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Image Denoising: An Overview of Noise Model, Denoising Methods and Applications

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Abstract

In recent years, image denoising has found its way into numerous applications, ranging from medical diagnosis to psychological education, where noise reduction plays a crucial role in improving the clarity and usability of visual data. In the field of computer vision, image denoising is considered a vital preprocessing step for a variety of image analysis tasks, including object detection, image segmentation, and feature extraction. This paper explores the fundamentals of noise models and their impact on image quality, demonstrating how different types of noise can degrade essential image details. A variety of denoising methods are presented, categorized into spatial filtering, transform domain, and machine learning-based approaches. Through a review of recent publications, this paper highlights the growing dominance of machine learning-based methods, which have been shown to outperform conventional techniques due to their ability to learn complex noise patterns and generalize across diverse datasets. However, the study also identifies potential challenges associated with machine learning methods, particularly concerning the availability of large, high-quality training datasets and the computational resources required to train these models effectively. These limitations create new direction for future research, aimed at optimizing machine learning techniques for more efficient and accessible image denoising solutions.

Keywords: *Image denoising, Noise, Spatial filtering, Transform domain, Machine learning.*

1.0 Introduction

Over the years, the need for image analysis and processing has grown tremendously due to its application in different areas including medical imaging, agricultural automation, forensic, remote sensing, biometrics, military surveillance and other field that involve image capturing [1, 2]. The image carries significant information and feature which are extracted and processed for further analysis for important decisions and conclusions. However, one major factor which limits the effectiveness of feature extraction in images is the present of noise[3]. Noise introduction into digital images often occur during the processes of acquisition and transmission. During image acquisition, noise can originate from the sensor itself. Image sensors such as the in digital cameras can generate electronic noise due to thermal effects or inherent limitations in sensor design. This noise manifests as random variations in pixel values, affecting the overall quality and fidelity of the captured image. When image edges, textures and resolution are weak or distorted due the present of noise, it significantly affects the stability of the system in application domain [4].

During the transmission of digital images, when images are transmitted over networks or communication channels, they are susceptible to interference and distortion. Factors such as electromagnetic interference, signal attenuation, and packet loss can all contribute to the corruption of image data during transmission. The presence of noise in digital images is not merely an artifact of the technology but is deeply rooted in the physics and engineering of image capture and transmission systems. These processes involve the conversion of real-world scenes into discrete digital representations, inherently susceptible to various sources of noise [5].

Numerous forms of noise, including Salt and Pepper noise, Gaussian noise, Poisson noise, Speckle noise, and various other fundamental types can significantly degrade the quality of an image. These types of noise are introduced due to a range of factors such as faulty memory locations, post-filtering processes, compression artifacts, weak focal lengths, and adverse environmental conditions during image capture [5]. Understanding the specific noise model affecting an image and employing an appropriate denoising strategy are crucial preprocessing steps essential for restoring the original quality of the image. Since the degradation caused by noise can vary widely based on the source and characteristics of the noise, knowing the intricacies of noise types and their impact enables the development of effective techniques to mitigate and improve overall image quality [6].

To recover original image from the corrupted image, numerous methods for reducing noise in images have been thoroughly researched, progressing from spatial domain filters to transform domain filters, as well as learning-based denoising approaches like sparse representation. In recent times, significant attention has been directed towards image denoising and deconvolution using machine learning methods [7].

2.0 Image Noise Type

Noise is classified based on its probability distribution function, correlation, nature, and source. Various types of noise can impact images, including salt and pepper noise, Gaussian noise, Poisson noise, and speckle noise. Noise is typically categorized as additive, multiplicative, or impulse in nature. Impulse noise specifically alters pixel values randomly. Impulse noise is further divided into static and dynamic (random) noise categories [8].

2.1 Gaussian Noise

Gaussian noise also known as amplifier noise, is a type of statistical noise characterized by a Probability Density Function (PDF) that follows a Gaussian distribution. This noise model utilizes the normal distribution curve. Gaussian distribution can also be defined as normal distribution such that the probability density function (PDF) must be equal to the statistical noise. Gaussian noise is typically either multiplicative or additive and is specifically associated with additive noise having a zero-mean. The primary source of Gaussian noise occurs during image acquisition, such as sensor noise introduced by inadequate illumination or high temperatures. This noise represents a significant component of the inherent "real noise" within an image sensor, manifesting as a consistent noise level particularly noticeable in darker regions of the image [8]. Gaussian noise can also be referred to as Electronic Noise and its Gaussian random variable 'z' probability density function P can be expressed as presented in equation (1) [4],

$$P(z) = \frac{1}{\delta\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\delta^2}} \tag{1}$$

where x is image pixel value, μ is the mean and σ is standard deviation. These parameters have a direct relationship with noise magnitude.

2.2 Salt and Pepper Noise

This form of noise is commonly known as impulse noise, random noise, or spike noise. It arises from abrupt and significant variations in the image signal and may also result from hardware defects or failures in the imaging system. Impulse noise manifests as randomly occurring black and white pixels, where bright pixels may appear in dark areas and dark pixels appears in bright areas within the image. Salt and Pepper noise can be classified into three distinct categories; Salt noise involves the addition of white pixels with a pixel value of 255, resulting in random brightness variations. Pepper noise on the other hand, adds black pixels with a pixel value of 0, causing random dark spots in the image. Lastly, Salt and Pepper noise combines random bright (salt) and random dark (pepper) pixels, resulting in a mixture of bright and dark artifacts across the image [9].

