International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V72I11P121

Volume 72 Issue 11, 192-206, November 2024

Review Article

Image Denoising: A Review about its Past, Present, and Future

Ana Cláudia Souza Vidal de Negreiros[1], Gilson Giraldi[2]

[1]*Federal Rural University of the Semi-Arid (UFERSA), Mossoró, Brazil.*
[2]*National Laboratory of Cientific Computing (LNCC), Petrópolis, Brazil.*

[1]*Corresponding Author : anaclaudia.negreiros@ufersa.edu.br*

Received: 23 April 2024 Revised: 26 September 2024 Accepted: 22 October 2024 Published: 29 November 2024

Abstract - *Digital images have played an important role in the modern world. In this sense, image noise reduction techniques have become an important research field for many reasons. This work presents a whole perspective of the image denoising field since the first published article to state-of-the-art research. In this context, we analyzed classical and modern methods and metrics applied to remove noise from images, considering the whole collection encountered in the SCOPUS database. It was verified that classical computer vision techniques were extensively used in this context, above all different image filters. On the other hand, modern techniques hold on deep learning models, including combining them with classical techniques. Models such as Generative Adversarial Networks (GANs), variational techniques, residual networks, denoising diffusion probabilistic models, and quantum computing appear as future trends in this knowledge area. Also, some research gaps were found.*

Keywords - *Classical computer vision techniques, Deep learning models, Image denoising, SCOPUS database, GANs.*

1. Introduction

Since the advent of digital images, noise presence has been an issue for many reasons, such as the inability to detect interested objects, difficulty in providing precise medical diagnostics based on visual analysis, aesthetic goals, security, etc. Indeed, noisy images are still found today due to various origins, such as limitations of acquisition devices and fetus movement during the image acquisition by magnetic resonance machines, for example. Also, different noises can occur in some stages of image formation, which results in poor image quality [1].

Consequently, image denoising is considered a classical problem of the computer vision field and has been extensively studied since always [2]. The first published article in the SCOPUS database was written in 1979, a work developed by Lim [3] that proposed a system to reduce random noise in Pulse Code Modulation (PCM) images. Afterwards, the image denoising area became widely studied, with many advances considering the techniques applied to perform noise reduction. For example, the first works developed in this field used methods involving linear and non-linear filters, Bayesian approaches, and wavelet transforms. Then, in modern days, artificial intelligence-based methods, especially deep learning-based ones [4], have played this protagonist role in recent years. An illustration of the importance of modern developed works in this area is the papers recently published by Krisha and Peram [5] and Chui et al. [6]. They created two case studies where they could provide enough proof that image denoising deep methods could increase the accurate rate of early oral and prostate cancer detection, respectively. In this sense, this study is a literature review about the general area of image denoising. Over the past few years, other reviews have been published in this field. In this sense, Kaur and Dong [2] performed a literature review of medical image denoising, pointing out various techniques applicable to noise reduction in this type of image and clarifying the importance of image denoising. On the other hand, Lakshmi et al. [1] considered various applications. They developed a literature review with the purpose of gaining knowledge about denoising filter algorithms used for noise removal from images.

Another correlated literature review was carried out by Nair et al. [7], which consisted of identifying relevant published articles from SCOPUS for denoising, detection, recognition, and restoration, among other goals in underwater imaging. The authors also proposed a research framework for systematically organizing the main underwater techniques. Another work, a more specific one, was performed by Reddy and Pawar [8], where they presented a study about Multispectral Image (MSI) denoising. Singh et al. [9] also provide a literature review about image denoising focusing on Convolutional Neural Networks (CNN) based techniques for image denoising. Taking these literature reviews into consideration. This study brings a different perspective on the history of the image denoising field.

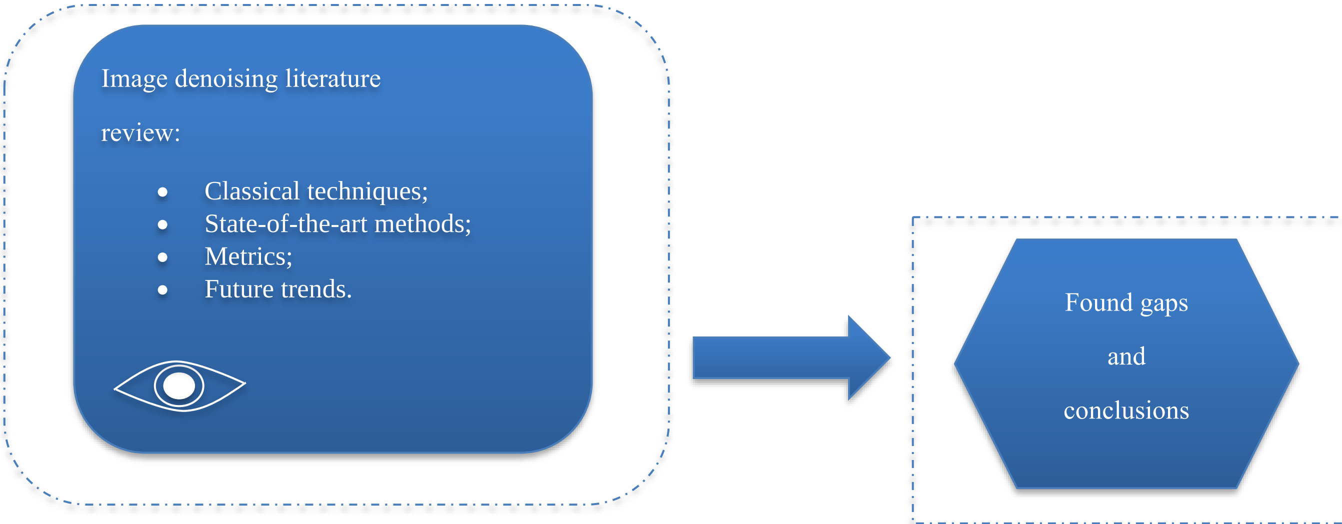

Fig. 1 Proposed article methodology

Also, this refers to the gap of this research: the lack of a panorama of the image denoising field listing and discussing classic and state-of-the-art techniques under a systematic and global perspective. In this sense, the main goal of this research is to analyze the evolution process of the image denoising field and to predict, based on this evolution process, future trends for this field. Thus, we will gather information from the first article published in SCOPUS until the most recent papers. Also, we will analyze some classical and state-of-the-art applied techniques.

The main contributions of this study are:

- A systematic analysis of the most used techniques in the image denoising problem using the SCOPUS database.
- Discussion about the future trends of the image denoising field and literature gaps.
- Information gathering is needed in the most important knowledge areas involving image denoising. This information helps us to construct a panorama of essential aspects in the image denoising field, which will be useful for contextual analyses.

Figure 1 brings a graphic representation of the idea of this study. This figure shows ideas, concepts, and elements that are in the scope of this work. Therefore, this review will perform searches in the SCOPUS database aiming to provide information about image denoising classical techniques, modern methods, most used quality image metrics, and future trends in this field, and, as a consequence, it will identify research gaps and reach conclusions. In addition, Figure 2 represents how part of this systematic review was carried out. The rest of this paper is organized as follows. Subsection 1.1. presents a glossary of some technical terms utilized in this study. Section 2 brings an entire perspective on the image denoising area, presenting aspects such as the details of the applied article methodology and important numbers related to this field. Section 3 is dedicated to discussing both classical and state-of-the-art techniques to perform image denoising, bringing also a small description of the noisy images issue. Section 4 presents the most known and applied quality image metrics, where such metrics are presented and briefly discussed. Section 5 leads us to the main objective of this research: the presentation of the future trends in the image denoising knowledge area. It also discusses observed literature gaps. Finally, Section 6 concludes the work and presents the literature gaps.

