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Review Article

Unleashing the Power of Image Denoising: A Comprehensive Review of Classical to Deep Learning Methods

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Abstract: Image denoising is a vital step in many image processing and computer vision professions that aims to improve picture quality by decreasing noise while maintaining important image information. In this article, a detailed overview is presented of traditional and deep learning-based picture denoising approaches. Classical methods, such as linear filtering, transform domain techniques, and patch-based approaches like Non-Local Means (NLM), are commonly employed because they are simple and effective in removing Gaussian noise. However, these approaches frequently struggle with complicated noise patterns and blur fine features. Recent advances in deep learning, including Convolutional Neural Networks (CNNs) and other designs such as Generative Adversarial Networks (GANs) and autoencoders residual networks, have considerably improved picture denoising performance. These data-driven techniques excel in learning complicated noise patterns from big datasets, providing superior generalization across various noise types, including non-Gaussian noise, and dealing with a larger range of image degradation conditions.

Keywords: Denoising, Spatial, Transform, Hybrid, CNN, Gaussian, Sparse Representation

Introduction

An image is a two-dimensional depiction that represents the appearance, shape, color, and texture of objects, scenes, or data. Images can be captured using a variety of methods, including photography, scanning, medical imaging, or computer graphics, and then saved, processed, and shown using digital technology. An image is made of a grid of tiny elements called pixels. Each pixel denotes a single point in the image and gives information about its color and brightness (Shahdoosti & Rahemi, 2019; Sui *et al.*, 2018). An image's resolution is defined by the number of pixels in its width and height. Higher resolution implies more pixels, which typically equals more detail. Pixels in an image could be either grayscale or colored. In an 8-bit picture, each pixel carries a single value that represents light intensity, which typically ranges from black (0) to white (255) (Chen *et al.*, 2021). In color images, each pixel includes numerous values that represent distinct color channels, usually Red, Green, and Blue (RGB). The combination of these three channels determines the pixel's final color (Rakheja & Vig, 2016).

An image is referred to as noisy when its quality is distorted. Environmental factors, transmission errors, and sensor limits can all produce noise. Image denoising is the technique used to eliminate the unwanted noise from an image (Kaur *et al.*, 2012). Maintaining the image's essential characteristics and structure during the denoising process is vital. Digital image devices have been broadly used in a variety of applications, including individual recognition and remote sensing (Izadi *et al.*, 2023). The acquired picture is a degraded version of the latent observation, and the degradation procedure is influenced by elements such as light exposure and noise pollution (Ismael & Baykara, 2021). Specifically, noise is formed during the transmission and compression procedures as a result of an unknown latent observation. It is critical to employ image denoising algorithms to eliminate noise and extract undetected information from a damaged image (Saxena & Kourav, 2014). Digital images invariably deteriorate during acquisition and transmission due to degradation imposed by a variety of factors. Research into image denoising is an important issue because it involves many areas where visual data plays a substantial role. The existence of noise in images can be represented as random changes in brightness or color and may badly affect the visual quality and, consequently, the usability of the images (Swamy & Kulkarni, 2020; Haneche *et al.*, 2021). This is especially critical in medical imaging, for instance, where clear and sharp images are highly needed for diagnosis and

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treatment planning. Noise might obscure the fine details of a medical scan, such as an MRI or X-ray, which could lead to misdiagnosis or additional imaging, furthering the exposure of a patient to radiation. In astronomy, noise may potentially affect the vision capabilities of objects captured in low-light settings, affecting observations and discoveries of new information (He *et al.*, 2019). Images that contain noise will significantly affect further image processing. The quality of further image processing, including image identification, segmentation, classification, and so forth, will be impacted by noise in the image. Removing noise from images can improve their visual quality and help future image analysis procedures perform better (Sathasivam & Rahamathulla, 2016). The rise in the development of digital photos and videos of all types, many of which were captured in inadequate environments, has increased the demand for effective image restoration solutions. Even with high-quality cameras, there is always scope for enhancement to expand their capabilities.

Research in image denoising is crucial and has wide impacts on several other disciplines and technologies. Research in denoising also covers challenges related to resource-constrained environments like smartphones, drones, and IoT devices due to limitations in processing power and energy consumption (Arbaoui *et al.*, 2021). Lightweight and efficient denoising algorithms have been developed so that high-quality imaging features can be extended to these resource-limited devices without compromising performance (Sagheer & George, 2020). This requires a sophisticated approach toward denoising, considering the cross-disciplinary applications in which image sets are put to use, such as remote sensing and environmental monitoring (Gaikwad *et al.*, 2016). Noise in these image sets due to atmospheric interferences or sensor limitations marks these fields and affects the accuracy of environmental assessments, disaster management, and agricultural planning. The inputs from vision are very important to robotics and autonomous systems either in navigation or operation (Bhujle & Vadavadagi, 2019). In the real world, images are generally noisy, but noise is random and so unknown. This noise can have numerous causes: Poor image quality can be caused by poor weather circumstances, light variations, a digital camera's image sensor, image acquisition conditions, or storage and compression techniques (Charmouti *et al.*, 2019). As a result, denoising is a significant preprocessing step for recovering better image quality. As new challenges arise and imaging systems continue to improve, further research into noise reduction will be crucial in developing robust methods that balance noise reduction against detail preservation and will form an integral part of ensuring the continued reliability and effectiveness of visual data in all applications (Huang & Hu, 2018).

- Image denoising is an essential milestone in image processing that is meant to minimize noise while retaining essential features such as edges and textures. However, several challenges make this process complex.
- The biggest challenge in image denoising is achieving the correct balance between noise reduction and the preservation of essential image features like edges and textures. Over-smoothing can blur these details, whereas under-smoothing may leave noise in the image.
- Images can be affected by many types of noise, including Gaussian noise, salt-and-pepper noise, Poisson noise, and speckle noise, all of which have distinct features. The development of a denoising algorithm that can properly handle many forms of noise is difficult.
- Noise in an image may not be equally generated; some areas may have higher noise levels than others. This non-uniformity required adaptive approaches that can adjust the denoising intensity throughout the entire image.
- For situations such as video denoising or real-time medical imaging, the denoising algorithm must be efficient enough to process images fast, which is difficult, particularly for sophisticated or non-linear denoising techniques.

Motivation

Traditional denoising approaches, while simple and efficient, are sometimes unable to adequately satisfy the demands of current imaging scenarios such as the requirement to maintain fine features, eliminate random noise, and manage large-scale, real-time data. Methods based on spatial filtering, frequency domain transformations, model-based methods, and, more recently, deep learning all have strengths and disadvantages that vary depending on the environment. The area of image denoising is wide, ranging from basic filters to extremely complicated machine learning-based algorithms, each specialized to a certain form of noise and application. Researchers and practitioners require advice when selecting the best techniques for their individual work, and knowing how different approaches have evolved may contribute to the creation of more efficient and inventive solutions.

Below the terms are defined which are used throughout the paper.

Noise

Noise in images is defined as random alterations in brightness or color information that may negatively affect the visual quality of an image. Noise can occur while an image is captured and might be caused by a transformation of images. In image processing, noise can often be seen as an additive or multiplicative component in mathematical image representations. The specific equation form used to represent noise is identified on the type of noise. The additive noise model describes the observed image as a sum of the original (clean) image and the noise. The multiplicative noise model describes the observed image as a product of the original (clean) image and the noise (Saxena & Kourav, 2014).

Types of Noise

Figure 1 illustrates the various types of noise. In this Figure there are 4 types are shown: Gaussian, Salt and Pepper, Speckle, and Poission Noise.