2.3 Poisson Noise

Poisson noise also known as shot noise exhibits a distribution closely related to the Gaussian distribution and is a result of statistical characteristics of electromagnetic waves affecting the image. This type of noise is sometimes referred to as photon noise, as it is modeled by the Poisson distribution arising from the random arrival of photons on the image sensor. Poisson noise becomes noticeable when the number of photons captured by the sensor in an image is insufficient to eliminate statistical fluctuations in a specific measurement [10]. The conditional probability of Poisson distributed image '*y*' for clean image "*x*" is given presented in equation (2) [11].

$$p(y|x) = \prod_{i,j=1}^{N} \frac{e^{-x_{i,j}}\, x_{i,j}^{y_{i,j}}}{y_i\, j_1} \tag{2}$$

2.4 Speckle Noise

Speckle noise also referred to as Gamma noise, is a granular type of noise that naturally exists within images and can degrade the quality of Synthetic Aperture Radar (SAR) images and active radar data. This noise is typically generated by signals reflected from various sources such as gravity-capillary waves and elementary scatters that appears as a textured background beneath images of sea waves. In SAR imagery, speckle noise poses significant challenges due to its complexity, making image interpretation more difficult [8]. Speckle noise can be modeled by Gamma distribution whose probability distribution function is given as presented in equation (3) [11].

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$$P(x) = \begin{cases} \frac{a^b x^{b-1}}{(b-1)} e^{-az}, & x \geq 0 \\ 0 & otherwise \end{cases} \quad (3)$$

Where parameters a and b are positive integers

3.0 Image denoising model

Generally, the problem of image denoising can be mathematically modeled as presented in equation (4).

$$y = x + n \quad (4)$$

In this expression, y denotes the acquired noisy image, x corresponds to the latent noise-free image, and n represents additive white Gaussian noise (AWGN) characterized by a standard deviation σ_n. In real-world scenarios, this noise parameter can be approximated using several estimation techniques, including the median absolute deviation approach. The main objective of image denoising is to suppress unwanted noise components while preserving important structural details of the original image, thereby enhancing the overall signal-to-noise ratio (SNR). Denoising ensure that edges are sharp and protected without blurring, plate are smooths and texture are preserved without generation of new artifacts [12].

4.0 Image Denoising Methods

Over the last two decades, the researchers are consistently working on enhancing effective image denoising algorithms. These algorithms are designed to recover significant information from distorted and corrupted images while preserving fine features and edges. In this survey work, image denoising methods have been broadly classified as spatial domain filtering, frequency domain filtering and machine learning based methods [4].

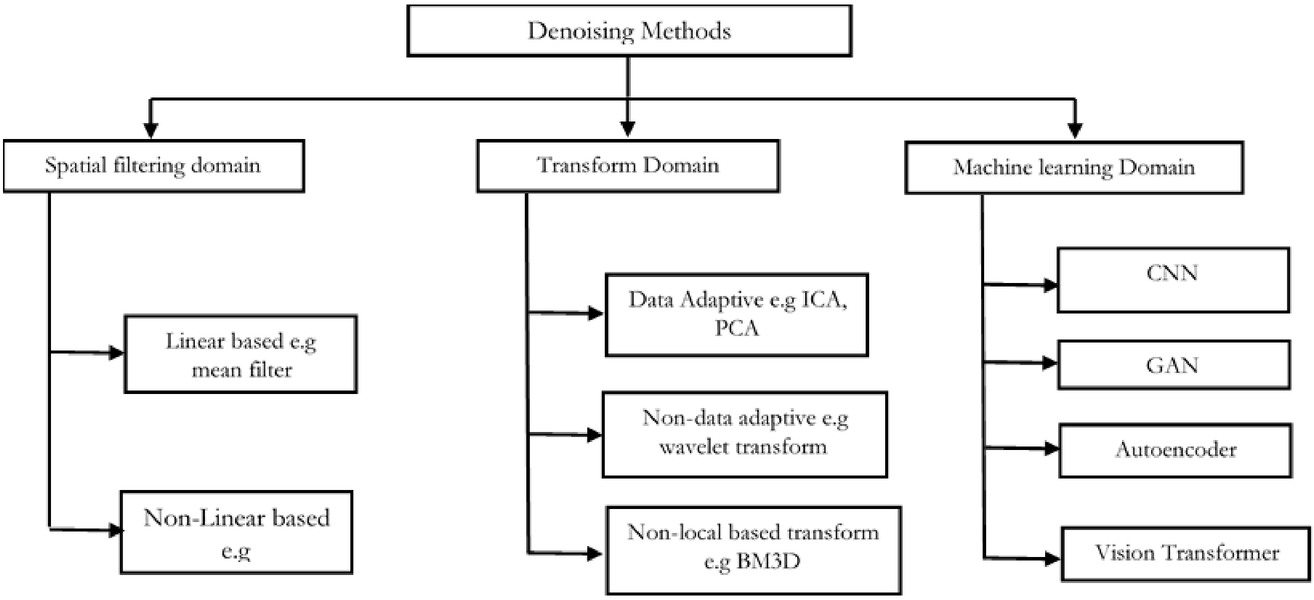

Figure 1: Classification of denoising methods

4.1 Spatial Domain Methods

Spatial domain method is a filtering method commonly employed for image restoration, involving direct application of filtering operations to image pixels. Spatial methods attempt to eliminate noise by determining the gray value of each pixel using the correlation between pixels or image patches within the original image [13]. Spatial filters apply low-pass filtering to groups of pixels under the assumption that noise tends to occupy higher frequency regions in the spectrum. While spatial filters generally reduce noise, they often do so at the expense of image clarity, leading to undesirable blurring and loss of sharp edges [12].