2. A Whole Perspective of the Image Denoising Field

To initiate this section, this study briefly presents a glossary in Table 1 with some technical terms and their respective definitions. Part of the applied methodology in this research is shown in Figure 2. The methodology is based on the SCOPUS database and VOSviewer software, which is a free bibliometric software for visual analysis of literature reviews [10]. Thus, this study searched works from 1979 to 2024 and identified some essential aspects, such as work volumes per year, more recurrent terms, and more important image denoising research areas.

In addition, to select the papers consulted to construct this work, some steps were followed:

- First, older (the first 40 published articles) publications were consulted to analyze initially applied techniques in the image denoising area. In this sense, only papers judged as relevant were cited in this work;
- Secondly, about 5% to 10% of the papers quantity in each analyzed decade were read to get specific information;
- Finally, some specific terms were searched aggregated with the key term “image denoising”, such as “generative adversarial networks”, “autoencoders”, “Deep Belief Networks”, “Deep Residual Networks”, and “Quantum Computing”.

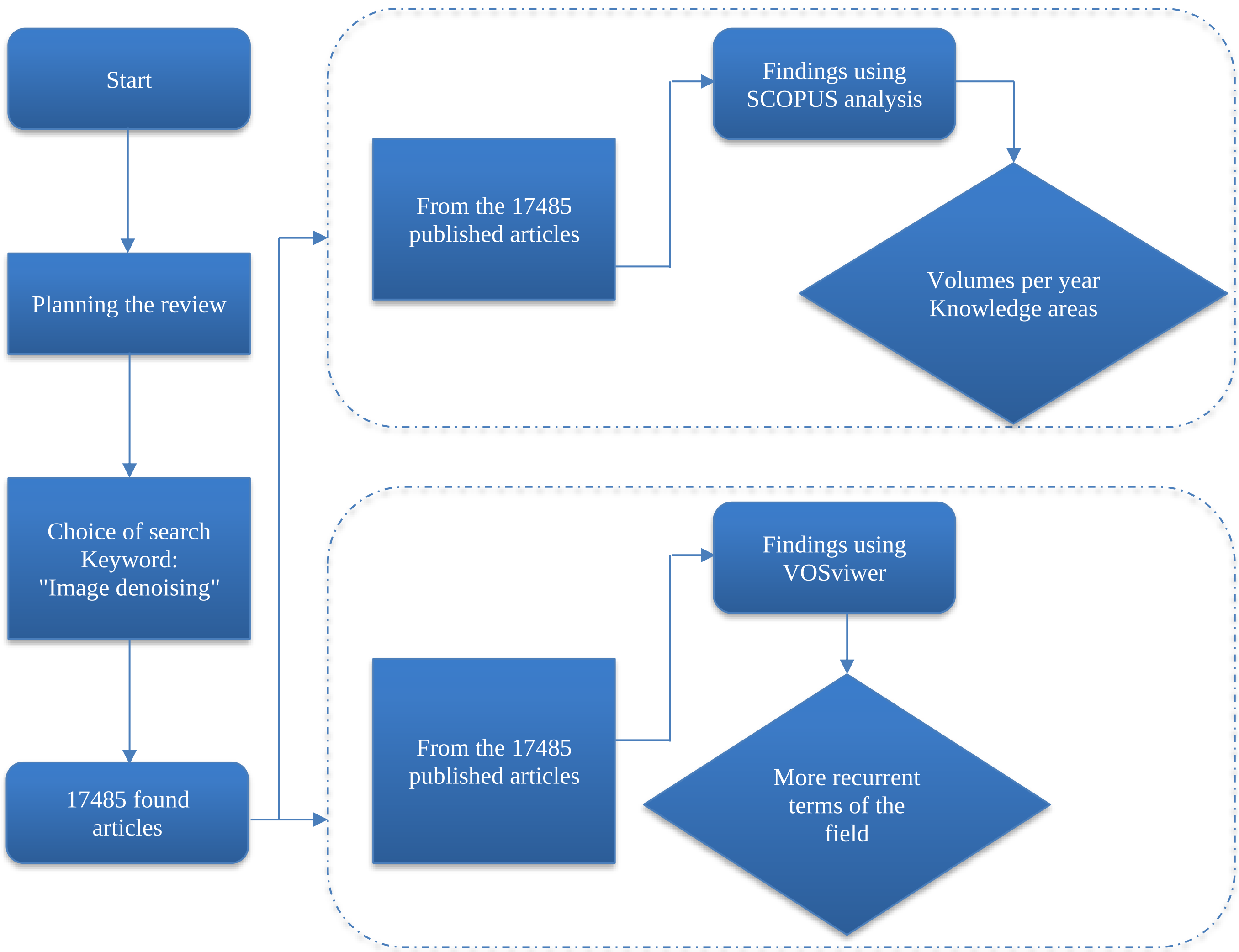

Fig. 2 Step-by-step systematic literature review for image denoising field

Table 1. Concept of some technical terms

Technical Term	Definition
Image restoration	The process of restoring corrupted images involves image denoising techniques.
Image denoising classical techniques	In general, conventional image denoising techniques include, for example, Wavelet Transforms and Wiener Filtering.
Deep learning methods	Specific machine learning methods use neural networks with multiple layers to analyze and learn from a great amount of data.
Bayesian approaches	Statistical approaches based on Bayes' theorem, which represents the probability of an event based on evidence or prior knowledge.
Generative Adversarial Networks (GANs)	A group of machine learning approaches is utilized to generate new data that resembles a specific training dataset.
Residual Networks	A class of deep neural network architecture with the purpose of addressing the issue of vanishing or exploding gradient, which can arise when training very deep models.

In general, analyzing Figure 3, it is possible to verify a crescent trend in the number of published works about image denoising, showing that this field has attracted more attention over the years, especially in recent years. Indeed, considering the years from 2008 to 2022, the number of published papers more than quadrupled. This can be explained by the great advances achieved in the image denoising field using state-of-the-art methods and by the importance of having high-quality images in many areas. Figure 4 shows that Computer Science is the area with major significance (in terms of quantity) in aspects of the publication of image denoising works, followed by the Engineering field.

