Indonesian Journal of Computer Science
ISSN 2549-7286 (*online*)
Jln. Khatib Sulaiman Dalam No. 1, Padang, Indonesia
Website: ijcs.stmikindonesia.ac.id | E-mail: ijcs@stmikindonesia.ac.id

Image Denoising Techniques Using Unsupervised Machine Learning and Deep Learning Algorithms: A Review

Barwar Mela Ferzo[1], Adnan Mohsin Abdulazeez[2]
Barwar.Ferzo@auas.edu.krd, Adnan.mohsin@dpu.edu.krd
[1]Technical College of Informatics, Akre University for Applied Sciences, Duhok, Iraq.
[2]IT Dept., Duhok Technical College, Duhok Polytechnic University, Iraq.

Article Information

Submitted : 23 Jan 2024
Reviewed: 26 Jan 2024
Accepted : 10 Feb 2024

Keywords

Image Denoising, Unsupervised Learning, Machine Learning, Deep Learning, Traditional Methods.

Abstract

The continuous evolution of imaging technologies has accentuated the demand for robust and efficient image denoising techniques. Unsupervised machine learning algorithms have emerged as promising tools for addressing this challenge. This review scrutinizes the efficacy, versatility, and limitations of various unsupervised machine learning approaches in the area of image denoising. The paper commences with a clarification of the foundational concepts of image denoising and the pivotal role unsupervised machine learning plays in enhancing its efficacy. Traditional denoising methods, encompassing filters and transforms, are briefly outlined, highlighting their insufficiencies in handling complicated noise patterns prevalent in modern imaging systems. Subsequently, the review delves into an exploration of unsupervised machine learning techniques tailored for image denoising. This includes an in-depth analysis of methodologies such as clustering deep learning. Each technique is surveyed for its architectural variation, adaptability, and performance in denoising diverse image datasets. Additionally, the review encompasses an evaluation of prevalent metrics used for quantifying denoising performance, discussing their relevance and applicability across varying noise types and image characteristics. Furthermore, it delineates the challenges faced by unsupervised techniques in this domain and charts prospective avenues for future research, emphasizing the fusion of unsupervised methods with other learning paradigms for heightened denoising efficacy. This review merges empirical insights, critical analysis, and future perspectives, serving as a roadmap for researchers and practitioners navigating the landscape of image denoising through unsupervised machine learning methodologies.

A. Introduction

The growing advancements in imaging technologies across diverse domains, spanning medical diagnostics, surveillance, satellite imaging, and computer vision applications, have propelled the need for robust and efficient image denoising techniques [1]. The clarity and fidelity of acquired images play a pivotal role in subsequent analysis, interpretation, and decision-making processes [2]. However, these images are invariably corrupted by various sources of noise, including sensor imperfections, environmental interferences, or transmission artifacts, which significantly impair their quality and utility [3].

Amidst this context, the field of image denoising has garnered substantial attention, aiming to restore images by effectively suppressing noise while retaining crucial details and structures [4]. Traditional approaches, including spatial filters [5], wavelet transforms [6], and statistical modeling [7], have long served as the cornerstone for mitigating noise in images. These methods, albeit effective in certain scenarios, often falter when confronted with complex noise patterns or when tasked with preserving intricate image features during denoising processes [8]. See fig. 1 for image denoising example.

The advent of unsupervised machine learning algorithms has promise a paradigm shift in the domain of image denoising [10]. Unlike their supervised counterparts that necessitate labeled datasets for training, unsupervised techniques leverage inherent data structures and patterns to glean insights and perform denoising tasks without explicit guidance [11]. This approach holds immense promise in addressing the inherent challenges posed by diverse noise distributions, variability in image content, and the absence of labeled training data in many practical scenarios[12].

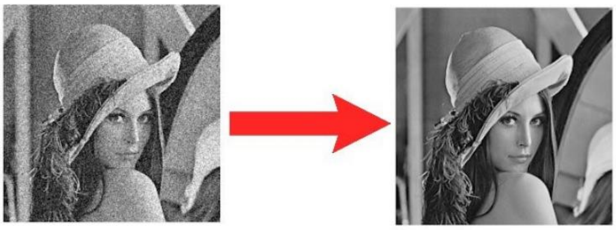

Figure 1. An example of denoising an image [9]

The aim of this review is to meticulously dissect and evaluate the efficacy, versatility, and limitations of unsupervised machine learning approaches in the domain of image denoising. The review will embark on an exploration that spans foundational concepts, classical denoising methodologies, and a deep dive into the spectrum of unsupervised algorithms adapted for image denoising.

The ensuing sections will commence with a succinct overview of traditional image denoising techniques, explaining their underlying principles, strengths, and inherent limitations. While these methods have laid the groundwork for image restoration, their efficacy diminishes when challenged with diverse noise distributions or in scenarios where intricate details must be preserved.