Gaussian Noise

One of the most common noises is Gaussian noise. The primary sources of Gaussian noise occur during acquisition, such as sensor noise caused by inadequate lighting, excessive temperature, and during the transmission. Gaussian noise is statistical noise whose Probability Density Function (PDF) is the same as the value of the normal distribution, consequently referred to as the Gaussian distribution. Noise can take on Gaussian-distributed values. The PDF for Gaussian random variables is shown by the mean value, gray level, and standard deviation. The average of all distributed pixels in an image that has been influenced by Gaussian noise is zero. Gaussian noise affects all pixels equally in an image (Han *et al.*, 2021).

Salt and Pepper Noise

Salt-and-pepper noise can be referred to as data dropout. Images with salt-and-pepper noise can have shady pixels in bright areas and in dark parts the pixels are bright. The comparable values for black and white pixels are 0 and 1 respectively. As a result, the image impacted by this noise has either an extremely low or very high value for pixels, i.e., 0 or 1. This sort of noise can be occasionally created by converter errors like analog-to-digital or bit errors during transmission. To eliminate this noise, use dark frame removal and interpolate around dark/bright pixels (Kumar *et al.*, 2024).

Speckle Noise

Speckle noise refers to noise caused by environmental conditions on imaging sensors during image capture. This form of noise can be recognized in medical and active radar imagery. Speckle noise takes place due to the continuous nature of imaging systems, in which the timing of the waves is extremely important. The noise is caused by constructive and destructive interference of returning waves from various scattering locations on the object being captured. Speckle noise in Synthetic Aperture Radar (SAR) and other radar imaging systems is caused by the interference of microwave signals reflected off diverse surfaces, such as topography, vegetation, or buildings. Speckle noise in medical ultrasound imaging is caused by the interference of sound waves reflected by tiny particles inside the tissue, such as blood cells or connective tissue. Speckle noise is also frequent in laser imaging and holography, when coherent light waves from a laser source reflect off a rough surface, resulting in interference patterns that cause speckle (Gai & Bao, 2019).

Poisson Noise

Noise is caused by the statistical character of electromagnetic waves, including x-rays, gamma rays, and visible light. X-rays and gamma rays release photons per unit time. These reasons include the random fluctuation of photons. The collected photos exhibit spatial and temporal unpredictability. Photon shot noise occurs in the lighter areas of an image due to stochastic quantum fluctuations in the amount of photons detected at a particular exposure level. Shot noise monitors a Poisson distribution, which is similar to Gaussian noise. Poisson noise sometimes known as shot noise, frequently occurs in photon-limited imaging circumstances (for example, low-light photography and medical imaging). It is defined by a Poisson distribution, and the noise is signal-dependent (Verma & Ali, 2013).

Image Denoising Techniques

Two main categories of denoising algorithms are now in use: internal algorithms and external methods. While external algorithms take advantage of natural, clean pictures that are associated with the noisy image, internal algorithms use the noisy image itself. Numerous industries, including photography, medical practice, remote sensing, surveillance, and automated systems like robots and self-driving automobiles, employ image denoising. In terms of image denoising, ”filters” refer to methods or algorithms that minimize noise in an image while maintaining crucial characteristics like textures and edges.

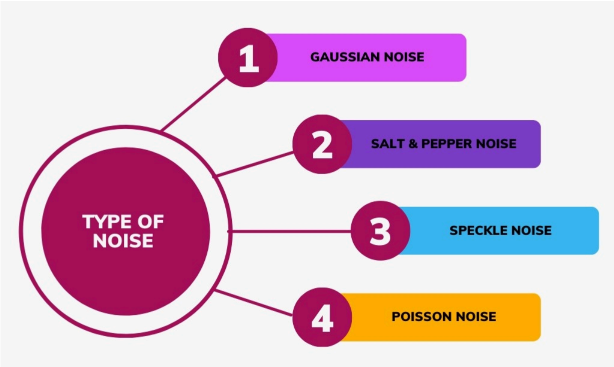

Fig. 1: Types of Noise

Traditional Approaches

Traditional denoising algorithms, including NLM, BM3D, wavelet transforms, and Total Variation (TV), depend on mathematical models and assumptions of image structures and noise characteristics.

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Advantages: Easy to implement with clear mathematical theory. These methods can be implemented in low resource environments and real-time systems. Their performance and limitations are better understood and predictable. They work well for general noise models like Gaussian or salt-and-pepper noise.

Disadvantages: Fail with non-white or complex noise distributions. They usually also discard fine details and subtle textures while removing the noises. Require extensive hand-tuning and never learn the noise characteristics within the dataset. It gets drastically ineffective on high intensity or white and colored noises.

Deep Learning-Based Methods

Deep learning models, Convolutional Neural Networks in particular, Generative Adversarial Networks, and auto-encoders, have dominated denoising pictures using purely data-driven approaches.

Advantages: Effective at extracting subtle picture patterns and noise distributions from high-capacity datasets. These techniques can handle massive variants of noise types and level, including mixed and non-gaussian noise. Effectively deletes noise while keeping delicate edge and texture information. Because of automation learning frameworks, it eliminate the need for manual parameter adjustment.

Disadvantages: It requires loads of processing power and sturdy gear. Quality and availability of training datasets largely impact the performance. Risk of overfitting can decrease generalization to new data. Unlike traditional methods, it does not have theoretical knowledge and interpretability.

Hybrid Approaches

Hybrid approaches attempt to leverage the best of both worlds through conventional methods' interpretability and the flexibility offered by deep learning. Examples of Hybrid Approach: Wavelet + CNNCombination; The wavelet decomposition splits the image into its respective frequency components; Each frequency component is then further processed for removal of noise with CNN. Filtering Using Neural Network Guidance: Conventional filtering techniques such as bilateral or directed filters are applied to CNN outputs either pre or postprocessing for preserving edges. Learning-Based Priors for Regularization: Deep learning models can be used as priors in conventional optimization-based frameworks (e.g., variational models).

Conventional Constraints on Deep Learning

Mathematical or physical constraints can be imposed on deep learning models obtained using conventional techniques.

Advantages: By combining the strengths of both strategies results in improved noise reduction and detail preservation. This method provides a fallback approach to enhance the robustness of deep learning models. The possibility of overfitting in deep learning models is minimized due to constraints imposed by conventional methods. By restricting deep learning to some specific subtasks, it reduces the computing overhead.

Disadvantages: Often it takes a lot of work and refinement to merge the two paradigms into a single, cohesive approach. High payoffs could not be guaranteed based on overlap features. It does require domain expertise of deep learning and classical methods. Fig. 2 illustrates the various image denoising techniques. In this figure there are basically 4 types: Spatial Domain, Frequency domain, Deep learning, and hybrid. The spatial domain is further classified into Gaussian, Weiner, Median, Anisotropic, and Bilateral. The frequency domain has also been further categorized into Fourier, Wavelet, Discrete, Curvelet, and Shearlet. Deep learning has further categories like CNN, GAN, Auto Encoder, and Deep Residual Network. One technique is the hybrid technique which is the combination of existing techniques.

Spatial Domain Techniques

Spatial denoising approaches aim to reduce noise directly in an image's spatial domain, represented as a grid of pixels. These algorithms work by examining the intensity values of pixels and their neighbors to discriminate between noise and actual image content. Spatial domain techniques are subsequently classified into 2 categories:

- Linear
- Non-Linear

In general, linear denoising methods act on the pixel intensities in an image as if they were numerical values. That is, the destination pixel value will be a linear combination of all these from source pixels. These weights are defined by a filter kernel, and combined in the same way (linear operation) across all parts of an image. They are simple and computationally efficient, but usually do not adapt well to image edges.

Most linear denoising methods share the fact that they perform some linear operation on the pixel values of an image, i.e., each output pixel value is computed as a weighted sum over a small neighborhood of input pixel values. The weights are specified by the filter kernel and the same linear operation is applied in a uniform manner across the entire image. These methods are simple and computational yet do not often adapt very well to local image features like edges.