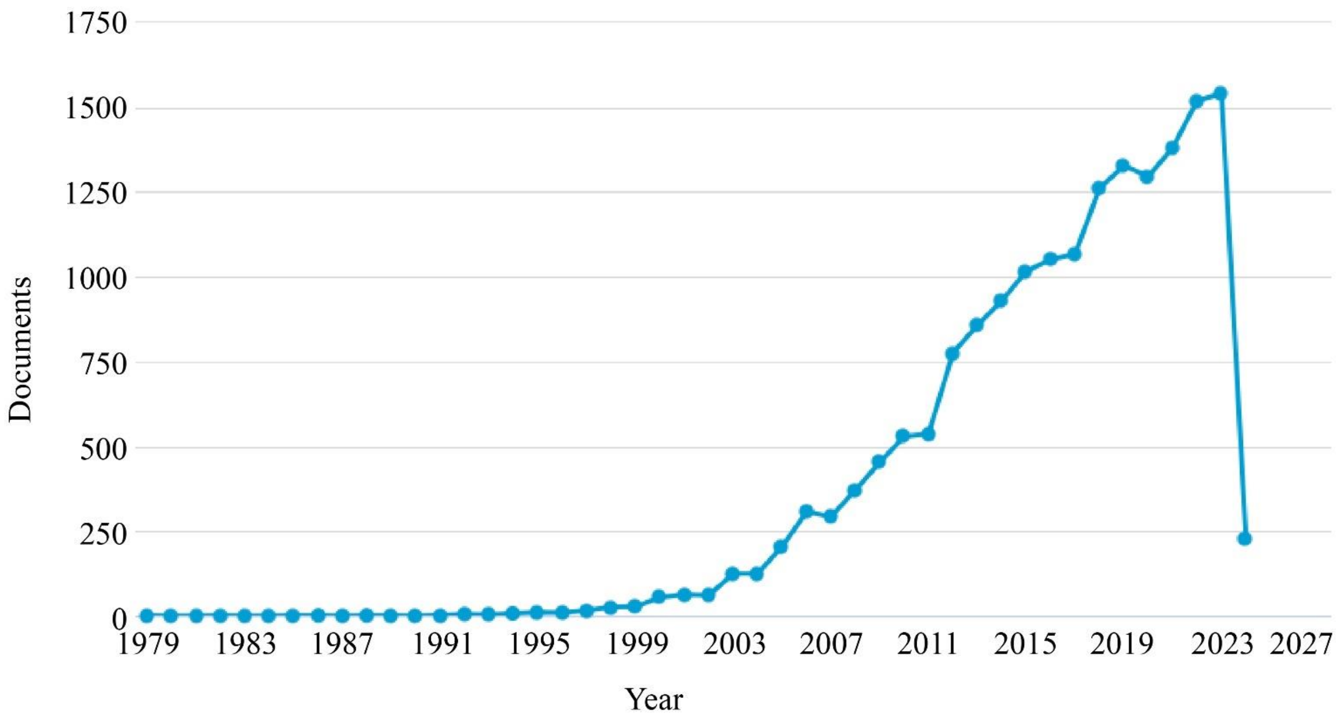

Fig. 3 Number of documents about image denoising over the years, from 2008 until January 2024