Subsequently, the review will pivot towards unsupervised machine learning algorithms, unraveling their nuances and applications in the context of image denoising. This includes an in-depth analysis of methodologies such as clustering

[13] and deep learning [14][15]. Each algorithmic approach will be dissected to comprehend its architectural complexity, adaptability across different image domains, and efficacy in suppressing various noise types commonly encountered in practical imaging scenarios [16].

Furthermore, the review will thought out in advance on the critical role of evaluation metrics in quantifying denoising performance, encompassing a discussion on widely adopted metrics such as Peak Signal-to-Noise Ratio (PSNR) [17], Structural Similarity Index (SSI) [18] , and Mean Squared Error (MSE) [19]. This evaluation will shed light on the suitability and limitations of these metrics in capturing the perceptual quality and fidelity of denoised images across diverse noise profiles and image characteristics.

Additionally, the review will navigate through the challenges confronted by unsupervised techniques in image denoising, ranging from the interpretability of learned representations to the scalability and adaptability of algorithms across heterogeneous datasets. Moreover, the paper will outline prospective paths for future research, elucidating potential synergies between unsupervised techniques and other learning paradigms to propel the efficacy and applicability of image denoising methodologies in real-world scenarios.

In essence, this review aims to integrate empirical insights, critical analyses, and forward-looking perspectives, offering a comprehensive roadmap for researchers, practitioners, and enthusiasts navigating the evolving landscape of image denoising through the lens of unsupervised machine learning methodologies.

The introduction includes background problems related to supporting theories (literature review) or previous studies (both from journals, as well as current phenomena/issues) as the basis for conducting research. The presentation of the introductory part that contains the background of the problem, theoretical basis, or related research does not have to be subtitled, but is integrated into a unified paragraph, and is presented in narrative form. At the end of the introduction, the purpose and usefulness of the research results are also explained. [Cambria 12, single space]

B. Traditional Image Denoising Methods

The realm of image denoising has witnessed a rich history of traditional methods aimed at restoring images corrupted by various noise sources [20]. Spatial filters, including mean [21], median [22][23], and Gaussian [24][25] filters, constitute some of the foundational techniques utilized for noise suppression in images. These filters operate on the pixel-level information, smoothing out noise while preserving image structures to a certain extent [26]. However, their simplistic nature often leads to the loss of finer details and edges, resulting in blurred or oversmoothed images, especially in scenarios where noise is non-uniform or complex.

In [21] proposed an Iterative Mean Filter (IMF) to reduce salt-and-pepper noise. In a fixed-size window, IMF utilises the mean of noise-free pixel grey values. They evaluate image quality using PSNR, Visual Information Fidelity, Image Enhancement Factor, SSIM, and Multiscale Structure Similarity in tests.

In [22] proposed a novel speckle noise-distorted image denoising method. They show their picture denoising research and explore thresholding methods as SureShrink, VisuShrink, and BayesShrink.

In [23] proposed an adaptive fan rotation median filtering method based on the regular median filtering method was presented to maximise image detail for better pepper and salt noise reduction. They calculate the grey difference value for different areas, judge the correlation between the centre point and different areas based on the grey difference value, and output the median value of the highest correlation area to restore image details and remove noise.

In [24] proposed a new image denoising method using the extended difference of Gaussian (DoG) filter and nonlocal low-rank regularisation. To improve patch matching, the suggested method uses a unique nonlocal self-similarity evaluation using the tight frame.

In [25] proposed an adversarial Gaussian denoiser network that leverages generative adversarial network-based adversarial learning for picture denoising. The denoiser network is encouraged to identify clear noise-free images instead of blurry ones, solving the blurriness problem.

Wavelet transforms have also been extensively employed in image denoising due to their multiresolution analysis capabilities [27][28], [29][29]. Techniques such as wavelet shrinkage exploit the sparse representation of images in the wavelet domain to suppress noise components while retaining essential image features. Despite their ability to preserve edges and textures better than conventional filters, wavelet-based approaches may struggle with adaptability to varying noise characteristics and the tendency to introduce artifacts in highly textured regions.

In [28] proposed a wavelet transform approach to denoise the image before edge identification to increase signal-to-noise ratio and retain edge information. This study decomposes, filters, and reconstructs the image using four wavelets' functions and four decomposition stages.

In [27] suggested a three-stage image denoising CNN using the wavelet transform MWDCNN, a dynamic convolutional block (DCB), two cascaded wavelet transform and enhancement blocks (WEBs), and a residual block. DCB dynamically adjusts multiple convolution parameters to balance denoising performance and computational costs. WEB suppresses noise using wavelet modification and discriminative learning to recover greater detail in picture denoising.

In [29] proposed a GAN-based WT domain solution that could handle remote sensing image denoising and SR challenges simultaneously using a single network topology. The suggested method focuses on wavelet transform-based optical remote sensing picture spatial denoising and super-resolution reconstruction.