Transform Domain Techniques

Transform domain approaches work by converting the image to a new domain (such as frequency or wavelet) in which noise and signal may be separated with greater ease. These approaches revolve around the assumption that noise and image characteristics may be better separated in the transformed domain, allowing for more influence over the denoising process. Transform domain is further classified into different categories:

- Fourier Transform Denoising
- Wavelet Transform Denoising
- Discrete Cosine Transform (DCT) Denoising
- Curvelet Transform Denoising
- Shearlet Transform Denoising

The Fourier Transform translates an image from the spatial domain to the frequency domain, portraying it as a sum of sinusoidal functions of varying frequencies. The Wavelet Transform divides an image into a set of wavelet coefficients that contain both spatial and frequency information. Unlike the Fourier Transform, wavelets offer multi-resolution analysis, making them ideal for denoising. The Discrete Cosine Transform depicts a picture as a sum of cosine functions with varying frequencies. It is commonly used for image compression (e.g., JPEG) and denoising. The Curvelet Transform is intended to handle edges and other singularities more successfully than wavelets by describing the picture as curves or ridges. This makes it especially suitable for photographs with strong directional elements. The Shearlet Transform is an extension of the wavelet transform that is especially designed to deal with anisotropic characteristics like edges more effectively. It breaks down the image into sizes, locations, and orientations, resulting in a sparse representation.

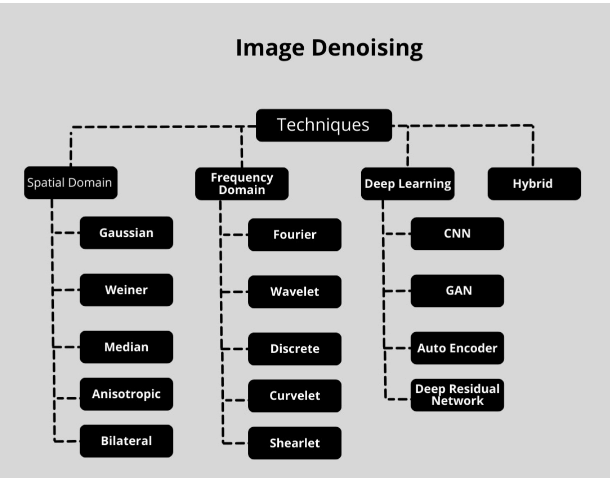

Fig. 2: Image Denoising Techniques

Convolutional Neural Networks (CNN) Based Techniques

CNNs have transformed image denoising by utilizing big datasets and learning complicated noise patterns via deep learning. The recent advancements of deep learning has influenced the denoising scenario. CNNs and autoencoders have shown an impressive capacity to learn complicated noise patterns directly from data, exceeding traditional approaches in many circumstances. These techniques have the benefit of being flexible to many types of noise and image techniques, but they are also limited by the requirement for huge datasets and computer systems (Oyelade & Ezugwu, 2021; Perez *et al.*, 2017).

Hybrid Techniques

Hybrid strategies integrate different approaches, exploiting their respective strengths to provide excellent denoising performance. Many recent methodologies use spatial, transform, and learning-based strategies to obtain better results (Meng *et al.*, 2022).

In this article, a detailed overview is presented of traditional and deep learning-based picture denoising approaches. By comparing PSNR and SSIM, the study attempts to understand how well image denoising algorithms, namely WNNM, Guided Filter, NLM, DnCNN, and BM3D, work for different NV and understand how these algorithms compromise between noise reduction and the preservation of structural and perceptual picture quality by comparing PSNR and SSIM. As the high PSNR does not directly relate to high perceptual quality (SSIM), the study emphasizes that it is important to use both metrics for a balanced assessment. It is to increase SSIM at higher noise variances without compromising PSNR for better structural and perceptual quality of pictures.

Literature Review

Spatial Domain

Li & Suen (2016) introduced the Grey theory applied in Non-Local Means (GNLM) image denoising method. Based on grey relational analysis, fewer testing samples are required and GNLM can achieve better performance compared with traditional methods by setting appropriate weights through grey relation coefficients. In contrast to traditional NLM methods, the proposed GNLM technique will not suffer from typical problems such as parameter setting, hence reducing computational complexity while successfully suppressing noise and preserving details, especially at edges and corners. A hybrid approach combining NLM and sparse representation techniques is presented in Zhou *et al.* (2016) to restore images corrupted with mixed noise, including Gaussian and impulse noises. The method adopted customized blockwise NLM filtering for initial denoising and separated noisy pixels into groups by using the 3-sigma rule before applying sparse coding on an over-complete dictionary. Excellent performance in suppressing mixed noise was achieved during clean image reconstruction. In forward zero-phase filtering of images with fractional differentiation, Verma & Saini (2017) suggested a method for designing a 2D Fractional Differentiation Zero-Phase (FDZP) filter. It is used for image denoising with forward-backward processing at noise suppression performances when under attacks of

Gaussian and speckle noises. For liver ultrasound images, edge preservation due to FDZP was the best among all filters because of maximum PSNR values in comparison with the ones in case of Gaussian smoothing, anisotropic diffusion and Kuan filters. In Zhuang & Bioucas-Dias (2018), two efficient hyperspectral image restoration algorithms are proposed, FastHyDe and FastHyIn, which is the denoising algorithm and the inpainting algorithm of hyperspectral images (HSIs) with missing data, respectively. These methods use low-rank and self-similarity properties to restore compact and sparse representations and, therefore, are efficient and effective for the restoration of HSIs.

Dhanushree *et al.* (2019) gave importance to underwater acoustic images captured by sonar, as this is the equipment to identify any object lying below the sea bottom. To remove de-speckling noise in auditory images, they have used spatial methods like bilateral and guided filter. Optimization with an augmented Lagrangian removes most speckle noises and helps in getting improved quality images for sonar applications. In Garg *et al.* (2019) various filtering techniques were analyzed, including mean, median, Wiener and adaptive filters to remove the Gaussian, salt-and-pepper or speckle noise from MRI images. The authors tested them based on statistical criteria PSNR and RMSE and, above all, the obtained values of PSNR significantly surpassed other filtering techniques in noise suppression. Mahdaoui *et al.* (2022) proposed a reconstructed-based compressed sensing approach: it used total variation regularization together with non-local self-similarity and utilized an augmented Lagrangian optimization approach both to reconstruct the image and remove noise simultaneously, achieving up to 25% improvement in terms of PSNR and SSIM performance metrics. Ramamurthy *et al.* (n.d.) pursued exploration on the application of bilateral filters for image denoising. This method, through non-linear spatial averaging, avoids edge smoothing and focuses on optimal parameter selection for the filters. This paper contributed to a better understanding of bilateral filters and provided insights in extending the technique for the best possible image-denoising performance.