Spatial filtering methods are categorized into linear and non-linear types. Linear filters, such as the mean filter, Gaussian filter, and Wiener filter. The mean and Gaussian filter operate by replacing each pixel with a value derived from a defined neighborhood. However, they often result in over-smoothing and edge blurring. To address the problem, the Wiener filter was introduced to give a better performance. However, it is not also effective for application where dealing with sharp edges is inevitable. Non-linear filters, which preserve edges, details, and textures through non-linear input-output relationships, were later developed. Examples include total variation filters, anisotropic diffusion filters, bilateral filters, and fourth-order partial differentiation filters. The bilateral filter, for instance, assigns new pixel values based on neighborhood weights calculated from both Euclidean distance and range differences [14]. Some spatial filter-based methods for both linear and non-linear are presented subsequently.

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I. Wiener filter

A Wiener filter is a linear and adaptive filter designed for the linear estimation of a non-noisy signal sequence from a noisy one. It effectively removes additive noise when the noise consists of stationary linear random processes with known spectral characteristics, but it is less effective in more general cases. The linear properties of the Wiener filter can be enhanced through a nonlinear extension or by combining it with nonlinear filters for improved performance [15].

II. Anisotropic Diffusion (AD) filter

An Anisotropic Diffusion (AD) filter which is also known as Perona–Malik diffusion, is a non-linear filter that aims to remove noise by smoothing or blurring the image without degrading significant details. Similar to a Median Filter (MF), AD seeks to preserve important features while eliminating noise[16].

III. Bilateral Filter (BF)

A Bilateral Filter (BF) is a non-linear, non-iterative filter that enhances images by considering both the spatial proximity and the intensity similarity of neighboring pixels. This dual consideration allows the filter to compute the new value of each pixel based on its neighboring pixels, effectively smoothing the image while preserving edges. Specifically, the filter evaluates the geometric closeness of surrounding pixels and the similarity in their gray levels to decide how much each neighboring pixel influences the central pixel's new value [16].

IV. Block-Matching Three-Dimensional (BM3D)

A Block-Matching Three-Dimensional (BM3D) filter operates by clustering image fragments of identical size that exhibit similar characteristics. This sophisticated filtering technique initially groups these similar fragments and processes them collectively to enhance image quality. The BM3D algorithm has been further developed to separately handle the tasks of deblurring and denoising, providing a more effective solution for image restoration by addressing these issues independently [15].

4.2 Frequency Domain Methods

Transform domain techniques involve converting an image into a different domain using a mathematical transform, performing operations on the transform domain coefficients, and then applying an inverse transform to reconstruct the denoised image. The Fourier transform was one of the earliest methods employed for this purpose, but numerous other techniques have since been developed. These include the Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Discrete Cosine Transform (DCT), and Dual-Tree Complex Wavelet Transform (DT-CWT), among others [17, 18].

Transform domain filtering can be categorized into data-adaptive and non-data-adaptive methods based on the nature of the transform functions used. Data-adaptive methods, such as Independent Component Analysis (ICA) and Principal Component Analysis (PCA), tailor the transform to the specific data. ICA is effective for denoising non-Gaussian noise, while PCA decorrelates the original image data, selecting the most significant principal components (highest Eigen-vectors) for image restoration [11].

Wavelet-based image denoising is a multi-resolution analysis technique that uses various mother wavelets, such as Daubechies and Haar, to derive wavelet coefficients. This approach is effective for denoising different types of noise, including Gaussian, salt-and-pepper, and Poisson noise, using appropriate thresholding operators [18].

4.3 Machine Learning Based Methods

Machine learning-based image denoising methods have experienced significant advancement due to the availability of standardized benchmark datasets tailored to specific applications, rapid progress in deep learning techniques and enhanced computational capabilities provided by Graphics Processing Units (GPUs) [9]. In recent years, research has increasingly shifted from traditional analytical approaches toward data-driven machine learning models, largely driven by improvements in image quality evaluation metrics. Consequently, various machine learning algorithms have been successfully applied to image denoising across a wide range of applications. Recent and commonly used model considered in this paper includes the convolutional neural network-based models, generative adversarial network-based models (GAN) [19], Autoencoders (AEs) [20] and vision transformers[21].

I. Convolutional Neural Network (CNN)

CNN-based techniques have consistently outperformed many modern methods in terms of image quality assessment metrics. This success is largely due to the extensive modeling capacity of CNNs and the advancements in network training and design. CNNs are specifically designed for grid or matrix-like data, drawing inspiration from the visual cortexes of animals [22].

In CNN models, the convolutional kernel, which contains learnable parameters, is applied uniformly across all positions of an image. This kernel acts as a feature extractor tailored to specific image restoration tasks. The convolutional layers are connected in a cascading manner, allowing the extracted features to become increasingly complex and hierarchical. typical Convolutional Neural Network (CNN) architecture consists of an input layer, multiple hidden processing layers, and a final output layer. Within each layer, convolution operations are performed using trainable filters, followed by nonlinear activation functions to introduce learning capability. The output generated at each stage becomes the input to the subsequent layer, while the intermediate outputs are referred to as feature maps [23]. During training, the network parameters, particularly the convolutional kernels, are learned from paired datasets containing noisy and corresponding clean images using optimization algorithms such as stochastic gradient descent (SGD) or Adam. The learning objective is to minimize a predefined loss function, most commonly the mean squared error (MSE), which measures the difference between the restored image and the ground-truth clean image [11].