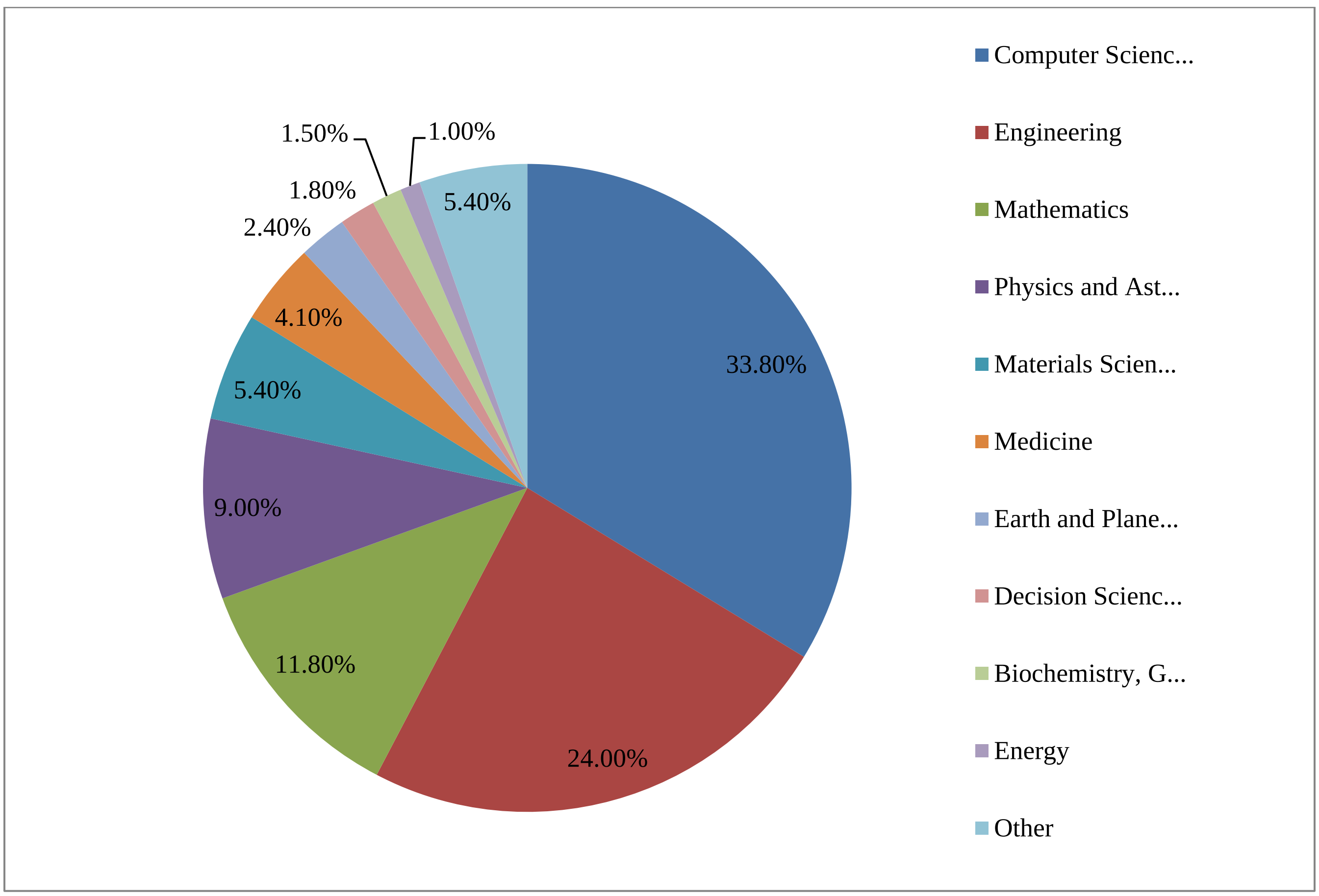

Fig. 4 Image denoising research in the knowledge areas

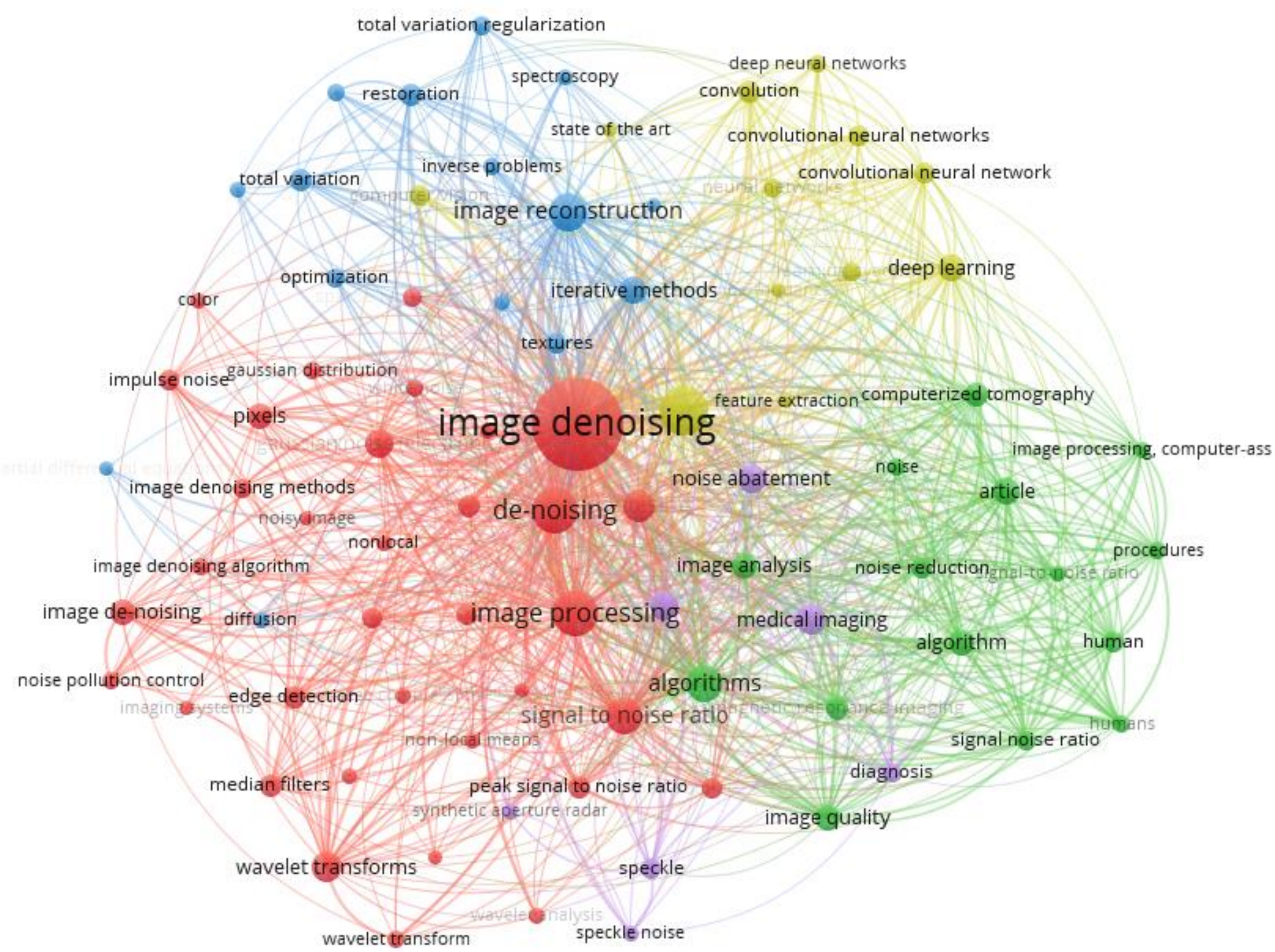

Fig. 5 The most recurrent terms found in a literature review about image denoising

Also, Figure 5, provided by the VOSviewer software, shows the relationship between the most recurrent terms used in the published documents in this area. Besides, analyzing Figure 5, it is possible to see that deep learning methods (see Table 1), wavelet transforms, and median filters appear strongly. Furthermore, some of the terms shown in Figure 5 are filter, wavelet, image quality, image restoration (see Table 1), neural network, medical images, and diagnosis.

3. Noisy Images and Denoising Process

Noise is a random process, and images are usually noisy for many reasons. Noise can be caused by light fluctuations, poor weather conditions (haze, wind, mist, fog, …), involuntary movements, the conditions under which the image was acquired, or simply the manner in which the image was stored and the techniques used to compact it, the image sensor, among others. Besides, image noise can be both signal independent (e.g. additive) and signal dependent (e.g. multiplicative) [11]. For instance, in the case of additive noise, a high-quality image x can be represented via a restoration model (see Table 1) given by $x = y - v$, where y denotes the acquired noisy image and v represents the noise [12]. Starting from this model, classical techniques (see Table 1) address the denoising problem by supposing some prior knowledge to v while recent neural network methods deal with this problem through learning approaches. Hence, based on this presented systematic literature review, in general, the methods applied to handle this drawback evolved over the years, as shown in the following subsections of this study.

3.1. Classical Approaches for Image Denoising

The first research that appears in the SCOPUS database when using the key term “image denoising” (Figure 2) is from 1979, a study developed by Lim [3] and published in Applications of Digital Image Processing III. This work proposed a noise reduction system to reduce random noise in Pulse Code Modulation (PCM) images. Also, this system was based on the fact that grayscale contouring due to quantization can be converted to a signal-independent additive random noise with a low mean square error by putting a known random noise to the sampled image before quantization and subtracting the same random noise after quantization. In this sense, from 1981 to 1990, only five works involving “image denoising” appeared in SCOPUS. However, one of them is actually about natural language. In 1982, Patil et al. [13] applied two-dimensional Kalman filtering, aiming at noise reduction in images. In 1986, Acheroy [14] proposed the use of Discrete Cosine Transform (DCT) for image noise reduction. Following in 1988, Park et al. [15] developed a binary image enhancement algorithm that smooths out the noise element while preserving thin contours. In 1989, Kramm and Keller [16] applied the Fast Fourier Transform (FFT) to improve the image quality. In general, those applications were still very limited in many aspects, such as the type of images and small test sets (authors did not have many images to work with). Besides, the methods were based on classical image processing. On the other hand, from 1990 to 2000, using the same keyword (“image denoising”) in SCOPUS, 163 works were found, a significant increase with respect to the previous decade.

However, in the 1990-2000 decade, according to works encountered in SCOPUS, the main types of applied approaches are wavelet-transform-based methods [17, 18], Bayesian-based methods [19, 20], and nonlinear filtering methods [21, 22]. Taking into consideration the decade from 2001 to 2010, 2529 articles were found in SCOPUS when this research was performed (January of 2024), again, a substantial increase compared to the previous decade. Considering the high number of papers, the VOSviewer was also used to help with the literature analysis. Other analyses were performed by searching for specific information in the articles. Thus, considering the most recurrent terms that appeared in the graphic representation designed by the VOSviewer (as shown in Figure 6), the most applied methods in the 2001-2010 decade were the ones involving wavelet transforms, Bayesian networks, and artificial intelligence. Also, wavelet transformations appear stronger than Bayesian networks and artificial intelligence in this period. However, artificial intelligence has started to be an alternative to handle the noisy image problem. Indeed, nowadays, the most applied techniques for the image denoising task involve deep neural networks. However, conventional approaches are still applied in this field. To understand the differences in the result performances between these two types of methods (classical and modern), it is possible to access some specific recent reviews [23-25].

3.2. Modern Approaches for Image Denoising

For modern approaches, this work separated papers from 2011 to 2020 and from 2021 to 2024, the last 14 years. The first period is marked as the start of a new perspective in the image processing field, with the development and wide application of new models based on machine learning methods. In that decade, 10130 articles were found in SCOPUS in image denoising.

Table 2. Concept of some technical terms

Deep Learning Technique	Recent Reference Works
Generative Adversarial Networks (GANs)	[27], [28], [29], [30], [31]
Auto-Encoder (AE)	[32], [33], [34], [35]
Deep Belief Networks (DBNs)	[36], [37]
Deep Residual Networks (DRNs)	[38], [39], [40]

Taking into consideration the next period, from 2021 to 2024, only four years in total, 4670 articles were found in SCOPUS when this research was performed (January of 2024), a substantial increase compared to previous decades. Figures 7 and 8 highlight that this is the beginning of the deep learning era for denoising, showing the power of deep neural networks in this task, besides many others [26].

In this context, Figures 7 and 8 show that methods and techniques groups involving deep learning have been the trend for the last two decades. Considering this, a new search in SCOPUS was performed to find the most used deep model groups in this field. Therefore, Table 2 presents these most applied specific deep techniques, considering the image denoising task followed by their respective recent works.

