the development of denoising methods for new imaging techniques which include medical imaging, hyperspectral imaging and low-light photography [10], [30], [35].

8.2 Conclusion

Image denoising remains a fundamental problem in image processing and computer vision because it serves various scientific, medical and consumer imaging needs. The review examined various approaches which included traditional spatial-domain filters and transform-domain methods, non-local, patch-based techniques, geometry-aware methods and current deep learning systems. Theoretical foundations and computational simplicity make classical methods valuable, but their usefulness is restricted because they cannot handle complex noise patterns. Deep learning techniques which use convolutional neural networks as their foundation, have improved denoising performance through their ability to learn features automatically and optimize end-to-end processes. The field still encounters difficulties because of its reliance on data, high computational demands and problems with generalizing results and understanding system operations. The integration of efficient architectures, strong learning approaches, hybrid modelling systems and visual evaluation systems will drive research progress. The future denoising systems will become more dependable and flexible when they solve existing problems which restrict their ability to function in various real-world imaging situations.

References:

[1] J. Wang and K. Xu, "A Convolutional Neural Network SAR Image Denoising Algorithm Based on Self-Learning Strategies," *Appl. Sci.*, vol. 15, no. 9, 2025, doi: 10.3390/app15094786.

[2] F. Ullah, K. Kumar, T. Rahim, J. Khan, and Y. Jung, "A new hybrid image denoising algorithm using adaptive and modified decision-based filters for enhanced image quality," *Sci. Rep.*, vol. 15, no. 1, pp. 1–29, 2025, doi: 10.1038/s41598-025-92283-3.

[3] L. I. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Phys. D Nonlinear Phenom.*, vol. 60, no. 1–4, pp. 259–268, 1992, doi: 10.1016/0167-2789(92)90242-F.

[4] Y. Quan, Y. Chen, Y. Shao, H. Teng, Y. Xu, and H. Ji, "Image denoising using complex-valued deep CNN," *Pattern Recognit.*, vol. 111, 2021, doi: 10.1016/j.patcog.2020.107639.

[5] V. Jain and H. S. Seung, "Natural image denoising with convolutional networks," *Adv. Neural Inf. Process. Syst. 21 - Proc. 2008 Conf.*, pp. 769–776, 2009.

[6] F. Yu and V. Koltun, "Multi-scale context aggregation by dilated convolutions," *4th Int. Conf. Learn. Represent. ICLR 2016 - Conf. Track Proc.*, 2016.

[7] C. Tian, Y. Xu, W. Zuo, B. Du, C. W. Lin, and D. Zhang, "Designing and training of a dual CNN for image denoising[Formula presented]," *Knowledge-Based Syst.*, vol. 226, pp. 1–12, 2021, doi: 10.1016/j.knosys.2021.106949.

[8] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising," *IEEE Trans. Image Process.*, vol. 26, no. 7, pp. 3142–3155, 2017, doi: 10.1109/TIP.2017.2662206.

[9] A. E. Ilesanmi and T. O. Ilesanmi, "Methods for image denoising using convolutional neural network: a review," *Complex Intell. Syst.*, vol. 7, no. 5, pp. 2179–2198, 2021, doi: 10.1007/s40747-021-00428-4.

[10] S. Lefkimmiatis, "Universal Denoising Networks : A Novel CNN Architecture for Image Denoising," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, no. 1, pp. 3204–3213, 2018, doi: 10.1109/CVPR.2018.00338.

[11] K. Dabov, R. Foi, V. Katkovnik, and K. Egiazarian, "BM3D image denoising with shape-adaptive principal component analysis," *Proc. Work. Signal Process. with Adapt. Sparse Struct. Represent.*, p. 6, 2009.

[12] R. K. Thakur and S. K. Maji, "Multi scale pixel attention and feature extraction based neural network for image denoising," *Pattern Recognit.*, vol. 141, 2023, doi: 10.1016/j.patcog.2023.109603.

[13] R. Sapkota and M. Karkee, "Object detection with multimodal large vision-language models: An in-depth review," *Inf. Fusion*, vol. 126, no. PA, p. 103575, 2026, doi: 10.1016/j.inffus.2025.103575.

[14] K. Zhang, W. Zuo, and L. Zhang, "FFDNet: Toward a fast and flexible solution for CNN-Based image denoising," *IEEE Trans. Image Process.*, vol. 27, no. 9, pp. 4608–4622, 2018, doi: 10.1109/TIP.2018.2839891.

[15] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," *Proc. IEEE Int. Conf. Comput. Vis.*, pp. 839–846, 1998, doi: 10.1109/iccv.1998.710815.