II. Generative Adversarial Network

The generative adversarial network (GAN) employs generative modeling through two sub-models: the generator and the discriminator. This architecture addresses the challenge of learning complex probabilistic distributions in deep generative models. The generator creates new realistic images from the problem domain, while the discriminator evaluates whether these generated images are real or fake. Acting as an adversarial network, the discriminator's primary role is to distinguish between genuine and generated images. Meanwhile, the generator aims to produce images that can deceive the discriminator [23].

Typically, the generator maps a noisy image to its ground truth, and the discriminator uses a loss function to measure the difference between the generator's output and the ground truth. The discriminator assesses whether the generator's predicted image is real or fake [24]. During training, the GAN simultaneously optimizes both the generator and discriminator networks until they reach Nash Equilibrium, at which point the generator is considered to have accurately captured the distribution of real samples [23].

III. Autoencoders

Autoencoders (AEs) represent a class of neural network models developed for data reconstruction tasks, particularly in image restoration applications. The architecture is composed of two fundamental parts which are the encoder and decoder. The encoder transforms the input data into a compact latent representation by extracting and retaining the most significant features, while the decoder utilizes this compressed representation to regenerate an approximation of the original input. Training of autoencoders is performed through the backpropagation process, where the network parameters are adjusted to reduce the reconstruction error between the input data and its reconstructed output data [25]. For image generation, the variational autoencoder (VAE) is widely used. VAEs have become a popular choice for generative tasks because they not only achieve high accuracy in data reconstruction but also ensure that the compressed representations of data samples are close to each other yet distinct [26].

IV. Vision Transformers

Transformer is a class of deep learning architectures that analyze data by learning long-range relationships through attention mechanisms, instead of processing information sequentially as done in many conventional neural network models. In recent years, transformer frameworks have increasingly been adopted for image restoration and denoising tasks [21, 27, 28]. Architectures such as Restormer are capable of capturing long-range feature interactions, while focusing on improving the refinement of local image details[27]. Conventional approaches based on CNN primarily depend on local receptive fields, which can restrict their ability to represent global contextual information and long-range dependencies. As a result, these models may produce outputs that appear overly smooth and lack fine structural details. Transformer-based architectures have therefore gained attention as effective alternatives, as their self-attention mechanisms enable the modeling of both global context and multi-scale relationships within images [28].

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Table 1: Key Studies that Define Different Denoising Application Domain

Area	Author (Ref)	Year	Model	Application
Medicine	[29]	2016	Wavelet decomposition	Obtaining abnormal MRI brain speckle noise image
	[30]	2017	encoder-decoder convolutional neural network (RED-CNN)	Computed tomography (CT) for X-Ray imaging
	[31]	2019	Digital filters to include mean, median and wiener filter	Medical MR Imaging
	[32]	2021	Wavelet based GAN model	Optical coherence tomography (OCT) images for retina
	[33]	2021	Dictionary-based deep residue network	Noise removal in MRI and CT images
Face Recognition	[34]	2019	Deep Stacked Denoising Sparse Autoencoders (DSDSA)	Representations of images with identity function
	[35]	2021	image sequence decomposition using principal component analysis (PCA)	Spatial filtering for degraded face images
	[36]	2014	low-light image denoising of low frequency noise (DeLFN)	automatic face recognition with illumination variation.
Remote Sensing	[37]	2021	Laplace pyramid transformation to form an optimized contour transformation	handle the texture information and edge information
	[38]	2022	Combined remote sensing image denoising network (RSIDNet) based on a deep learning approach	Complex texture feature extraction
	[39]	2019	Denoising object function based on coefficient sparsity and edge similarity	Dictionary learning and edge-feature prediction
	[40]	2012	Partial differential equations (PDEs) of multicomponent image	Multispectral remote-sensing images and hyperspectral remote-sensing images
Education	[41]	2022	Calibration principle of Dirckx method	Identification of student's behavior and expressions.

5.0 Survey on Application of Denoising Methods

5.1 Image Denoising in Medicine

Eliminating noise from images is crucial in biomedical image processing due to the poor visual quality caused by noise. Medical images such as X-ray, CT, and MRI scans can be affected by noise during processing, which can be detected and reduced using various methods [42, 43]. However, some noise removal techniques can result in blurred images, making the choice of noise removal methods particularly important in biomedical image processing. Numerous techniques have been presented in literatures to prevent unwanted noise in images.

The study presented in [32] introduced a deep generative approach based on wavelet transform for denoising Optical Coherence Tomography (OCT) images, which are often affected by speckle noise. Noise presence degrades image quality and complicate subsequent diagnostic processes. Their method employs wavelet transforms to extract multi-scale features aimed at denoising OCT images. The model utilizes a generator within a GAN architecture, incorporating a novel edge-sensitive mixed loss function that integrates Sobel edges, L1 distance, and SSIM values. Knowing that the OCT images contain crucial edge information from different retinal layers, the proposed loss function based on Sobel edge detection aims to preserve edge details and prevent over-smoothing effects and loss of edge content. The performance of the proposed approach is assessed by comparing it with conventional techniques and existing deep learning methods using widely adopted image quality evaluation metrics, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and edge preservation capability quantified through the variance of the Laplacian operator.

Similarly, the work presented in [30] introduced a residual encoder-decoder convolutional neural network (RED-CNN) designed specifically for low-dose CT imaging to address the concerns about potential X-ray radiation risks to patients. In the medical imaging field, there is significant interest in low-dose CT techniques. Since, current mainstream methods include vendor-specific sinogram domain filtration and iterative reconstruction algorithms, which require access to raw data formats not readily understandable to most users. The challenge lies in effectively modeling the statistical characteristics within the image domain, as existing methods for directly processing reconstructed images often struggle to simultaneously reduce image noise while preserving structural details. Motivated by advancements in deep learning, the authors combined elements of autoencoders, deconvolution networks, and shortcut connections to develop the RED-CNN framework for low-dose CT imaging. Through patch-based training, their proposed RED-CNN demonstrates competitive performance compared to state-of-the-art methods in both simulated and clinical scenarios. Particularly noteworthy is its effectiveness in noise suppression, preservation of structural details, and enhancement of lesion detection capabilities.