Transform Based

In Luo *et al.* (2015) an algorithm was introduced to adaptively identify the best set of patches from the corpus to use for image denoising. This work was approached as a design problem of a filter, and key contributions included a group sparsity-based minimization technique for obtaining the basis function for the filter and a localized Bayesian prior for minimizing the computational cost. In Xiong *et al.* (2016) a special denoising method that relies on adaptive signal modeling and regularization was proposed. The approach regularizes each band of the image patch by modeling distribution in a band-wise manner, thus utilizing adaptive models while coping with non-stationarity and variations across the transform bands. Restored images rely on band-wise adaptive soft thresholding while ensuring noise suppression is increased. In Veena *et al.* (2016) wavelet filter-based least square approach was developed for image denoising by extending 1D least square approach to 2D. It was tested on benchmark images of different types of noise and different wavelet filters with high PSNR values as shown in the results, thereby proving the prominence of wavelet filters in denoising. In Rakheja & Vig (2017) surveyed various work on image restoration by applying wavelet transforms. The Wavelet Transform was a useful noise removal technique, and its evaluations were carried out with PSNR, MSE, and quality indexes; however, the work said that images can be denoised effectively only if there are optimized statistical models and thresholding techniques. In Lin (2018) an impulse noise removal method using a combination of an adaptive median filter (AMF) along with a wavelet thresholding technique based on a Gaussian Mixture Model (GMM) was proposed to remove mixed noise. Experimental results showed that the performance of this method was superior when compared to the efficiency in the filtering step for both AMF and wavelet thresholding alone. In Gopatoti (2018) wavelet, contourlet, and curvelet transforms were compared in the context of image denoising for contourlet transforms, finding these superior in terms of noise removal capabilities and preserving edges in images better than other transform techniques. In Chen *et al.* (2019) wavelet, contourlet, and curvelet transforms were compared in the context of image denoising for contourlet transforms, finding these superior in terms of noise removal capabilities and preserving edges in images better than other transform techniques. Qian (2019) presented an AMF-WT-based noise removal methodology which combined adaptive median filtering with wavelet decomposition for salt-and-pepper noise removal. The proposed approach used a new adaptive threshold function and was outperforming the classical hard and soft thresholding.

CNN Based

In Zhang *et al.* (2017) the deep CNN proposed for image denoising uses residual learning that differs the noise from an image. The DnCNN model performed well in the case of blind Gaussian denoising as well as the JPEG image deblocking and achieved improved speed of training as well as denoising. Tian *et al.* (2019) presented the enhanced CNN (ECNDNet) with difficulty in training deep networks and performance saturation. It expanded the context range by having residual learning and batch normalization in addition to dilated convolutions and was computationally inexpensive. In Bajaj *et al.* (2020) a deep convolutional denoising autoencoder is designed for removing Gaussian noise in images. For the reconstruction of clean images at the output, skip connections were used in order to prevent gradient fading, and thus higher PSNR values compared to classical methods were obtained. Thamilselvan & Sathiaseelan (2018) developed a unique pre-processing approach called the Profuse Clustering Technique (PCT), which is based on superpixel clustering. This technique includes K-Means clustering, Fusing Optimization algorithms and , Simple Linear Iterative Clustering and , which are then utilized to denoise Lung Cancer images for more accurate decision-making.

Hybrid Techniques

Gopatoti *et al.* (2018) assessed various denoising techniques using wavelet transforms and CNN. Here by PSNR and MSE comparison was done and CNN proved to reconstruct the original images from noisy inputs. The authors of (Yang *et al.*, 2020) applied Ensemble Learning to boost performance of image denoising by iteratively combining simple denoisers in a sequential ensemble. The authors compared a few groups of denoisers and exhibited noise removal improvements. Goceri (2023), the researchers applied the same datasets of images with either speckle or Gaussian noise to the methods available in the literature. The main three contributions that this work has made are as follows: (i) A thorough investigation of the denoising methods available for dermoscopy images was provided. (ii) The same images were used for the denoising approaches to allow for meaningful comparisons. (iii) The visual and quantitative assessments on a variety of measures were carried out, with comparison performance ratings provided for each approach. Chandra *et al.* (2023) presented the deep CNN-based color balancing and denoising method (CNN-CBDT) to improve underwater photos. Color, particularly green and blue, is a benefit of underwater properties. Because of its poor color contrast, the image is fuzzy in nature. The CNN-CBDT recovers the image with the aid of the CNN's ReLU team. Finally, the cutting-edge performance of this technique is proven by comparing experimental results to those of the GLNet, Histeq, and ACE algorithms under SSIM, PSNR, UCIQE, and UIQM. It increases PSNR by 17%, with the greatest value of 19.580, and SSIM by 15%, with a value of 0.952. This approach had a calculation speed of 9.868 frames/second. In Shi *et al.* (2021) a hyperspectral image denosing approach which consists of two parallel branches, involving one to handle spatial information and one handling spectral information was developed. Using the two modules of position and channel attention established interdependencies and correlations to enhance image restoration. Oguzhanoglu *et al.* (2022) used two test sites of land cover-use as examples for noise impact assessment on optical satellite images. To this end, the effect of denoising methods was tested at different spatial resolutions on both Landsat 8 and Sentinel 2 satellites. Since raw images for selected satellite images were not available, two types of noise were generated on these images: Gaussian and Stripe Noise. The methods used for the comparison of both spatial and frequency domain techniques including median and wavelet-based methods have been analyzed concerning their performance in terms of statistical evaluation in terms of PSNR and MSE. In Ismael & Baykara (2022) one of the main objectives that researchers accomplished is introducing and applying a new hybrid system to the removal of noise from images caused by the Additive White Gaussian Noise (AWGN). The Hybrid system uses spatial domain filters with Median and Wiener filters; it includes a multi-resolution analysis technique, which includes 2D-Stationary and 2D-Discrete wavelet transform. The hybrid approach that combines spatial and multi-resolution filters was proposed in order to remove Additive White Gaussian Noise from images. Here, the system consisting of wavelet and median filters shows a higher performance both in the removal of noise and edge preservation. Neole *et al.* (2024) proposed the the hybridization method which uses the Bivariate Wavelet Shrinkage to modify the wavelet coefficients. The SSIM value and PSNR value are used for assessment about quality. Modify the existing Wavelet Transform to perform image denoising that increases the PSNR and SSIM compared with the PSNR and SSIM given by the use of the existing Wavelet denoising methods. It works well in highlighting the edges in those images that may be corrupted by additive white Gaussian noise, at the same time preserving essential detail information in the denoised output.

Summary of Key Findings from Literature Survey

Several image-denoising approaches have been established by researchers, highlighting diverse methodologies and their contributions to image restoration. Here's an overview of the important contributions:

- The Grey Theory Applied in Non-local Means (GNLM) technique employs a grey relational analysis to address parameter setting concerns in Non-local Means, enhancing noise suppression while maintaining image characteristics such as edges and corners.
- The Fractional Differential Zero Phase Filter uses R-L integral principles and fractional differentiation to denoise images, demonstrating remarkable resistance against Gaussian and speckle noise while retaining edges.
- Deep learning models like DnCNN and ECNDNet employ residual learning and batch normalization to effectively remove noise, resulting in improved Gaussian noise removal and image restoration.
- Hybrid approaches that incorporate spatial domain filters and wavelet transformations are offered to deal with Additive White Gaussian Noise (AWGN) while maintaining image quality.

Research Gaps

- Handling Multiple Noise Types: Only a few methods handle mixed noise scenarios (e.g., combinations of Gaussian and Poisson noise), although several papers focus on specific noise types, such as Gaussian, salt-and-pepper, or speckle noise. This is still challenging, especially when dealing with complex noise distributions in real-world applications.

- Small Structures Preservation: Accurate diagnosis and treatment planning require a minute anatomical detail comprising blood arteries, characteristics of delicate tissue, and very tiny lesions. Most denoising algorithms tend to blur out or remove these small features in an attempt to get rid of noise. So, there is a need for research to come up with techniques that will recognize the noise from these indispensable tiny structures for correct reconstruction.
- Trade-offs in Image Quality: A common dilemma is balancing image quality and denoising performance. While some algorithms are quite effective at removing noise, they often reduce the quality and structural integrity of the image as a whole. This is particularly problematic in clinical settings where high-quality images are necessary for diagnostic purposes. The lack of generally applicable remedies underscores the need for further research into adaptive and hybrid denoising techniques that enhance image quality without sacrificing critical diagnostic information.
- Adapting to Domain-Specific Challenges: Many denoising methods are developed for general-purpose photos, but they are not targeted to solve domain-specific problems such as underwater images, medical imaging, or hyperspectral data. These domains often have different noise properties that require specific denoising approaches.
- High Complexity of Computation: Advanced methods often incur a large computational cost, particularly those based on deep learning (such as CNNs, 3D attention networks). This limits their applicability in real-time or resource-constrained environments, such as drones or mobile devices.
- Ground Truth Data Not Always Available: The paired noisy-clean picture datasets that are critical for supervised algorithms are hard to obtain in practical applications. There is a need to close this gap by exploring unsupervised or self-supervised denoising methods that can work without pristine ground truth pictures.