Additionally, statistical modeling techniques, such as Bayesian methods [30] or non-local means [31], have gained prominence for their ability to exploit statistical priors and image self-similarity to enhance denoising performance. These methods leverage patch-based approaches, comparing similar patches within an image to estimate and reduce noise while preserving fine details. However, their computational complexity and sensitivity to parameter tuning pose challenges in real-time applications and across diverse image datasets with varying noise profiles.

In [30] to improve robustness, defined a set of clustering-based latent variables (CLV) in Bayesian framework that may be retrieved using clustering operators to determine spatial-spectral similarity criteria.

In [31] the unique denoising method uses Adaptive Non-Local Means (ANL) and Method Noise Thresholding (MNT) to improve image quality. Method Noise (MN) image is the difference between noisy and pre-filtered image information. Some key image components are recovered from the MN using thresholding. These computed values are added to pre-filtered images to recover original features.

C. Unsupervised Methods With Image Denoising

The realm of image denoising has included a numerous of unsupervised techniques, harnessing the power of machine learning algorithms to restore image reliability within noisy environments. This section explores and dissects the operational principles, architectural intricacies, and practical applications of key unsupervised methodologies employed in image denoising.

1. Deep Learning with Image Denoising

In [32] proposed a denoising autoencoders to reduce wall interference and reconstitute a ground truth image in open space. By training the algorithm, distorted through-wall radar images can be denoised into clean line-of-sight images. They used simulated narrowband Doppler-Azimuth images in free space and through walls to prove the technique works.

In [33] proposed a multi-scale denoising convolutional neural network (MSDCNN) model to decrease visual noise. Transfer learning improved the model. Gaussian noise was added to source datasets before knowledge transfer to target datasets.

In [34] presented a densely connected hierarchical network-based residual dense neural network (RDUNet) for picture denoising. The RDUNet's encoding and decoding layers use densely linked convolutional layers to reuse feature maps and local residual learning to overcome the vanishing gradient problem and speed up learning.

In [35] propose an X-BDCNN blind denoising convolutional neural network for low-dose X-ray picture enhancement. Two networks form X-BDCNN. A noise estimate is made from the input noise X-ray image. The noisy X-ray image and estimated noise level are fed into the other to get the residual noise image. Subtracting the residual noise image from the input noise X-ray image yields the denoised image.

In [36] Proposed a parallel generative adversarial network for unsupervised real-world picture denoising was proposed as precedent. They also offer a novel self-collaboration SC technique to boost denoising performance and self-boost.

In [37] suggested a convolution neural network-based unsupervised multichannel SAR interferometric phase denoising algorithm. It minimizes phase noise standard deviation using weighted least-squares (WLS) regularization and multichannel interferometric phase covariance to reconstruct TomoSAR accurately and completely.

In [38] suggested an unsupervised deep learning method for removing noise from positron emission tomography (PET) images. The patient's previous picture was used as the network input, and the noisy PET image was used as the training label. Simulations, PET/CT, and PET/MR datasets show that the proposed denoising approach outperforms Gaussian, anatomically guided NLM, BM4D, and Deep Decoder.

In [39] evaluated two unsupervised approaches to denoise Magnetic Resonance Image, MRI, one approach based on a Stein's Unbiased Risk Estimator and another one based on a Blindspot network. Both networks were compared against Non-Local Means using quantitative and qualitative measures.

2. Machine Learning with Image Denoising

In [40] suggested a dictionary learning method for clustering-based natural image denoising in the wavelet domain (CDLW). This approach uses second-generation wavelet clustering coefficients in decomposition levels. The suggested approach uses second-generation wavelet transform to increase sparsity and multiresolution.

In [41] suggested using total variation and non-local self-similarity to create a compressed sensing-based image denoising method dubbed denoising-compressed sensing by regularization terms (DCSR). The augmented Lagrangian optimizes this technique, avoiding the challenging problem of regularization term nonlinearity and non-differentiability.

In [42] suggested an unsupervised learning-based wavelet denoising method. Using the wavelet transform's sparsity, multi-resolution structure, and closeness to the human visual system, an unsupervised dictionary learning technique is used to create a noise reduction dictionary. They learn from the wavelet decomposition of the noisy image and use the K-Singular Value Decomposition (K-SVD) method to get an adaptive dictionary.

In [43] proposed that the adversarial loss and cycle-consistency loss are used in unsupervised learning to offset the lack of matched data. Unlike the image-domain cycleGAN, they use wavelet directional learning to denoise without compromising high-frequency components like edges and detailed information.

In [44] suggested a fully unsupervised diffusion probabilistic model to learn from noise instead of signal. Adding Gaussian noise to self-fused OCT b-scans defines diffusion. A Markov chain-modeled reverse diffusion technique enables tunable denoising.