The method in [33] introduced an innovative unsupervised deep learning method tailored for medical image denoising, accommodating both 2D and 3D inputs for image or voxel processing. Their framework addresses Rician noise in MRI and Poisson noise in CT images. Instead of requiring clean (denoised) images for training, their approach employs patch-based dictionaries to indirectly learn noise characteristics while directly handling residue (noise) contents from available MRI/CT datasets using a proposed deep residue network. The authors emphasize overcoming the inherently challenging nature of the problem by carefully selecting optimal regularization parameters estimated from the data. The dictionary-based deep residue network effectively reduces noise in images, preserving image edges and maintaining visual quality without sacrificing details as demonstrated in their results.

5.2 Image Denoising in Face Recognition

Face recognition continues to attract significant research attention because of the numerous variations that affect recognition performance, including changes in pose, lighting conditions, facial expressions, occlusions, aging effects, and background environments. In recent years, deep learning techniques have demonstrated outstanding performance in image representation and recognition tasks. These approaches automatically learn discriminative features directly from images, enabling dimensionality reduction while generating more informative and compact representations of the original data. However, the present of noise in available dataset is one major issue which limits the face recognition accurate. Several works have been done to address this problem.

The study presented in [35] proposed an effective algorithm for denoising sequences of degraded face images within the principal component analysis (PCA) domain, aimed at enhancing face recognition accuracy. Initially, a temporal filter is applied to compensate for motion, combined with a weighted average filter. Subsequently, an adaptive spatial filter utilizing PCA transformation decomposes the temporally filtered image into two sub-images. This decomposition is based on a threshold determined by the noise variance and the intensity retained by the leading eigenvectors. The first sub-image, characterized by significant intensity variance, highlights small features, while the second sub-image, characterized by higher noise levels and lower intensity variance, emphasizes larger features. This adaptive spatial filtering approach adjusts according to the information content in each area: small features are reconstructed efficiently in the Kernel PCA domain to preserve image details, while large features are denoised using an anisotropic diffusion filter to restore homogeneous regions. Finally, the restored image is utilized in the recognition process. Experimental results on the Cohen-Kanade facial expression (CKFE) database, subjected to various noise levels and types of blur (Gaussian, motion, and pillbox) demonstrate superior restoration and recognition performance of the proposed algorithm compared to other methods.

The method proposed in [34] introduced a face recognition system named Deep Stacked Denoising Sparse Autoencoders (DSDSA), which integrates deep neural network technology with sparse autoencoders for denoising tasks. Autoencoders are neural networks designed to approximate an identity function while imposing constraints to learn refined representations of input data, thereby generating more meaningful outcomes. Their unique capability in interpreting input data has proven successful in various object recognition applications. For classification purposes, the proposed system employs two classifiers: a multi-class SVM and a Softmax classifier. Experimental evaluations conducted on well-known face databases such as ORL, Yale, Caltech, and a subset of PubFig demonstrate that the DSDSA system delivers promising performance and achieves accuracy comparable to state-of-the-art methods.

The study presented in [36] introduced a novel and efficient approach for denoising low-light images, termed Low-Light Image Denoising of Low Frequency Noise (DeLFN). Based on extensive experimental results, the frequency distribution of noise in low-light images reveals dominance of low and very low frequencies. DeLFN operates as a three-level denoising method: the first level employs histogram equalization (HE) to address mixed noises and enhance overall contrast. The second level utilizes logarithmic transformation (LOG) to denoise low frequency components, thereby enhancing image details. The third level focuses on denoising residual very low frequency noise using high-pass filtering to recover additional image features. To evaluate recognition performance, Principal Component Analysis (PCA) is applied to preprocessed face images enhanced by DeLFN. Comparative assessments are conducted against several representative illumination preprocessing methods using the Yale Face Database B, Extended Yale Face Database B, and CMU PIE Face Database. DeLFN demonstrates superior performance in enhancing visual quality and face recognition rates compared to alternative algorithms, while maintaining simplicity and computational efficiency suitable for real-time applications.

5.3 Image Denoising in Remote Sensing

Denoising of remote sensing imagery plays a vital role in several application domains, including aerospace systems, geophysical surveying, and communication engineering. Conventional wavelet-based approaches often struggle to accurately preserve texture and contour information, as denoising may introduce artifacts such as pseudo-Gibbs phenomena, ringing effects, and edge blurring. Optical remote sensing images are extensively utilized for tasks such as object identification, scene understanding, semantic segmentation, and various other analytical applications [38]. However, the presence of different types of noise significantly degrades the quality of remote sensing images, thereby limiting their practical applicability. Compared to conventional images, remote sensing data contain more complex and intricate texture structures, which reduces the effectiveness of many existing denoising algorithms and prevents them from achieving optimal performance [37, 38]. Therefore, several denoising method to address this problem have been presented in literatures.