Applications of Image Denoising

Image denoising has been an important preprocessing step in a variety of application areas where noise can significantly affect the quality of the images or the accuracy of the subsequent analysis. Among the important application areas, the following are somewhere denoising is frequently applied:

Medical Imaging

In medical imaging, techniques such as MRI, CT scans, and X-rays are generally noisy because the radiation dose is too low or the acquisition times are too fast, or due to the limitations of imaging instruments. Therefore, denoising in these cases is very important for image quality, accuracy in diagnosis, and good visualization of anatomical structures and pathological conditions.

Astronomical and Space Imaging

Astronomical images, obtained through telescopes and space probes, are usually noisy due to low light, extended integration times, and cosmic radiation. Therefore, in this field, denoising is extremely important for the detection of faint celestial objects, quality images of remote galaxies and stars, and precision scientific measures derived from them. Astronomical data are not only visual, but also include measurements regarding the brightness of stars, distances of galaxies, and movements of other celestial objects. Noise could inject errors in these observations; hence denoising provides the required precision and reliability of data for scientific research and purposes, such as dark matter research, cosmic expansion, or atmospheric study on other planets. Fig. 3 depicts noised and denoised astronomical images.

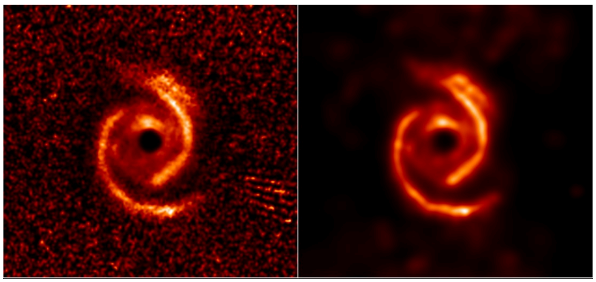

Fig. 3: Astronomical and Space Image

Surveillance and Security

In surveillance systems, most particularly low-light camera devices and those Operated in bad weather conditions, image noise greatly affects video quality. Denoising helps improve the clarity of the footage and helps in better recognition of faces, license plates, and other details, which is important for security and law enforcement purposes. Figure 4 depicts the noisy and clear images after filtering.

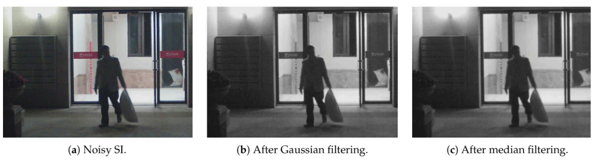

Fig. 4: Surveillance and Security Image

Microscopy

In microscopy, in particular, fluorescence and electron microscopy, images are often noised due to low signal levels that are usually associated with high sensitivity detectors. In such fields, denoising enhances the visibility of fine cellular structures and allows quantitative measurements for biological and material science applications to be done more precisely. Figure 5 illustrate noised and clear images of microscopy.

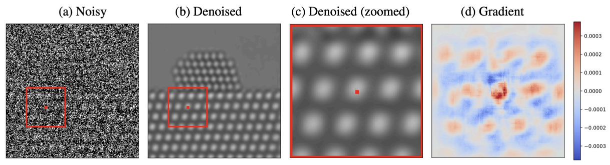

Fig. 5: Microscopy Image

Photography and Videography

Noise in consumer photography and professional videography may happen because of high ISO settings, low light, or small sensors in the cameras. Denoising is applied to enhance the quality of images and videos, so their final outputs will be more pleasing to the eye and suitable for commercial or artistic reasons. Noise can be very bothersome in professional video-shooting events that occur in low light, such as evening or nighttime productions, or in indoor conditions, or when shot at night. For this reason, as video is made up of a lot of frames per second, noise appears as quite irritating spots or grain at different junctures of the stream. Denoising techniques clear up the film so that the image becomes more smoothened, clearer, and looks like film as well, which promotes higher viewership. Figure 6 depicts the noisy and clear images of photography.

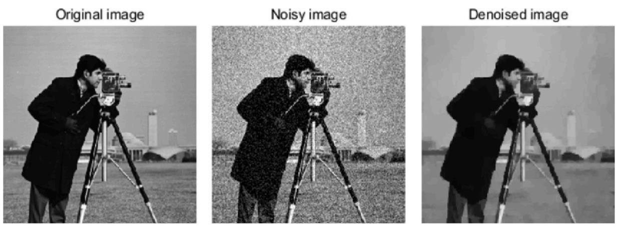

Fig. 6: Photography and Videography Image

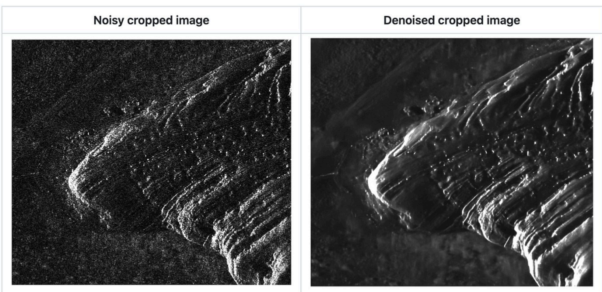

Fig. 7: Remote Sensing Image

Remote Sensing

Remote sensing images, acquired by satellites or drones, are usually contaminated by noise, which may emanate from atmospheric disturbances, sensor limitations, and transmission errors. In this regard, denoising the images is important for correctly classifying land cover, conducting environmental monitoring, managing disasters, and planning cities. Figure 7 depicts the noised and clear images of remote sensing.

Robotics and Autonomous Vehicles

Cameras and sensors are perception devices for robotics and independent vehicle systems. Denoising is critical for enhancing the reliability of the visual information, as it is critical for navigation, detection of obstacles, and object recognition; hence, improving general safety and performance. Figure 8 depicts the noisy and clear images of the autonomous vehicle (Le *et al.*, 2023).

Fig. 8: Robotics and Autonomous Vehicles Image

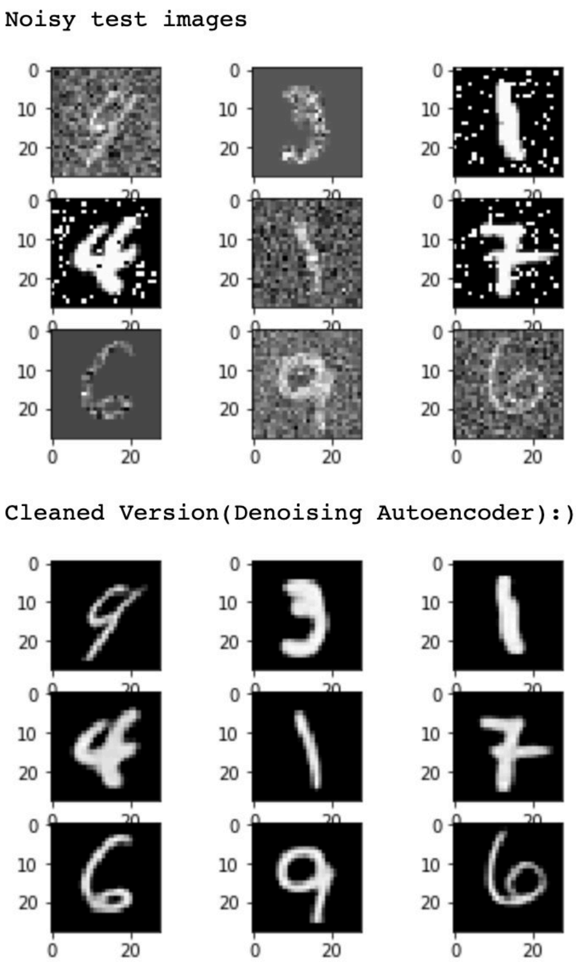

Fig. 9: Optical Character Recognition (OCR) Image

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Optical Character Recognition (OCR)

Noisy images in OCR systems misrecognize the character and lower accuracy. Denoising techniques improve text clarity, hence bettering the performance of OCR algorithms in various applications, including document digitizing, automated data entry, and license plate recognition. Figure 9 illustrates noised and clear images of OCR.