In [45] suggested an unsupervised denoising framework for super-resolution UDSR that applies a distinct denoising network to Real-World Super-Resolution. Measurement of the performance of SR and denoising networks showed that the combination improves both.

In [46] presented a more generic strategy for complex noise models. We define a denoising solving system using score function, the gradient of logarithmic probability. The solution system can denoise noisy photos after estimating the score function.

In [47] proposed a texture-preserving non local denoising algorithm. In the proposed algorithm, an adaptive clustering method is designed to adaptively and robustly cluster similar patches. A state-of-the-art PCA-based denoising filter is proposed in a transform-domain texture variation adaptive filtering approach to perform a texture-preserving denoising of each cluster.

In [48] propose a novel denoising method for hyperspectral images HSI, termed PCASpC, which is based on the theory of PCA transform and adaptive sparse coding extended to the transform domain.

Unsupervised techniques in image denoising, offer diverse avenues for noise suppression in images. Each technique exhibits unique strengths, adaptabilities, and limitations, underscoring the need for a nuanced understanding of their operational principles and applicability across diverse imaging scenarios. See Table 1 for a summary about the literature review in details.

Table 1. Summary About The Literature Review on Details

Ref.	Datasets	Algorithm	Evaluation Metrics	Experimental results	Limitations
[32]	Azimuth-Elevation	Denoising Autoencoder.	NMSE	Low inaccuracy in denoised reconstructed images compared to clear line-of-sight photos.	The technique requires huge corrupted and clean radar image training databases.
[23]	Not Mentioned	adaptive fan rotating filtering	MSE PSNR SSIM	Noise removal and detail recovery are superior than other methods.	N/A
[29]	UCMERCED, NWPU-RESISC45, GaoFen-1	Restoration Generative Adversarial Network with ResNet and DenseNet (RRDGAN)	PSNR MSE perceptual index	remote sensing images' salt & pepper noise and white gaussian noise could be removed and spatial resolution improved.	different high frequency corresponding different detailed information cannot be distinguished well in the spatial domain.
[28]	Private images for bridge in Wenzhou	wavelet transform	PSNR MSE	Using wavelet transform to eliminate noise improves edge detection performance.	Cannot work on colored images
[27]	Berkeley segmentation dataset (BSD)	multi-stage image denoising CNN with the wavelet transform MWDCNN	PSNR SSIM	In quantitative and qualitative analysis, the suggested model outperforms popular denoising approaches.	it depends on a supervised manner to train a denoising model
[31]	Standard images of Lena, Barbara, and Girl face	Adaptive Non Local Means (ANL) along with Method Noise Thresholding (MNT)	PSNR SSIM IQI	This technique works well with high-noise, high-contrast photos.	N/A
[25]	Partial-CelebA DIV2K	adversarial Gaussian denoiser network (AGDN)	PSNR SSIM VIF UQI	This approach addresses blurriness by directing the denoiser network to focus on clear, noise-free images rather than blurry ones.	focuses only on additive white Gaussian noise not real complex noise
[24]	Brainweb-simulated	difference of Gaussian (DoG) filter and nonlocal low-rank regularization	PSNR RLNE QILV SSIM	The proposed technique preserves more edges and fine features while reducing noise.	N/A
[22]	Private ultrasound images	hybrid median filter	PSNR MSE	The filter effectively removes speckle noise from medical photographs and improves their visual quality.	N/A

[21]	IMAGESTEST BSDS	Iterative Mean Filter (IMF)	PSNR VIF SSIM IEF MSSIM	IMF removes noise well and preserves image structures, edges, and features.	cannot handle an extensive IMF to remove the random-valued impulse noise
[37]	TomoSAR	CNN	MAE STD	Noise and missing points were efficiently suppressed, according to the results.	N/A
[46]	Kodak CBSD68 CSet9 DIV2K CBSD500	Score Function	PSNR	The denoising performance is competitive for simple noise models and excellent for complicated ones.	The denoising performance is competitive for simple noise models
[45]	NTIRE-2020 Real World-SR DIV2K	Unsupervised Denoising framework for Super-Resolution (UDSR)	RMSE Perceptual Index PSNR SSIM LPIPS	In many perceptual indicators, denoising and SR networks perform better.	Due to stability issues, training a multitasking network is difficult.
[44]	optic nerve head (ONH)	diffusion probabilistic model	SNR PSNR CNR ENL	Results indicate that the model effectively suppresses speckle.	This technique is limited by its Gaussian speckle pattern assumption.
[43]	multispectral images from a high-resolution satellite	wavelet directional cycle-consistent adversarial network (WavCycleGAN)	PSNR SSIM	Satellite image noise is removed and high-frequency characteristics preserved using the proposed approach.	For efficient noise removal, wavelet directional learning could reconstruct just directional noise pattern components.
[42]	Standard images of Barbara, House, Flinstones, Bridge, and Fingerprint	K-Singular Value Decomposition (K-SVD)	PSNR SSIM	They learn over the noisy image's wavelet decomposition to create an adaptive dictionary.	N/A
[36]	SIDD DND	generative adversarial networks (GANs)	PSNR SSIM	They offer a novel way to give the denoiser self-boosting power and raise performance.	Each iteration requires laborious manual selection of the best model iteration or metric-based retraining inside the phase.
[33]	NaF Prostate TCGA-PRAD Prostate-3T OSTATE-DIAGNOSIS	A multi-scale denoising convolutional neural network (MSDCNN)	k-fold cross validation	Model accuracy increased by almost 10% over previous works.	Images with more Gaussian noise challenged the model.
[34]	DIV2K	residual dense neural network (RDUNet)	PSNR SSIM	Modelling additive Gaussian noise does not require image noise level information.	The suggested model requires training for each noise category.
[35]	ChestX-ray8	blind denoising convolutional neural network (X-BDCNN)	SNR PSNR	The model showed that X-BDCNN outperformed quantitative and qualitative quality	The hybrid Poisson-Gaussian noise model may differ from the