In addition, considering the models presented in Table 2, it is possible to access the following classical references to encounter more information about each of these deep methods. The GANs were introduced by Godfellow et al. [41]. The concept of AE for denoising tasks was proposed in 1987.

However, a more recent autoencoder model can be detailed in [42]. The DBNs were developed by Hinton et al. [43], and the DRNs were introduced by He et al. [44]. Figure 9 illustrates the most applied techniques in image denoising over the years. While analyzing Figure 9, some methods appear more than once, such as Wavelet Transform, Bayesian Methods, and Deep Neural Methods.

4. Image Denoising Metrics

In the image denoising field, there are some metrics used to evaluate the performance of the models besides visual analysis, which is more subjective. In this sense, this subsection describes, also based on the performed literature review, the most applied image quality metrics. First of all, the Peak Signal-to-Noise Ratio (PSNR) is the most frequent metric for assessing the quality between the original image and the resultant image [45].

PSNR is an engineering term that refers to the ratio of a maximum signal's possible value to the power of corrupting noise that affects the representation's quality. Also, it is calculated in logarithmic decibel units, and the higher the value of PSNR, the better will be the quality of the output image [45, 46].

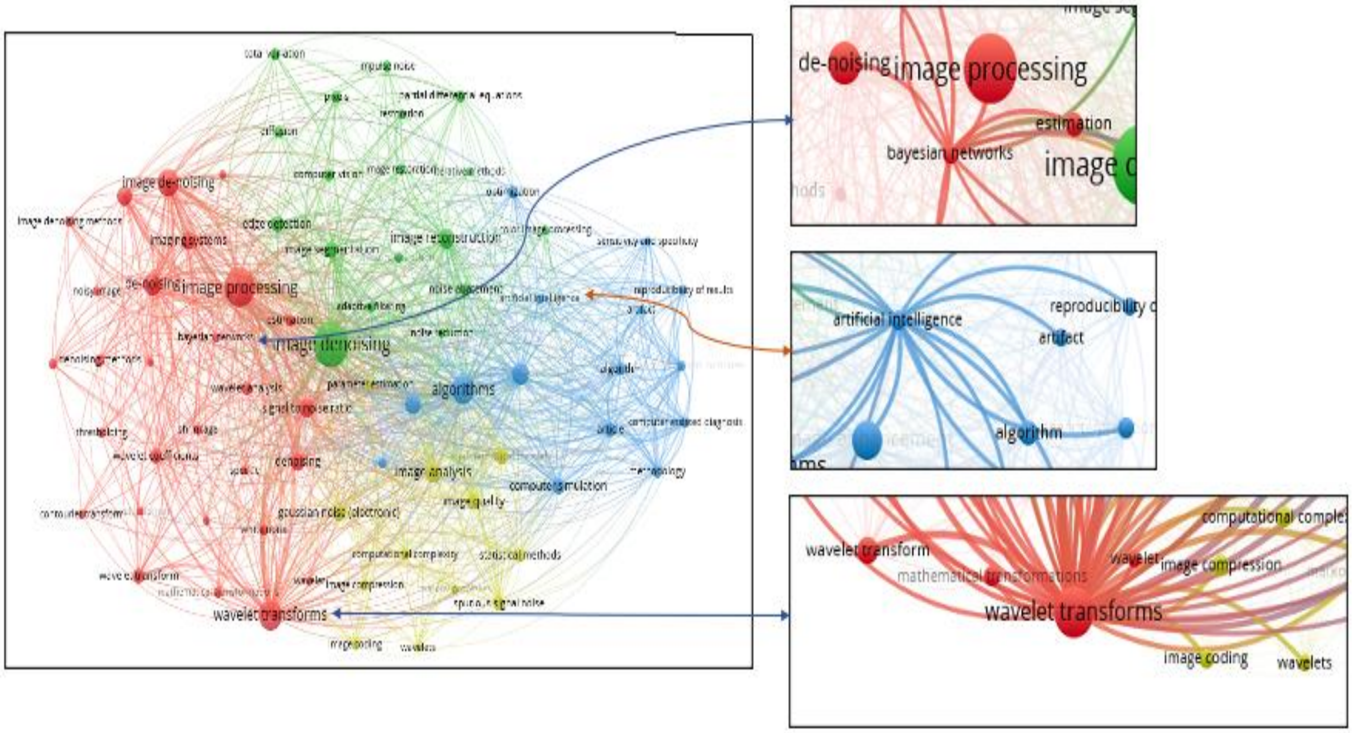

Fig. 6 The most recurrent terms found in a literature review about image denoising, considering the period from 2001 to 2010

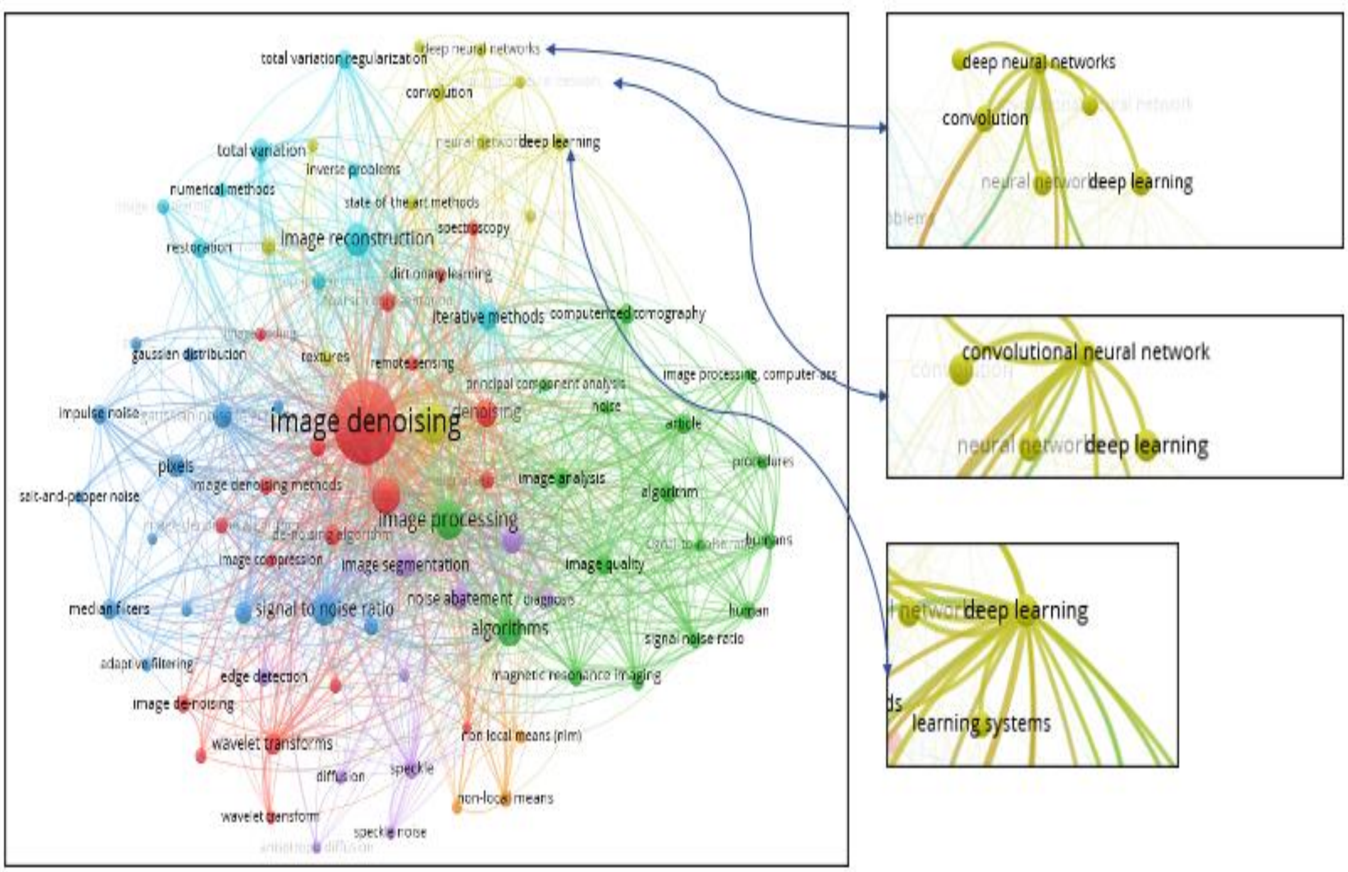

Fig. 7 The most recurrent terms found in a literature review about image denoising, considering the period from 2011 to 2020