The study reported in [37] improved upon limitations associated with conventional directional filtering techniques by introducing an eight-directional filter bank capable of independently decomposing image information along multiple orientations. This framework integrates directional subband filtering with a Laplacian pyramid scheme to construct an enhanced contourlet-based transformation model. Based on this optimized contourlet representation, a threshold-based denoising approach for remote sensing imagery was developed. Unlike traditional denoising strategies, the proposed method provides multi-scale and multi-directional analysis, allowing more effective preservation of fine structural details within images. An improved semi-soft thresholding function was applied to the transform coefficients to enhance edge recovery during reconstruction. Experimental simulations demonstrated that the approach delivers superior visual quality and higher Peak Signal-to-Noise Ratio (PSNR) compared with conventional wavelet thresholding as well as contourlet hard and soft threshold techniques. The method achieved approximately 0.11% improvement in denoising performance, confirming the effectiveness of the proposed threshold formulation in preserving both texture characteristics and edge information in remote sensing images.

The study presented in [39] introduced a novel approach for denoising remote-sensing images that leverages multi-source information. Unlike conventional denoising methods, their approach integrates features from noise-free reference images obtained from different bands, sensors, or multi-temporal sources. These reference images serve as priors in the denoising objective function. The method explores the prior information from reference images in two main aspects: dictionary learning and edge-feature prediction. In dictionary learning, they enhance the basis training process using incremental singular value decomposition. For edge-feature prediction, they establish relationships between gradients of the target image and reference images through linear ridge regression. The denoising objective function integrates both coefficient sparsity and edge similarity between the target and reference images. Their optimization scheme for this denoising model is also presented. Detailed discussions cover various scenarios based on different feature relationships between target and reference images. By effectively utilizing similarities between these images, the proposed algorithm achieves enhanced noise reduction while preserving more image details concurrently. Comparative evaluations demonstrate superior performance of the proposed method compared to other state-of-the-art reference-based denoising techniques.

The work presented in [39] proposed a novel approach for denoising remote-sensing images using partial differential equations (PDEs). This method capitalizes on similarities among different band images within a multicomponent image. Initially, a noise-free image from the multicomponent set serves as a prior in the PDE-based denoising process. To effectively integrate the noise-free image priors, a new smoothing term is introduced into the PDE formulation to compute total variation. This smoothing term specifies a particular direction and intensity derived from the reference image during denoising of the noisy image. By incorporating this specific smoothing constraint, the method enhances noise reduction while preserving image details, leveraging edge direction similarities between the noisy and reference images. The discrete formulation of the proposed denoising model is also presented. Experimental evaluations on multispectral and hyperspectral remote-sensing images demonstrate that the proposed method achieves superior performance compared to other denoising techniques.

5.4 Image denoising in Education

The approach presented in [41] enhanced the quality of psychological teaching for college students, by integrating an image denoising algorithm and data mining approach to develop a psychological teaching quality evaluation system. The denoising algorithm is employed primarily to recognize students' behaviors and expressions, thereby facilitating the exploration of their psychological states. Additionally, the study incorporates a data mining algorithm to quantitatively analyze students' psychological states. It also comprehensively examines and enhances the calibration principle of the Dirckx method, proposing a refined calibration method. Furthermore, the study introduces a novel two-frame random phase-shift fringe image phase extraction algorithm based on the arctangent function. The findings indicate that the image denoising algorithm and data mining techniques proposed in this research significantly improve the evaluation of psychological teaching quality. Moreover, it positively impacts on students' mental health by effectively contributing to their overall well-being.

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6.0 Discussion

In this paper, the authors have presented the overview of image denoising concept with regards to noise types, noise model, denoising methods and certain domain applications. The survey proves that image carries significant information and feature which are extracted and further processed for important analysis to deduce certain decisions and conclusions. One major factor which limits the effectiveness of feature extraction in images is the presence of noise that are introduced during the process of acquisition and transmission. Noise manifests as random variations in image pixel values, affecting the overall quality of the captured image. When image edges, textures and resolution are weak and becomes distorted due the presence of noise, it significantly affects the stability of the system in application domain as such medicine, biometrics, remote sensing and education.

Considering recent denoising methods, machine learning de-noising techniques have made considerable progress and outperform other previous techniques with increase in computational power with Graphical Processing Unit's (GPU's) ([11, 12]. The recent and commonly deep learning model available in literature are convolutional neural network-based models, generative adversarial network-based models (GAN)[19] and Autoencoders (AEs) [20]. These deep learning-based method have the capacity to learning and understanding certain hidden feature or information in an image and regenerate or reconstruct the image with very close identities. However, their implementation relies on the regularity of the dataset especially when trained with image pairs.

7.0 Future Works

The effectiveness of machine learning-based techniques for image denoising has been widely recognized and thoroughly examined across numerous studies, highlighting their potential in improving image quality by removing noise. These methods have demonstrated a high performance in a range of applications, from medical imaging to photography, where noise reduction is crucial for enhancing visual clarity and data accuracy. However, while existing literature provides a strong foundation, there remains significant scope for further exploration, especially in terms of comparing various deep learning models.

In future research, a comprehensive experimental analysis could be conducted to systematically compare the performance of different deep learning-based denoising methods. This comparison could focus on key models such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and autoencoders, which have shown distinct strengths in tackling image denoising tasks. These models could be intensively evaluated using diverse datasets that differ in terms of size, complexity, noise levels, and feature types, providing insights into their relative strengths and weaknesses across various scenarios.

Further exploration could consider other variants and recent advancements in deep denoising techniques, exploring innovative approaches that could further enhance denoising performance. This could include the integration of hybrid models, optimization algorithms, or transfer learning techniques aimed at improving efficiency and accuracy.