				evaluations.	low-dose X-ray image noise model, which is hard to characterize.
[40]	Standard images of girl, baboon, couple and bark	clustering-based natural image denoising using dictionary learning algorithm in wavelet domain (CDLW)	PSNR SSIM	To demonstrate objective and subjective competitive performance, many tests were done.	the proposed method has high complexity computation
[41]	Standard images of Lena, Barbara, and Cameraman	denoising-compressed sensing by regularization (DCSR)	PSNR SSIM	The algorithm will reconstruct and denoise images.	computationally, the recommended approach is not the best.
[38]	PET/CT PET/MR	DNN	CNR	The proposed approach reduces noise and restores image details.	N/A
[47]	McGill dataset USC-SIPI dataset	PCA-transform-domain texture Variation Adaptive filtering for Adaptive Clustered patches (ACVA)	PSNR SSIM FSIM	This denoising method effectively preserves texture, both visually and numerically, particularly for irregular textures.	works poorly on the real images that have irregular or stochastic textures
[39]	Knee MRI	Stein's Unbiased Risk Estimator Blindspot network	MSE PSNR SSIM	Both networks outperformed NLM in all scoring parameters except extreme noise.	N/A
[48]	Indian Pines dataset	PCASpC	PSNR SSIM	The proposed model preserves the details and alleviates the blocking artifacts well.	N/A

D. Evaluation Metrics for Unsupervised Denoising

Evaluating the performance of unsupervised image denoising techniques necessitates a comprehensive suite of metrics that can effectively quantify the fidelity, perceptual quality, and efficacy of noise suppression in denoised images. Robust evaluation metrics play a pivotal role in benchmarking different algorithms, guiding parameter tuning, and understanding the trade-offs between noise reduction and image fidelity. Widely adopted metrics encompass Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSI), Mean Squared Error (MSE), and perceptual metrics derived from deep neural networks.

PSNR, a commonly used metric, quantifies the ratio between the maximum possible power of a signal and the power of corrupting noise, providing a measure of fidelity between denoised and clean images. However, PSNR fails to capture perceptual nuances and may not correlate well with human perception, especially in scenarios where high PSNR values do not guarantee visually pleasing denoised images [49].

SSI, an index measuring the similarity between two images, evaluates the structural information preservation in denoised images compared to their clean counterparts. SSI accounts for structural variations, edge preservation, and texture similarity, offering a more comprehensive assessment of denoising performance than PSNR alone [50].

MSE, computed as the average of squared differences between pixel values of denoised and clean images, offers a simple yet informative measure of reconstruction error. However, MSE's sensitivity to outliers and inability to account for human perception limitations necessitate complementing it with other perceptual metrics for a holistic evaluation [51].

Recent advancements in image quality assessment leverage deep neural networks' representations to derive perceptual metrics such as perceptual loss functions or feature similarity metrics. These metrics align more closely with human perception, capturing higher-level image semantics and perceptual differences between denoised and clean images [52].

The selection of evaluation metrics should be aligned with the specific denoising task and application requirements. A holistic evaluation might involve a combination of metrics to comprehensively assess denoising quality, accounting for both quantitative measures like PSNR and MSE, as well as more perceptually aligned metrics like SSI or those derived from deep neural networks.

E. Challenges and Future Directions

1. Scalability and Adaptability

Unsupervised techniques in image denoising often face challenges in scalability and adaptability across diverse datasets and noise distributions. Algorithms that demonstrate efficacy in controlled settings might falter when applied to real-world data with varied noise characteristics. Future research endeavors aim to develop scalable and adaptable unsupervised approaches that generalize well across diverse imaging scenarios and noise profiles.