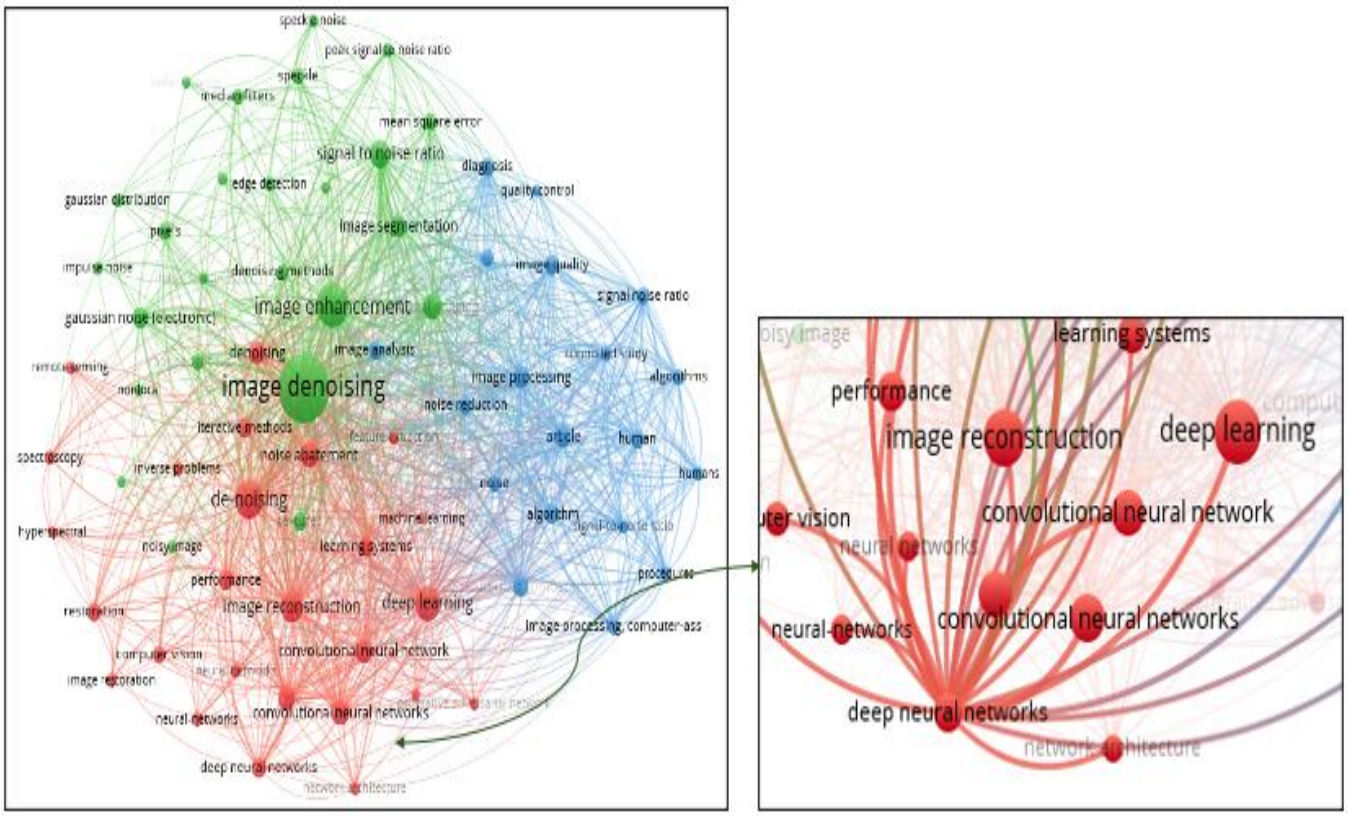

Fig. 8 The most recurrent terms found in a literature review about image denoising, considering the period from 2021 to 2024

PSNR has been recently applied in [47, 48, 49, 50]. Besides, it is calculated using Equation 1.

$$PSNR = 20log(MAX_I) - 10log(MSE). \quad (1)$$

In the above formula, MAX_I is the maximum pixel value of image I and MSE (Equation 2) is the mean squared error that considers the "true" numeric values for comparison between actual and degraded images [51].

$$MSE = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} [g(i,j) - f(i,j)]^2, \quad (2)$$

Where M and N are the pixel amount in the x and y directions, respectively, of the images, and $g(i,j)$ and $f(i,j)$ are the grey values of the original and the cleaned images, respectively, at point (i,j).

The Structural Similarity (SSIM) index is a metric that allows the evaluation of the level of harmony between two images. To evaluate the similarity, SSIM (see Equation 3) merges three components: Luminance, structural information, and contrast differences. Luminance is evaluated as the distortions among both images in bright parts. In SSIM, the structural information is computed by the magnitude of the spatial interdependencies between the pixels of both images. The contrast differences also demonstrate an evaluation of the degree of variability or "texture" in both images [52]. Some works that recently applied SSIM were [47, 49, 50]. Given two images (or two windows) x and y of common size NxN, the SSIM index is calculated as:

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}, \quad (3)$$

Where

- μ_x is the pixel sample mean of x;
- μ_y is the pixel sample mean of y;
- σ_x^2 is the variance of x;
- σ_y^2 is the variance of y;
- σ_{xy} is the covariance of x and y;
- $c_1 = (k_1L)^2$ and $c_2 = (k_2L)^2$ are two variables to stabilize the division with a weak denominator;
- L is the dynamic range of the pixel values;
- $k_1 = 0.01$ and $k_2 = 0.03$ by default and the closer it is to 1, the better the similarity between the two images.

In addition, the Root Mean Squared Error (RMSE) is another metric applied in this field. When the correlation is higher, and the RMSE is lower, the filtering performance should be better.