Underwater Imaging

This would mean that the imaging underwater is often subject to scattering and absorption of light, which introduces high noise. Denoising finds an application in enhancing the quality of underwater photographs and videos used in marine biology research, underwater archaeology, and environmental monitoring. Figure 10 depicts the noisy and clear underwater images (Chandra *et al.*, 2023).

Fig. 10: Underwater Image

Preserving Cultural Heritage

In the cultural heritage domain, denoising is applied to enhance digital images of artifacts, manuscripts, and artworks. In this way, such a process assists in the restoration and analysis of historical pieces for their better preservation and documentation. Figure 11 depicts the noisy and clear images of cultural heritage preserving (Lefkimmiatis, 2017).

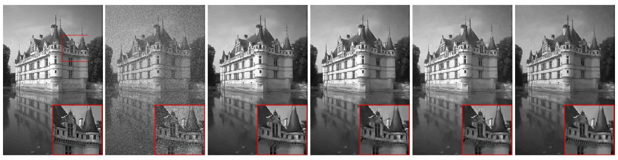

Fig. 11: Heritage Image

Augmented Reality (AR) and Virtual Reality (VR)

AR and VR applications require clear images with high quality. Denoising ensures that artifacts are completely removed, which provides clear images that are necessary for users to have more vivid experiences in the virtual environment. Figure 12 depcits and application of AR.

Evaluation Metrics for Denoising Techniques

The effectiveness of image denoising algorithms must be evaluated using objective and quantitative measures that assess the quality of the image. The basic aim is to eliminate noise while retaining important picture characteristics including borders, textures, and structure. Several performance measures are widely employed in image denoising, each concentrating on a distinct component of picture quality.

Fig. 12: AR Image

Peak Signal-to-Noise Ratio (PSNR)

PSNR is the most popular measurement for measuring image denoising performance. It calculates the ratio of the highest potential power of a signal (i.e., the original picture) to the power of noise, which influences the quality of its representation.Higher PSNR values mean better performance on denoising and higher image quality. Typically, the PSNR will lie between 30 and 40 dB for a high-quality output of denoising, which depends on the noise level and algorithm efficiency. PSNR is not adjusted to the human vision; the measure becomes insensitive to important perceptual differences, for instance, edge blurring or loss of texture. Equation 1 is the mathematical representation of PSNR.

$$PSNR = 10\log_{10}\frac{R^2}{MSE} \tag{1}$$

where R is the maximum pixel value in the image and MSE is tne mean square error.

Structural Similarity Index (SSIM)

The SSIM is a perception-motivated metric to measure the similarity of localized patterns of pixel intensities, normalized for luminance and contrast. It has been proven to be perceptually more aligned than PSNR and MSE. SSIM values lie between -1 and 1; a value of 1 expresses perfect similarity between the denoised and original image. It considers texture and structural details; hence, it acts as a better indicator of perceptual quality compared to PSNR and MSE. SSIM is a very computational measure and sensitive to small changes in texture; this could make evaluation problematic in images with a lot of fine detail. Equation 2 is the mathematical representation of SSIM.

$$SSIM = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{\left(\mu_x^2+\mu_y^2+C_1\right)\left(\sigma_x^2+\sigma_y^2+C_2\right)} \tag{2}$$

where C_1 andC_2 are the constant, μ_x is the mean of original image and μ_y is the mean of denoised image, and σ is standard deviation.

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Mean Squared Error (MSE)

MSE estimates the average of a squared difference between the original image and the denoised image. It will directly indicate the closeness of a restored image concerning the original image. Lowering the value of MSE indicates an even better match of original and denoised images; hence, good performance in denoising. Similar to PSNR, MSE itself does not consider any aspects of how humans perceive noise or image quality. Equation 3 is the mathematical representation of MSE.

$$MSE = \frac{1}{M \cdot N} \sum_{a=1}^{M} \sum_{b=1}^{N} \left(I_o(a,b) - I_d(a,b)\right)^2 \tag{3}$$

where I_o is the original image and I_d is the denoised image and $M.N$ indicates the size of image.

Natural Image Quality Evaluator (NIQE)

NIQE is a no-reference image quality metric that estimates the perceptual quality without involving any ground truth, especially making it helpful in real-world images where the original clean image is unavailable. Effective in the case of practical scenarios where the reference image is either unknown or inaccessible. Less effective in synthetic noise removal tasks since it might fail to capture the fine details of the noise structure. Equation 4 is the mathematical representation of NIQE.

$$NIQE = d\left(I_t \text{ Model},\ I_n \text{ Model}\right) \tag{4}$$

where I_t is the test image I_n is the natural image and d is the distance function between the test image and the natural image.

Universal Quality Index (UQI)

UQI belongs to the family of image quality assessment metrics with full reference, and it estimates the quality of an image from the viewpoint of its visual appearance, considering an original noise-free image as the reference. The UQI metric was initially developed for quantifying image distortions based on several perceptual features: luminance, contrast, and structural similarities. Equation 5 is the mathematical representation of UQI.

$$UQI = \frac{4\mu_o \mu_d \sigma_{o,d}}{\left(\mu_o^2 + \mu_d^2\right)\left(\sigma_o^2 + \sigma_d^2\right)} \tag{5}$$

where μ_o is the mean of original image and μ_d is the mean of denoised image $\sigma_{o,d}$ is the covariance between original and denoised image, and $\sigma_o{}^2$, and $\sigma_d{}^2$variance of original and denoised image respectively.

Normalized Absolute Error (NAE)

NAE is used to test the performance of image denoising algorithms. It compares the pixel intensities between the original (noise-free) image and the denoised image. It gives the absolute difference in the pixel values across the whole image that is normalized by the sum of pixel values of the original image. Equation 6 is the mathematical representation of NAE.

$$NAE = \frac{\sum_{a=1}^{M} \sum_{b=1}^{N} |I_o(a,b) - I_d(a,b)|}{\sum_{a=1}^{M} \sum_{b=1}^{N} |I_o(a,b)|} \tag{6}$$

where $I_o(a,b)$ is the pixel value of the original image at *(a,b)* position and $I_d(a,b)$ is the pixel value of the denoised image at *(a,b)* position,and *M.N* indicates the size of the image.

Perception-based Image Quality Evaluator (PIQE)

PIQE is a no-reference image quality assessment metric based on the perception of human visual characteristics. Unlike NAE, it does not require any reference image, that is, the original image; hence, this finds a very useful application in real scenarios where the original-that is, noise-free-image may not be available. Equation 7 is the mathematical representation of PIQE.

$$PIQE = \frac{1}{N_{\text{block}}} \sum_{a=1}^{N_{\text{block}}} D_a \tag{7}$$

where N_{block} is the number of blocks in the image and D_a is the distortion score for a^{th} block.