2. Robustness to Complex Noise Patterns

Real-world images often exhibit complex noise patterns, making it challenging for unsupervised algorithms to effectively distinguish between noise and signal components. Handling non-Gaussian noise distributions, spatially variant noise, or mixed noise types remains a significant hurdle. Future directions involve exploring robust unsupervised techniques capable of modeling and suppressing diverse noise patterns without sacrificing image details or introducing artifacts.

3. Integrating Domain Knowledge and Priors

Incorporating domain-specific knowledge and priors into unsupervised denoising frameworks holds promise for improving algorithm performance. Hybrid approaches that combine unsupervised learning with domain-specific information, such as physics-based models or prior knowledge about imaging modalities, can enhance denoising accuracy and robustness. Future research will focus on integrating domain knowledge to guide unsupervised algorithms towards more effective noise suppression.

4. Real-time and Resource-efficient Algorithms

Developing resource-efficient and real-time unsupervised denoising algorithms is imperative for practical deployment in various applications. Future research aims to devise lightweight architectures, efficient training strategies, and algorithms capable of performing denoising tasks in real-time without compromising accuracy or quality.

In conclusion, the field of unsupervised image denoising presents a multitude of challenges and opportunities for future research. Addressing these challenges, embracing innovative methodologies, and leveraging domain-specific knowledge will pave the way for the development of more robust, adaptable, and efficient unsupervised techniques in image denoising, ultimately benefiting a wide array of applications across diverse domains.

F. Conclusion

Unsupervised image denoising stands as a dynamic and evolving field, marked by remarkable advancements and determined challenges. The review highlights the diverse array of unsupervised methodologies, each offering unique strengths and challenging distinct limitations.

Challenges continue in deciphering learned representations, handling complex noise patterns, and ensuring scalability and adaptability across varied imaging scenarios. Ethical considerations, explain ability, and continual learning are emerging focal points, aiming to fortify unsupervised algorithms for real-world deployment.

The future of unsupervised image denoising lies in collaborating domain knowledge, mitigating biases, and developing robust, adaptable algorithms capable of handling diverse noise distributions. Establishing standardized evaluation protocols, assembling benchmark datasets, and integrating supervised techniques for hybrid models present avenues for enhancing algorithmic performance and generalization.

As the field advances, bridging the gap between quantitative measures and human perception, ensuring ethical deployment, and fostering explainable and transparent methodologies will be essential. Addressing these challenges and embracing innovative methodologies will chart the course for more effective, interpretable, and practical unsupervised image denoising techniques, fostering advancements across various domains reliant on clean and accurate image data.

G. Acknowledgment

We express our heartfelt gratitude to our family, friends, and all those who contributed to this study.

H. References

[1] J. N. Saeed, A. M. Abdulazeez, and D. A. Ibrahim, "2D Facial Images Attractiveness Assessment Based on Transfer Learning of Deep Convolutional Neural Networks," in 2022 4th International Conference on Advanced Science and Engineering (ICOASE), IEEE, 2022, pp. 13–18.

[2] D. A. Zebari, A. M. Abdulazeez, D. Q. Zeebaree, and M. S. Salih, "A fusion scheme of texture features for COVID-19 detection of CT scan images," in 2020 international conference on advanced science and engineering (ICOASE), IEEE, 2020, pp. 1–6.