Also, some works have recently been applied to RMSE, such as [47, 53, 54]. The mathematical representation for RMSE is given in Equation 4

$$RMSE(g,f) = \sqrt{MSE}, \quad (4)$$

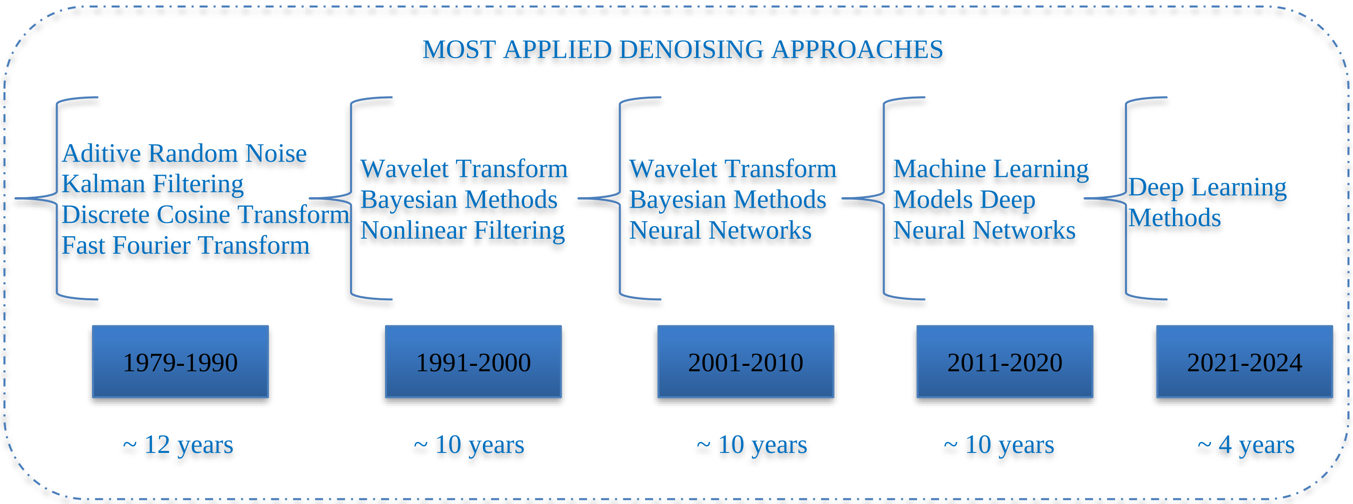

Fig. 9 Denoising approaches most applied over the years

Where MSE is defined in Equation 2, g is the original signal, and f is the denoised signal.

On the other hand, spectral angle mapping (SAM) is the only evaluation index used to calculate the spectral consistency of hyperspectral data. The formula for SAM is given by Equation 5

$$SAM = cos^{-1}\left(\frac{\langle v, \hat{v}\rangle}{\|v\|_2 \cdot \|\hat{v}\|_2}\right). \quad (5)$$

Where v represents the pixel vector of the reference image, while $\hat{v}$ represents the pixel vector of the denoising image. The lower the SAM value, the better the denoising performance [55]. Some works have been recently applied SAM, such as [56, 57, 58]. Global Error in Synthesis (ERGAS) is a metric that provides an overall quality rate of the denoising result and is computed by Equation 6.

$$ERGAS = 100\frac{h}{l}\sqrt{\frac{1}{N}\sum_{i=1}^{N}[RMSE(i)/Mean(i)]}. \quad (6)$$

ERGAS indicates the rate of the spatial resolution of the two images (reference and denoising images), i denotes the number of bands of the denoising image, $Mean(i)$ represents the mean value of differences among the i-th band of the reference and denoising images, and $RMSE(i)$represents the root mean squared error of the i-th band between the reference image and that of the denoising image. The lower the ERGAS value, the better the denoising result. Some works have been recently applied ERGAS, such as [56, 59, 60]. Figure 10 shows how the metrics are analyzed.

5. Discussions and Future Trends

Noisy images are generated constantly because noise is considered a common and recurrent image aspect. Indeed, this happens because the image generation process is full of specificities that yield artifacts. Sources of image noise include sensor noise, compression artefacts, quantization noise, and environmental effects (*e.g.* atmospheric distortion). Besides, noisy imaging domains include low light, medical imagery (*e.g.* MRI and US), remote sensing (e.g. multispectral and Synthetic Aperture Radar), and infrared. In this context, image noise can be modeled by some probabilistic distributions [61]. Over time and according to the performed literature review in this work, the more common models of image noise distributions are Gaussian, Laplacian, Uniform, Poisson, Gamma, Exponential, and Alpha-Stable [18, 62, 63, 64].

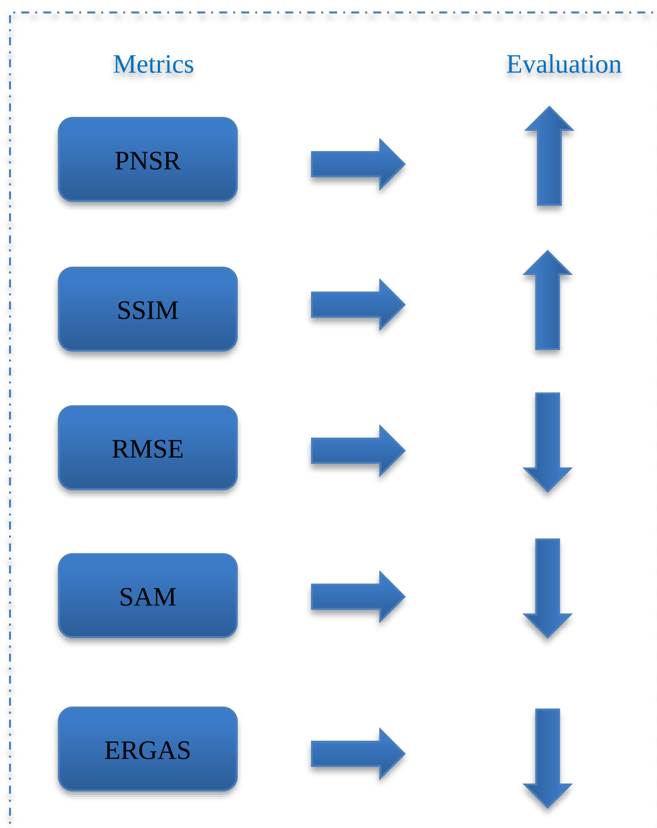

Fig. 10 Representation of how the metrics are analyzed

Knowing how noise is the up arrow indicates that the greater the metric, the better it is. And, the down arrow means that the lower the metric, the better it is distributed could be interesting because this can help in the choice of the best method of image recovery. Besides, this study showed that the first research about image denoising issues applied traditional methods based on wavelet transforms, Bayesian models, and nonlinear filters. Indeed, these techniques are still used today; however, in general, they are combined with deep learning models, which have revolutionized many fields and delivered many state-of-the-art methods for different classical and modern tasks. However, classical methods, even though in smaller proportions, are still being improved nowadays, such as those in the domain of non-local means and sparse representation. In this sense, the total variation method image denoising proposed in 1992 by Rudin et al. [65] opened the field to subsequent image denoising methods ideas considering the image property sparsity [66, 67]. The Non-Local Means (NLM), introduced in 2005 by Buades et al. [68], is an algorithm for the image denoising task that has reached significant success in this field since it was proposed. Also, it continues to be applied and holds excellent results in this area, as shown by the recent works of Guo et al. [69] and Direk [70]. Also, considering the sparse representation domain, important results proceed to be achieved by late research in the image denoising area, as can be seen in [71, 72].Although taking the entire literature review performed in this research, it is possible to conclude that deep learning models are the future for the image denoising problem. There are also some reasons to believe in this belief. First, deep learning methods can learn from data, which means that with a representative dataset, it is possible to reach great results.

Secondly, deep learning techniques require, in general, a huge amount of data to deliver high performances, which is easily found nowadays, with Big Data being one of the pillars of Industry 4.0. Thirdly, the majority of developed works (about 90% of them) aiming at denoising images apply some model based on deep learning, which is justified by the deep neural network's power. In fourth place, the rapid technological development of hardware allows the development of new deep neural network architectures trained with enormous quantities of data. On the other hand, diverse types of filters are still applied with the aim of image denoising, which is also a trend for the future. Some of the most applied filters are Kalman [73], Laplacian [62], Median [74], and Wiener [75]. Besides, the combination of image filters and deep learning methods remains a very strong and promising tendency in this field due to its important results [76].