Table 1 gives a brief description of evaluation metrics that are used in denoising techniques.

Table 1: Comparison of different performance metrics

Metric	Description	Advantages	Disadvantages
PSNR	Measures the ratio of the maximum possible pixel value to the noise level (in decibels).	Simple, widely used, easy to compute.	Sensitive to large errors, does not reflect perceptual quality well.
SSIM	Measures structural similarity based on luminance, contrast, and structure.	Correlates better with human perception, sensitive to structural distortions.	Can be less effective for texture preservation and fine noise details.
MSE	Average squared difference between the original and denoised images.	Simple to compute, foundational metric.	Does not correlate with human perception.
NIQE	No-reference metric estimating perceptual quality without ground truth.	Suitable when reference images are unavailable.	Less reliable for synthetic noise.
UQI	Simplified version of SSIM that measures similarity using correlation coefficients.	Simple and interpretable.	Does not fully capture complex perceptual nuances.
NAE	Computes the sum of absolute differences normalized by the sum of pixel intensities.	Provides normalized error measurement.	Less commonly used, lacks perceptual insight.
PIQE	No-reference metric that evaluates block-based perceptual distortions.	Can assess perceptual distortions with no reference.	Sensitive to high texture areas.

Figure 14 displays the denoising performance of five different methods (WNNM, Guided, NLM, DnCNN, and

BM3D) applied to noise-corrupted MRI images at different noise variance levels (0.01, 0.05, 0.09, and 0.50). The result of the algorithms for each noise variance level is shown in the images in each column. More severe noise applied to the original picture is correlated with a higher noise variance. Each row represents the effect of a specific denoising technique on all values of noise. WNNM performance significantly deteriorates with increased noise variability. At high levels of noise, for example NV = 0.50, the image loses definition and becomes fuzzy. Guided filter's performance is moderately good at low noise variances (NV = 0.01 and 0.05) but struggles to maintain details when noise levels are high, causing noticeable distortions. Similar to the Guided filter, NLM performs reasonably well at low noise but severely degrades with larger noise fluctuations. Compared to classical filters, DnCNN maintains robust performance with only slightly better structure and detail preservation (e.g., NV = 0.05, 0.09). The best visual quality is achieved by BM3D at all noise levels. In comparison, it retains details even at high noise variance (NV = 0.50). In terms of detail preservation and noise removal, BM3D always outperforms the competition. DnCNN holds promise, probably due to its deep learning structure, particularly at medium noise levels. With increasing noise variance, the conventional methods such as WNNM, Guided, and NLM fail and lose important picture information.

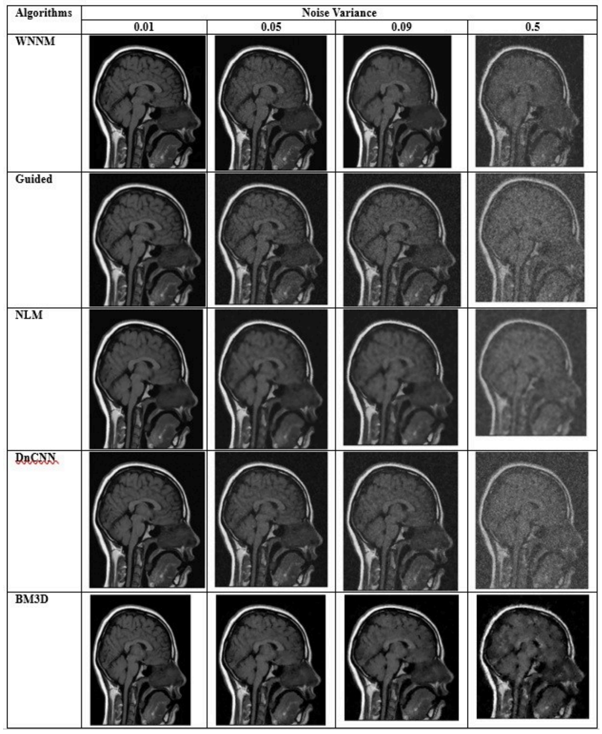

Fig. 14: Sample images with different algorithms at different Noise Variance

Table 2 compares the performance of five different image denoising algorithms—WNNM (Weighted Nuclear Norm Minimization), Guided Filter, NLM (Non-Local Means), DnCNN (Deep Convolutional Neural Network), and BM3D (Block-Matching and 3D Filtering)—under various levels of noise variance (NV). The results are evaluated using two metrics: PSNR and SSIM. NV used here are 0.01, 0.05, 0.09, and 0.50, respectively, covering a low to high range of noise. Higher PSNR shows better noise removal and closeness to the original clean image. Higher SSIM denotes better structural and perceptual quality preservation. WNNM performs poorly at low NV (for example, NV = 0.01) with PSNR of 16.98 and SSIM of 0.36. Significantly improves at higher NVs, especially at NV = 0.50, with PSNR of 30.16. SSIM decreases drastically for higher noise levels; structural content is not preserved well. Guided Filter reasonable PSNR even at lower NVs-for example, 29.98 at NV = 0.01. Performance degrades at high noise levels, with a PSNR of 18.56 at NV = 0.50. SSIM values are generally steady but low for all the noise levels, and it indicates moderate structural preservation. NLM is excellent at low NV; the PSNR is 30.64 at NV = 0.01. Performance degrades with an increase in NV; the PSNR drops to 18.23 at NV = 0.50.

Table 2: Comparison of different algorithms at various noise variances by using PSNR and SSIM

Algorithms	Noise Variance(NV)	PSNR	SSIM
WNNM	0.01	16.98	0.36
	0.05	23.25	0.22
	0.09	23.06	0.25
	0.50	30.16	0.06
Guided	0.01	29.98	0.44
	0.05	25.60	0.31
	0.09	23.82	0.26
	0.50	18.56	0.13
NLM	0.01	30.64	0.33
	0.05	24.94	0.19
	0.09	23.20	0.15
	0.50	18.23	0.07
DnCNN	0.01	31.27	0.39
	0.05	25.60	0.25
	0.09	23.48	0.20
	0.50	17.09	0.06
BM3D	0.01	35.72	0.48
	0.05	31.10	0.36
	0.09	29.38	0.31
	0.50	24.18	0.18

SSIM values also exhibit a similar trend, which suggests that structural integrity is difficult to maintain at higher noise levels. DnCNN achieves the highest PSNR at low NV (31.27 at NV = 0.01), which is indicative of the strength of deep learning-based methods. The performance drops drastically at high NV, and PSNR drops to 17.09 at NV = 0.50. SSIM values are moderate but consistent, which reflects good detail preservation at lower noise levels. BM3D algorithm outperforms all other algorithms at most noise levels. At NV = 0.01 reaches the maximum PSNR of (35.72) as well as SSIM value of (0.48). It has great performance at high levels,

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even the noise with 24.18 of PSNR and 0.18 of SSIM was obtained when NV = 0.50. BM3D indicates the highest performance among others both PSNR and SSIM when tested in varying levels of noise and its the most resilient of the above compared algorithms. DnCNN is performing excellent at low noise, but it fails with higher noise, possibly because it overfits on particular noise levels during training. NLM and Guided filters work reasonably good at low to medium noise but fail with a higher noise level. WNNM improves very significantly with higher noise level by PSNR but failed in the structural details with poor SSIM. BM3D would excel both in metrics whereas DnCNN and Guided Filters maybe useful when a specific noise is more dominant, or structures are dominant in the respective images to be denoised.