[3] S. M. S. Abdullah and A. M. Abdulazeez, “Facial expression recognition based on deep learning convolution neural network: A review,” Journal of Soft Computing and Data Mining, vol. 2, no. 1, pp. 53–65, 2021.
[4] J. Saeed and A. M. Abdulazeez, “Facial beauty prediction and analysis based on deep convolutional neural network: a review,” Journal of Soft Computing and Data Mining, vol. 2, no. 1, pp. 1–12, 2021.
[5] D. A. Zebari, D. Q. Zeebaree, A. M. Abdulazeez, H. Haron, and H. N. A. Hamed, “Improved threshold based and trainable fully automated segmentation for breast cancer boundary and pectoral muscle in mammogram images,” Ieee Access, vol. 8, pp. 203097–203116, 2020.
[6] A. M. Abdulazeez, D. Q. Zeebaree, and D. M. Abdulqader, “Wavelet applications in medical images: A review,” Transform. DWT, vol. 21, p. 22, 2020.
[7] S. Sahu, A. K. Singh, A. K. Agrawal, and H. Wang, “Denoising and enhancement of medical images by statistically modeling wavelet coefficients,” in Digital Image Enhancement and Reconstruction, Elsevier, 2023, pp. 95–113.
[8] J. N. Saeed, A. M. Abdulazeez, and D. A. Ibrahim, “FIAC-Net: Facial image attractiveness classification based on light deep convolutional neural network,” in 2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA), IEEE, 2022, pp. 1–6.
[9] A. H. Ali, M. RASHEED, S. SHIHAB, T. RASHID, and S. H. A. Hamed, “A Modified Heat Diffusion Based Method for Enhancing Physical Images,” Journal of Al-Qadisiyah for computer science and mathematics, vol. 13, no. 1, p. Page-77, 2021.
[10] J. N. Saeed, A. M. Abdulazeez, and D. A. Ibrahim, “An Ensemble DCNNs-Based Regression Model for Automatic Facial Beauty Prediction and Analyzation,” Traitement du Signal, vol. 40, no. 1, p. 55, 2023.
[11] D. M. Sulaiman, A. M. Abdulazeez, H. Haron, and S. S. Sadiq, “Unsupervised learning approach-based new optimization K-means clustering for finger vein image localization,” in 2019 International Conference on Advanced Science and Engineering (ICOASE), IEEE, 2019, pp. 82–87.
[12] N. A. Kako and A. M. Abdulazeez, “Peripapillary Atrophy Segmentation and Classification Methodologies for Glaucoma Image Detection: A Review,” Curr Med Imaging, vol. 18, no. 11, pp. 1140–1159, 2022.
[13] N. S. Hassan, A. M. Abdulazeez, D. Q. Zeebaree, and D. A. Hasan, “Medical images breast cancer segmentation based on K-means clustering algorithm: a review,” Asian Journal of Research in Computer Science, vol. 9, no. 1, pp. 23–38, 2021.
[14] H. M. Yasin and A. M. Abdulazeez, “Image Compression Based on Deep Learning: A review,” 2021.
[15] L. D. Tran, S. M. Nguyen, and M. Arai, “GAN-based noise model for denoising real images,” in Proceedings of the Asian Conference on Computer Vision, 2020.
[16] R. S. Thakur, S. Chatterjee, R. N. Yadav, and L. Gupta, “Image de-noising with machine learning: A review,” IEEE Access, vol. 9, pp. 93338–93363, 2021.
[17] O. M. S. Hassan et al., “An Efficient Robust Color Watermarking Algorithm Based on DWT, DCT, BFO and Implementation,” in 2021 IEEE 11th

International Conference on System Engineering and Technology (ICSET), IEEE, 2021, pp. 90–95.
[18] N. Yuan, L. Wang, C. Ye, Z. Deng, J. Zhang, and Y. Zhu, "Self-supervised Structural Similarity-based Convolutional Neural Network for Cardiac Diffusion Tensor Image Denoising," Med Phys, 2023.
[19] S. H. Haji and A. M. Abdulazeez, "Comparison of optimization techniques based on gradient descent algorithm: A review," PalArch's Journal of Archaeology of Egypt/Egyptology, vol. 18, no. 4, pp. 2715–2743, 2021.
[20] B. M. Ferzo and F. M. Mustafa, "Digital image denoising techniques in wavelet domain with another filter: A review," Academic Journal of Nawroz University, vol. 9, no. 1, pp. 158–176, 2020.
[21] D. N. H. Thanh and S. Engínoğlu, "An iterative mean filter for image denoising," IEEE Access, vol. 7, pp. 167847–167859, 2019.
[22] R. Seetharaman, M. Tharun, and K. Anandan, "A novel approach in hybrid median filtering for denoising medical images," in IOP Conference Series. Materials Science and Engineering, IOP Publishing, 2021.
[23] Wang and Huang, "Image denoising based on adaptive sector rotation median filter," in Journal of Physics: Conference Series, IOP Publishing, 2021, p. 012056.
[24] Z. Chen, Z. Zhou, and S. Adnan, "Joint low-rank prior and difference of Gaussian filter for magnetic resonance image denoising," Med Biol Eng Comput, vol. 59, pp. 607–620, 2021.
[25] A. Khan, W. Jin, A. Haider, M. Rahman, and D. Wang, "Adversarial gaussian denoiser for multiple-level image denoising," Sensors, vol. 21, no. 9, p. 2998, 2021.
[26] B. M. Ferzo and F. M. Mustafa, "Image Denoising in Wavelet Domain Based on Thresholding with Applying Wiener Filter," in 2020 International Conference on Computer Science and Software Engineering (CSASE), IEEE, 2020, pp. 106–111.
[27] C. Tian, M. Zheng, W. Zuo, B. Zhang, Y. Zhang, and D. Zhang, "Multi-stage image denoising with the wavelet transform," Pattern Recognit, vol. 134, p. 109050, 2023.
[28] N. You, L. Han, D. Zhu, and W. Song, "Research on image denoising in edge detection based on wavelet transform," Applied Sciences, vol. 13, no. 3, p. 1837, 2023.
[29] X. Feng, W. Zhang, X. Su, and Z. Xu, "Optical remote sensing image denoising and super-resolution reconstructing using optimized generative network in wavelet transform domain," Remote Sens (Basel), vol. 13, no. 9, p. 1858, 2021.
[30] P. Azimpour, T. Bahraini, and H. S. Yazdi, "Hyperspectral image denoising via clustering-based latent variable in variational Bayesian framework," IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 4, pp. 3266–3276, 2021.
[31] P. Panchaxri, B. N. Jagadale, B. S. Priya, and M. N. Nargund, "Image denoising using adaptive NL means filtering with method noise thresholding," Indian J Sci Technol, vol. 14, no. 39, pp. 2961–2970, 2021.
[32] S. Vishwakarma, V. Ummalaneni, M. S. Iqbal, A. Majumdar, and S. S. Ram, "Mitigation of through-wall interference in radar images using denoising