Additionally, a critical aspect of the research will involve examining the limitations and challenges inherent in machine learning-based image denoising. This includes potential issues such as overfitting, the computational cost of training large models, and the difficulty in generalizing across different types of noise or datasets. By identifying these challenges, further research could aim to propose solutions and areas for improvement, contributing to the ongoing development of more robust and efficient denoising techniques.

8.0 Conclusion

An overview of image denoising methods and their diverse applications has been presented in this paper, highlighting the importance of noise reduction techniques in improving image quality. Noises in images often obscure critical features and detailed information, making it challenging to extract relevant insights, particularly in fields such as medical imaging, remote sensing, and photography. Noise can significantly affect image clarity, leading to compromised performance in tasks like object detection, image segmentation, and feature extraction. Thus, effective denoising is essential to enhance the accuracy and reliability of these processes. This paper categorizes denoising methods into three main domains: spatial filtering, transform domain, and machine learning-based approaches. Spatial filtering methods typically involve direct manipulation of image pixels to smooth out noise while retaining as much detail as possible, whereas transform domain techniques operate by converting images into a different domain, such as the frequency domain, where noise can be isolated and removed more efficiently. However, these traditional approaches often face limitations in handling complex noise patterns and preserving fine image details.

With the recent shift in technological paradigms, deep learning-based denoising methods have gained significant attention due to their superior performance in a wide range of image denoising tasks. Recent literature has demonstrated the effectiveness of deep learning approaches in surpassing traditional methods, particularly in terms of handling large, complex datasets and providing more accurate denoising outcomes. In this work, commonly employed deep learning models for image denoising, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Autoencoders and Vision transformers are discussed. Each model offers distinct advantages in addressing specific denoising challenges, with CNNs excelling at feature extraction, GANs offering realistic image reconstructions, autoencoders being effective in dimensionality reduction and noise suppression and vision transformers captures a long-range feature interaction that focuses on improving the refinement of local image details. Additionally, the paper explores several practical applications of image denoising models to showcase their significance across various fields. From enhancing the quality of medical images for better diagnostics to improving satellite imagery for more precise environmental monitoring, the applications of denoising techniques are vast and impactful. By presenting a comprehensive analysis of denoising methods across different domains, this paper underscores the critical role of deep learning-based approaches in pushing the boundaries of image processing and setting new standards for noise reduction in modern applications.

References

[1] Ilesanmi, A.E. and Ilesanmi, T. O., Methods for image denoising using convolutional neural network: a review. Complex & Intelligent Systems, 2021. 7(5): p. 2179-2198.
[2] Pathak, K. and Bhandari, A. K., Advances in Deep Learning and Filtering Models for Medical Image Denoising: A Review of Current and Future Trends. Circuits, Systems, and Signal Processing, 2026: p. 1-75.
[3] Saini, A., Singh, G. N., Gulia, P., Hashmi, A., Kumar, S. P. and Vishnoi, S., An Empirical Study for Image Denoising and Image Quality Enhancement: A Challenging Overview. International Journal of Computational Intelligence Systems, 2026.
[4] Bharati, S., Khan, T.Z., Podder, P. and Hung, N. Q, A comparative analysis of image denoising problem: noise models, denoising filters and applications. Cognitive Internet of Medical Things for Smart Healthcare: Services and Applications, 2021: p. 49-66.
[5] Khaw, H.Y., Soon, F. C., Chuah, J. H. and Chow, C. O., Image noise types recognition using convolutional neural network with principal components analysis. IET Image Processing, 2017. 11(12): p. 1238-1245.
[6] Hosseini, H., F. Hessar, and Marvasti, F., Real-time impulse noise suppression from images using an efficient weighted-average filtering. IEEE Signal Processing Letters, 2014. 22(8): p. 1050-1054.
[7] Irum, I., Shahid, M. A. Sharif, M. and Raza, M., A Review of Image Denoising Methods. Journal of Engineering Science & Technology Review, 2015. 8(5): p. 41-48.
[8] Owotogbe, J.S., T.S. Ibiyemi, and B.A. Adu, Edge detection techniques on digital images-a review. International Journal of Innovation Science, Resources and Technology, 2019. 4(11): p. 329-332.
[9] Firas, A.J., Kriging interpolation filter to reduce high density salt and pepper noise. arXiv preprint arXiv:1302.1300, 2013. 3(1): p. 8-14
[10] Bhat, O.V., A Review on Image De-Noising Techniques. sensors, 2021. 4: p. 1-6.
[11] Thakur, R. S., Chatterjee, S., Yadav, R. N. and Gupta, L., Image de-noising with machine learning: A review. IEEE Access, 2021. 9: p. 93338-93363.
[12] Fan, L., Zhang, F., Fan, H. and Zhang, C., Brief review of image denoising techniques. Visual Computing for Industry, Biomedicine, and Art, 2019. 2(1): p. 1-12.
[13] Li, X., Hu, Y., Gao, X., Tao, D. and Ning, B., A multi-frame image super-resolution method. Signal Processing, 2010. 90(2): p. 405-414.
[14] Mafi, M., Martin, H., Cabrerizo, M., Andrian, J., Barreto, A. and Adjouadi, M., A comprehensive survey on impulse and Gaussian denoising filters for digital images. Signal Processing, 2019. 157: p. 236-260.
[15] Agarwal, S.K. and Kumar, P., Denoising of a mixed noise color image using new filter technique. in 2015 International Conference on Computational Intelligence and Communication Networks (CICN). 2015. IEEE.
[16] Abdalla, A. M., Osman, M.S., Aishawabkah, H. A., Rumman, O. and Mherat, M., A review of nonlinear image-denoising techniques. in 2018 Second World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4). 2018. IEEE.
[17] Maggioni, M., Katkovnik, V., Egiazarian, K. and Foi, A., Nonlocal transform-domain filter for volumetric data denoising and reconstruction. IEEE transactions on image processing, 2012. 22(1): p. 119-133.
[18] Goyal, B., Dogra, A., Agrawal, S., Sohi, B. S. and Sharma, A., Image denoising review: From classical to state-of-the-art approaches. Information fusion, 2020. 55: p. 220-244.
[19] Goodfellow, I.J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S. and Courville, A., Generative adversarial nets. Advances in neural information processing systems, 2014. 27: p. 2672–2680.
[20] Im, D. I., Ahn, S., Memisevic, R. and Bengio,Y., Denoising criterion for variational auto-encoding framework. in Proceedings of the AAAI conference on artificial intelligence. 2017.
[21] Gautam, A., Pawar, A., Joshi, A., Tazi, S. N., Chaudhary, S., Hambarde, P., Dudhane, A. and Vipparthi, S., Pureformer: Transformer-based image denoising. in Proceedings of the Computer Vision and Pattern Recognition Conference. 2025.