Discussion

Image denoising methodologies have evolved, each improving upon the previous techniques. First-generation Gaussian Filtering applies a Gaussian kernel to regularize an image and hence remove noise. Median Filtering is an adaptive linear filter that does a better job in preserving details but relies on knowledge of noise characteristics. Wavelet Thresholding is a sophisticated multi-scale analysis approach; it is more effective yet suffers from limitation due to threshold selection and possible artifacts. NLM is an improvement of patch-based filtering that keeps fine details but increases the computation. BM3D-Block Matching and 3D filtering-is based on those patch-based methods and is considered by the community as the gold standard of classical denoising. TV denoising seeks the minimum of total variation so as to suppress noise while preserving sharp edges. Deep learning—such as DnCNN—handles complex patterns of the noise and establishes realistic clean images. Even though deep learning-based image denoising techniques have revolutionized the industry, there are some practical issues that need to be addressed before they can become mainstream. Some challenges associated with deep learning methods are:

1. Large Datasets Are Required: Large labeled datasets are required for a deep learning model to learn efficiently, especially in cases of CNNs and GANs.
   - Data Gathering: Finding huge datasets with noisy and clean corresponding images is not easy, especially when considering specialized domains like astronomy or medical imaging.
   - Data Heterogeneity: The diversity in the data must come at different levels of noising, types, and possibly image characteristics for generalized cases. However, getting it in reality is typically problematic.
   - Costs of Annotation: It takes a lot of effort and money to produce clean ground truth images for supervised algorithms. Either way, taking clear images in real-world situations often requires either special tools or good luck.
   - Limitations of Synthetic Data: Even though synthetic datasets are often used to compensate for the lack of real data, they could not completely represent the complexity of noise in real-world scenarios, which may lead to suboptimal model performance when used on real images.
2. Significant Computer Power: Because deep learning models involve iterative optimization and many parameters, training them is computationally expensive.
   - High-End Hardware: Researchers and small businesses might find the high memory and processing capacity of GPUs or TPUs necessary for training too expensive.
   - Energy Consumption: Deep model training consumes a lot of energy, thereby increasing the cost of operations and environmental issues.
   - Inference Costs: Even implementing deep learning models for real-time applications (such video denoising or medical imaging) may require a significant amount of processing power, even though training requires a lot of resources.
   - Delay Problems: Complex models can cause delay, which can impair performance in time-sensitive applications like surveillance or driverless cars.
3. Specific Issues with Generalization and Overfitting for the Domain: Models created using certain datasets could not be carried over to new data or different noise distributions. For example, a model that has been trained using Gaussian noise will not work on speckle or salt-and-pepper noise.
   - Overfitting: Deep learning models may do great on training data but bad on noisy pictures in the real world if there is either inadequate or uneven training data.
4. Model Design and Training Architecture Selection Complexity: To find the best architecture for image denoising is very difficult because it requires a lots of experience and trial.
   - Hyperparameter Tuning: It can be some trial and error in order to find the correct hyperparameters, like learning rates, batch sizes, and regularization factors.
   - Long Training Times: Based on the size of the dataset and the sophistication of the model, a deep learning model may be trained for hours or days.
5. Interpretability and Black-Box Nature: The inability of deep learning models to be interpreted is one of the common criticisms. Unlike traditional approaches with well-established mathematical underpinnings, it may be hard to understand or

justify the predictions made by a deep learning model. Trust and acceptability are limited in critical applications like medical imaging due to its black-box nature.

6. Problems with Real-Time Deployment:
    - Footprint of Memory: This model is enormous, making it challenging for large-scale deployment on resource-limited edge devices, like drones and smartphones.
    - Instant Inference: An always-open problem to decrease inference time with model size in ways that don't deteriorate the performance. Although deep learning techniques for image denoising provide unmatched performance, the difficulties posed by the need for a lot of data and a lot of processing power continue to be major obstacles. Making these approaches accessible and useful for wider applications requires addressing these problems through creative data collection strategies, effective model design, and computational optimizations.

Case Study

Medical imaging is a notable area of current real-world denoising applications. In recent years, denoising techniques have been applied widely in MRI and CT scans to enhance the clarity of pictures. Noise in medical imaging may be caused by low-dose scans or ambient conditions during imaging, which complicates diagnosis. Algorithms like BM3D, DnCNN, and deep learning-based techniques have been used to enhance picture quality. For example, COVID-19 CT scans Denoising techniques were applied to CT scan data in the COVID-19 era to help identify lung diseases while minimizing radiation exposure and scanning time. Even with noisy or limited data, algorithms helped create sharper images for more accurate diagnosis. Another vital application domain of denoising is underwater photography. For example, Coral Reef Monitoring In aquatic settings, imaging often has issues with noise due to lessened visibility, especially when operating at deeper depths and scattering caused by water particles as it filters the light. The images of underwater environments are being made better by BM3D and DnCNN that now easily track the status of a reef or follow how the biodiversity changes with time. AI models have been applied using deep learning techniques to improve the quality of camera or sonar data for autonomous submarines and underwater robots. Underwater Archaeology Case Study Denoising methods are used in underwater archaeology to improve the visibility of submerged buildings or historic shipwrecks that have been photographed by Remotely Operated Vehicles (ROVs).

Conclusion

In this study, a comprehensive overview of image-denoising techniques is provided, paying attention to the development from classical methods to the most recent advances in deep learning-based systems. Image denoising, a fundamental pre-processing step in image analysis, makes an effort to improve the quality of images by eliminating undesirable noise while retaining important information like edges and textures. Various ways to address this difficulty have evolved throughout time, each with its own set of strengths and limitations based on the nature of the noise and the image's features. Traditional image denoising approaches, such as linear filtering (Gaussian filters, Wiener filters) and transform-domain methods (wavelet transforms, Fourier transforms), have been widely researched and utilized in real-world circumstances. These algorithms are straightforward to apply and produce good denoising results, particularly in the case of Gaussian noise. However, they frequently struggle with more complicated noise patterns such as speckle, Poisson, or salt-and-pepper noise, which can result in over-smoothing of edges and loss of fine information in the image. Transform-based approaches, such as wavelet denoising, contourlet, and curvelet transformations, enhanced performance by exploiting multi-resolution analysis and collecting geometric patterns in pictures. Non-Local Means (NLM) and dictionary learning methodologies established a strategy of utilizing self-similarities in images. By averaging comparable patches from the images themselves, these approaches effectively retained image structures and outperformed previous denoising methods. The development of deep learning has drastically changed the field of image denoising. CNNs and other deep architectures, such as autoencoders, residual networks, and Generative Adversarial Networks (GANs), have outperformed standard approaches for denoising applications. These models can automatically learn complicated noise patterns and image characteristics using data-driven methods, allowing them to handle a broad range of noise types, including Gaussian, Poisson, and mixed noise. CNN-based denoising algorithms, such as DnCNN and its derivatives, have demonstrated a high degree of generalization across varied noise levels without previous knowledge of noise distribution. Despite their success, deep learning-based methods come with their own set of challenges. These models require substantial amounts of labeled training data, high computational resources, and careful architecture design to avoid overfitting or performance degradation on unseen data. Additionally, while deep networks excel at noise removal, they may occasionally produce artifacts or fail to preserve very fine image details, especially in edge-sensitive applications. To mitigate these issues, hybrid methods combining the strengths of classical and deep learning techniques are emerging. Such methods aim to leverage the interpretability and simplicity of traditional approaches while harnessing the powerful feature extraction capabilities of deep networks. To summarize, the field of image denoising has made great progress, moving from traditional approaches to more advanced and automated deep learning algorithms. The particular application, noise characteristics, and available computer resources primarily determine the optimal denoising approach.

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Author's Contributions

Archana Saini: Conceptualization, Methodology, Coding, Formal Analysis, Writing - Original Draft.

Ayush Dogra: Conceptualization, Methodology, Formal Analysis, Analysis, Proofreading.

Ethics

This research did not involve human participants, animal subjects, or any material that requires ethical approval.

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