autoencoders," in 2018 IEEE Radar Conference (RadarConf18), IEEE, 2018, pp. 1543–1548.
[33] K. T. Chui et al., "Transfer learning-based multi-scale denoising convolutional neural network for prostate cancer detection," Cancers (Basel), vol. 14, no. 15, p. 3687, 2022.
[34] J. Gurrola-Ramos, O. Dalmau, and T. E. Alarcón, "A residual dense u-net neural network for image denoising," IEEE Access, vol. 9, pp. 31742–31754, 2021.
[35] J. Wang, H. Cong, X. Wei, B. Qi, J. Li, and T. Cai, "X-ray Image Blind Denoising in Hybrid Noise Based on Convolutional Neural Networks," in IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, 2021, pp. 203–212.
[36] X. Lin, C. Ren, X. Liu, J. Huang, and Y. Lei, "Unsupervised Image Denoising in Real-World Scenarios via Self-Collaboration Parallel Generative Adversarial Branches," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 12642–12652.
[37] J. Li, Z. Xu, Z. Li, Z. Zhang, B. Zhang, and Y. Wu, "An Unsupervised CNN-Based Multichannel Interferometric Phase Denoising Method Applied to TomoSAR Imaging," IEEE J Sel Top Appl Earth Obs Remote Sens, vol. 16, pp. 3784–3796, 2023.
[38] J. Cui et al., "PET image denoising using unsupervised deep learning," Eur J Nucl Med Mol Imaging, vol. 46, pp. 2780–2789, 2019.
[39] M. Moreno López, J. M. Frederick, and J. Ventura, "Evaluation of MRI denoising methods using unsupervised learning," Front Artif Intell, vol. 4, p. 642731, 2021.
[40] A. Khmag, A. R. Ramli, and N. Kamarudin, "Clustering-based natural image denoising using dictionary learning approach in wavelet domain," Soft comput, vol. 23, no. 17, pp. 8013–8027, 2019.
[41] A. El Mahdaoui, A. Ouahabi, and M. S. Moulay, "Image denoising using a compressive sensing approach based on regularization constraints," Sensors, vol. 22, no. 6, p. 2199, 2022.
[42] K. Bnou, S. Raghay, and A. Hakim, "A wavelet denoising approach based on unsupervised learning model," EURASIP J Adv Signal Process, vol. 2020, no. 1, pp. 1–26, 2020.
[43] J. Song, J.-H. Jeong, D.-S. Park, H.-H. Kim, D.-C. Seo, and J. C. Ye, "Unsupervised denoising for satellite imagery using wavelet directional CycleGAN," IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 8, pp. 6823–6839, 2020.
[44] D. Hu, Y. K. Tao, and I. Oguz, "Unsupervised denoising of retinal OCT with diffusion probabilistic model," in Medical Imaging 2022: Image Processing, SPIE, 2022, pp. 25–34.
[45] K. Prajapati et al., "Unsupervised Denoising for Super-Resolution (UDSR) of Real-World Images," IEEE Access, vol. 10, pp. 122329–122346, 2022.
[46] Y. Xie, M. Yuan, B. Dong, and Q. Li, "Unsupervised Image Denoising with Score Function," arXiv preprint arXiv:2304.08384, 2023.
[47] W. Zhao, Q. Liu, Y. Lv, and B. Qin, "Texture variation adaptive image denoising with nonlocal PCA," IEEE Transactions on Image Processing, vol. 28, no. 11, pp. 5537–5551, 2019.

[48] S. Xiaorui and W. Lingda, "Denoising of hyperspectral images based on principal component analysis and adaptive sparse coding," in 2018 10th IAPR Workshop on Pattern Recognition in Remote Sensing (PRRS), IEEE, 2018, pp. 1–6.
[49] M. Prodan, G. V. Vlăsceanu, and C.-A. Boiangiu, "Comprehensive evaluation of metrics for image resemblance," Journal of Information Systems & Operations Management, vol. 17, no. 1, pp. 161–185, 2023.
[50] K. N. S. Behara, A. Bhaskar, and E. Chung, "Geographical window based structural similarity index for origin-destination matrices comparison," J Intell Transp Syst, vol. 26, no. 1, pp. 46–67, 2021.
[51] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," PeerJ Comput Sci, vol. 7, p. e623, 2021.
[52] A. Wright and V. Välimäki, "Perceptual loss function for neural modeling of audio systems," in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2020, pp. 251–255.