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[22] Zhang, K., Zuo, W., Gu, S. and Zhang, L., Learning deep CNN denoiser prior for image restoration. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
[23] Aggarwal, A., M. M. and Battineni, G.G., Generative adversarial network: An overview of theory and applications. International Journal of Information Management Data Insights, 2021. 1: p. 1-9.
[24] Chen, J., Chen, J., Chao, H. and Yang, M. Image blind denoising with generative adversarial network based noise modeling. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.
[25] Mohandas, A., Joseph, S. M. and Sathidevi, P.S., An autoencoder based technique for DNA microarray image denoising. in 2020 International Conference on Communication and Signal Processing (ICCSP). 2020. IEEE.
[26] Bajaj, K., Singh,D. K. and Ansari, M. A., Autoencoders based deep learner for image denoising. Procedia Computer Science, 2020. 171: p. 1535-1541.
[27] Marcos, L., Babyn, P. and Alirezaie, J., Pure vision transformer (CT-ViT) with Noise2Neighbors interpolation for low-dose CT image denoising. Journal of Imaging Informatics in Medicine, 2024. 37(5): p. 2669-2687.
[28] Xu, K., Li, W., Wang, X., Hu, X., Yan, K., Wang, X. and Dong, X., CUR transformer: A convolutional unbiased regional transformer for image denoising. ACM Transactions on Multimedia Computing, Communications and Applications, 2023. 19(3): p. 1-22.
[29] Sowjanya, V., Rao, G. S. and Sarvani, A., Investigation of optimal wavelet techniques for de-noising of MRI brain abnormal image. Procedia Computer Science, 2016. 85: p. 669-675.
[30] Chen, H., Zhang, Y., Kalra, M. K., Lin, F., Chen, Y., Liao, P., Zhou, J. and Wang, G., Low-dose CT with a residual encoder-decoder convolutional neural network. IEEE transactions on medical imaging, 2017. 36(12): p. 2524-2535.
[31] Garg, S., Vijay, R. and Urooj, S., Statistical approach to compare image denoising techniques in medical MR images. Procedia Computer Science, 2019. 152: p. 367-374.
[32] Sengupta, S., Singh, A., and Lakshminarayanan. V., EdgeWaveNet: edge aware residual wavelet GAN for OCT image denoising. in Medical Imaging 2021: Imaging Informatics for Healthcare, Research, and Applications. 2021. SPIE.
[33] Rai, S., Bhatt, J.S. and Patra, S. K., An unsupervised deep learning framework for medical image denoising. arXiv preprint arXiv:2103.06575, 2021.
[34] Görgel, P. and Simsek, A., Face recognition via deep stacked denoising sparse autoencoders (DSDSA). Applied Mathematics and Computation, 2019. 355: p. 325-342.
[35] Berrimi, F., Benmahammed, K. and Hedli, R., Denoising of degraded face images sequence in PCA domain for recognition. Journal of King Saud University-Computer and Information Sciences, 2021. 33(7): p. 836-843.
[36] Kang, Y. and Pan, W., A novel approach of low-light image denoising for face recognition. Advances in Mechanical Engineering, 2014. 6: p. 1-13.
[37] Lei, S., Lu, M., Lin, J., Zhou, X. and Yang, X., Remote sensing image denoising based on improved semi-soft threshold. Signal, Image and Video Processing, 2021. 15: p. 73-81.
[38] Han, L., Zhao, Y., Lv, H., Zhang, Y., Liu, H. and Bi, G., Remote sensing image denoising based on deep and shallow feature fusion and attention mechanism. Remote Sensing, 2022. 14(5): p. 1243.
[39] Liu, P., Wang, M., Wang, L. and Han, W., Remote-sensing image denoising with multi-sourced information. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2019. 12(2): p. 660-674.
[40] Liu, P., Huang, F., Li, G. and Liu, Z., Remote-sensing image denoising using partial differential equations and auxiliary images as priors. IEEE geoscience and remote sensing letters, 2011. 9(3): p. 358-362.
[41] Li, L., Application of Image Denoising Algorithm and Data Mining in Psychological Teaching Quality Evaluation. Security and Communication Networks, 2022. 2022(1): p. 4172887.
[42] Velayudham, A. and R. Kanthavel, A survey on medical image denoising techniques. International journal of Advanced research in Electronics and Communication Engineering (IJARECE), 2013. 2(3).
[43] Kaur, A. and Dong, G., A complete review on image denoising techniques for medical images. Neural Process. Lett., 2023. 55(6): p. 7807-7850.