[16] S. Gu, L. Zhang, W. Zuo, and X. Feng, "Weighted nuclear norm minimization with application to image denoising," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2, no. 1, pp. 2862–2869, 2014, doi: 10.1109/CVPR.2014.366.

[17] R. K. Thakur and S. K. Maji, "Gradient and Multi Scale Feature Inspired Deep Blind Gaussian Denoiser," *IEEE Access*, vol. 10, pp. 34170–34184, 2022, doi: 10.1109/ACCESS.2022.3162608.

[18] E. Micheal and A. Michal, "Image Denoising Via Sparse and Redundant Representations Over Learned Dictionaries," *IEEE Trans. Image Process.*, vol. 15, no. 12, pp. 3736–3745, 2006.

[19] S. K. Maji, R. K. Thakur, and H. M. Yahia, "Structure-Preserving Denoising of SAR Images Using Multifractal Feature Analysis," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 12, pp. 2100–2104, 2020, doi: 10.1109/LGRS.2019.2963453.

[20] Y. Yuan, Y. Wu, P. Feng, Y. Fu, and Y. Wu, "Segmentation-Guided Semantic-Aware Self-Supervised Denoising for SAR Image," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, pp. 1–16, 2023, doi: 10.1109/TGRS.2023.3323485.

[21] S. Wang, "Research on Image Denoising Method Based on Convolutional Neural Network," *Adv. Comput. Commun.*, vol. 6, no. 3, pp. 102–106, 2025, doi: 10.26855/acc.2025.07.001.

[22] C. Tian, Y. Xu, and W. Zuo, "Image denoising using deep CNN with batch renormalization," *Neural Networks*, vol. 121, pp. 461–473, 2020, doi: 10.1016/j.neunet.2019.08.022.

[23] C. Liu and X. Hu, "Deep neural network with deformable convolution and side window convolution for image denoising," *Pattern Recognit. Lett.*, vol. 171, pp. 92–98, 2023, doi: 10.1016/j.patrec.2023.05.015.

[24] Z. Song, Z. Zhang, F. Fang, Z. Fan, and J. Lu, "Deep semantic-aware remote sensing image deblurring," *Signal Processing*, vol. 211, 2023, doi: 10.1016/j.sigpro.2023.109108.

[25] F. Karagulian *et al.*, "Review of the performance of low-cost sensors for air quality monitoring," *Atmosphere (Basel).*, vol. 10, no. 9, 2019, doi: 10.3390/atmos10090506.

[26] C. Tian, L. Fei, W. Zheng, Y. Xu, W. Zuo, and C. W. Lin, "Deep learning on image denoising: An overview," *Neural Networks*, vol. 131, pp. 251–275, 2020, doi: 10.1016/j.neunet.2020.07.025.

[27] L. Fan *et al.*, "A Semantic-Aware Detail Adaptive Network for Image Enhancement," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 35, no. 2, pp. 1787–1800, 2025, doi: 10.1109/TCSVT.2024.3483191.

[28] P. H. T. Binh, C. Cruz, and K. Egiazarian, “Flashlight CNN image denoising,” *Eur. Signal Process. Conf.*, vol. 2021-Janua, pp. 670–674, 2021, doi: 10.23919/Eusipco47968.2020.9287793.

[29] C. Liu and X. Hu, “Deep neural network with deformable convolution and side window convolution for image denoising,” *Pattern Recognit. Lett.*, vol. 171, pp. 92–98, 2023, doi: 10.1016/j.patrec.2023.05.015.

[30] S. Guo, Z. Yan, K. Zhang, W. Zuo, and L. Zhang, “Toward convolutional blind denoising of real photographs,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2019-June, pp. 1712–1722, 2019, doi: 10.1109/CVPR.2019.00181.

[31] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” *5th Int. Conf. Learn. Represent. ICLR 2017 - Conf. Track Proc.*, pp. 1–14, 2017.

[32] “A Novel Self Adaptive Deformable Convolution Based U-Net for Low Light Image Denoisin.pdf.”

[33] I. Batool and M. Imran, “A dual residual dense network for image denoising,” *Eng. Appl. Artif. Intell.*, vol. 147, no. September 2022, 2025, doi: 10.1016/j.engappai.2025.110275.

[34] J. Zhang, J. Huang, S. Jin, and S. Lu, “Vision-Language Models for Vision Tasks: A Survey,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 46, no. 8, pp. 5625–5644, 2024, doi: 10.1109/TPAMI.2024.3369699.

[35] “A Lightweight Denoising Convolutional Neural Network for On-Device Artifact Suppression.pdf.”