However, the fact that deep learning models are seen as the future of the image denoising field by many researchers in this field was a conclusion already expected. Thus, this work analyzed the specific deep learning methods that will be most applied in the future and shows the reasons why. In general, four groups of deep models can be pointed to as future trends: generative adversarial networks, residual networks, variational inference, and Denoising Diffusion Probabilistic Models (DDPM).In this context, the GANs have received great attention in a variety of applications, including in image denoising tasks [41]. They gained a reputation because of their interesting ability to generate new examples drawn from an existing distribution of samples. Recent works, considering the image denoising task, applied variations of GANs that resulted in very good results [29, 30, 31].Deep Residual Networks use an assisting technique called skip connection [44] to try to learn the residue between the noisy and clean images. Also, a large number of works applied related deep residual networks [38, 39, 40]. Variational inference techniques perform both noise estimation and noise removal in a Bayesian framework [77]. Such a method is also a future trend and has been extensively applied in this area [63, 72, 78]. Also, DDPM, initially introduced by Ho et al. [79], has emerged as a modern machine learning approach with the capability to learn from data distributions and synthesize high-quality images outperforming well-known conventional methods [80, 81, 82]. In addition, accoupled with these models, there are the main applied end-to-end network architectures in this kind of task, which are U-Net [83], Res-Net [44], and VGG [84]. Nevertheless, another modern approach appears to be a strong future trend in this field: the quantum image computing-based denoising methods.This technique aims to use the advantage of quantum computing for handling and analyzing images using quantum machines. In this sense, some works were able to find very promising results for image denoising tasks applying Quantum Image Computing (QIC), and that is the reason why this approach plays an important place as a future promise.

For example, Zhou and Liang [85] developed a method based on a quantum machine learning model that restores images. Chinnaiyan and Sylam [86] proposed a deep approach that applies Quantum Wavelet Transform (QWT) specifically in the image denoising process. Also, Guntupalli et al. [87] introduced a novel methodology for image denoising using Quantum Generative Adversarial Networks (QGANs) and performed a comparison between their proposed approach and non-quantic techniques. In Section 4, some image denoising evaluation metrics are presented. Those alternatives are used when there is ground truth available. However, visual analysis is another option to evaluate the image quality when ground truth is not available, although they are strongly subjective. Also, when machine learning methods are used, the value of the loss function can be used to evaluate the model's performance. Nevertheless, there are situations in which obtaining pairs of images (clean and corrupted) is a big challenge or even impossible. In that kind of situation, it is necessary to try to handle this problem by using methods that can provide restored images without the respective clean images. Taking this into consideration, some ground truth free models can handle this problem, such as:

- Deep image prior [88]: truncated learning of single image;
- Noise2Noise [89]: multiple noisy images used for training;
- Noise2Self [90]: Similar to Noise2Noise but use one image;
- Noise2Void [89]: Similar to Noise2Noise but use a blind-spot masking scheme;

Indeed, methods that do not require ground truths to obtain good results in image denoising and restoration tasks are fundamental and will open the doors to an abundance of applications, *e.g.* on medical image data. Also, in general, the image denoising field requires more benchmarking developments. In other words, proposed methods require testing in known datasets to make results comparisons.

6. Conclusion

The main goal of this paper was to analyze the evolution process of the image denoising field and to predict, based on this evolution process, future trends for this field and literature gaps. This research identified the method applied in the first published work that appeared on the SCOPUS database in 1979 and performed an analysis passing for all the decades since then to understand the changes in science techniques and methods used to perform improvements in image quality.

Besides, this work detected too many works developed over the years, showing a crescent number of articles published since the 1980s and the knowledge areas that most apply denoising techniques. This study showed that the type of methods applied to remove noise from images changed over the years. The first ones, in general, involved classical computer vision techniques, such as nonlinear filters. On the other hand, the new methods converged to artificial intelligence, more specifically to the deep learning model, once they were state-of-the-art in this field. In this sense, hardware developments, together with a huge amount of data available to train deep models in many knowledge fields, contribute to the idea of a future that will bring more advances in image denoising using deep learning models. This literature review also presented that GANs, residual networks, variational inference, denoising diffusion probabilistic methods, and quantum computing-based approaches are the future trends in the image denoising field. However, it is important to highlight that classical techniques, such as different kinds of filters, are still applied in this knowledge area, especially when combined with modern deep techniques. Besides, computer science is the knowledge area, with more articles published on image denoising followed by engineering.

Regarding literature gaps that emerged when analyzing image denoising works in SCOPUS, this study detected that there is a lack of information about the correlation between different kinds of images and appropriate denoiser techniques. Also, this research verified that a robust study that correlates the visual analysis with quality image evaluation metrics is also missing in the literature. Another gap is the rare possibility of performing benchmarking since many applied datasets are not public, which makes it impossible to compare results. In addition, a study that could search for the reasons why some classical methods are still applied for the image denoising task would be an advance in science. This research should present the advantages of using conventional methods compared to deep learning approaches specifically for this field.

Funding Statement

The authors would like to thank FAPERJ (“Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro”) for funding this paper.

References

[1] Gali Rama Lakshmi et al., "A Review on Image Denoising Algorithms for Various Applications," *Proceedings of Fourth International Conference on Communication, Computing and Electronics Systems*, Coimbatore, India, pp. 839-847, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Amandeep Kaur and Guanfang Dong, "A Complete Review on Image Denoising Techniques for Medical Images," *Neural Processing Letters*, vol. 55, pp. 7807–7850, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Jae S. Lim, "Reduction of Quantization Noise in Pulse Code Modulation (PCM) Image Coding," *Proceedings of the 23rd Annual Technical Symposium, Applications of Digital Image Processing III*, San Diego, United States, 1979. [CrossRef] [Google Scholar] [Publisher Link]

[4] Zhenyong Rui, and Xiugang Gong, "Black Box Adversarial Defense Based on Image Denoising and Pix2Pix," *Journal of Computer and Communications*, vol. 11, no. 12, pp. 14-30, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Patibandla Sandhya Krisha, and Subba Rao Peram, "CT Image Precise Denoising Model with Edge Based Segmentation with Labeled Pixel Extraction Using CNN Based Feature Extraction for Oral Cancer Detection," *Traitement du Signal*, vol. 40, no. 3, pp. 1297-1304, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Kwok Tai Chui et al., "Transfer Learning-Based Multi-Scale Denoising Convolutional Neural Network for Prostate Cancer Detection," *Cancers*, vol. 14, no. 15, pp. 1-13, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Rashmi S Nair et al., "Image Mining Applications for Underwater Environment Management - A Review and Research Agenda," *International Journal of Information Management Data Insights*, vol. 1, no. 2, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] P. Lokeshwara Reddy, and Santosh Pawar, "Multispectral Image Denoising Methods: A Literature Review," *Materials Today: Proceedings*, vol. 33, pp. 4666-4670, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Katyani Singh et al., "A Comprehensive Review of Convolutional Neural Network based Image Enhancement Techniques," *2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)*, Pondicherry, India, pp. 1-6, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Enrique Orduña-Malea, and Rodrigo Costas, "Link-Based Approach to Study Scientific Software Usage: The Case of Vosviewer," *Scientometrics*, vol. 126, pp. 8153-8186, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Benjamin Salmon, and Alexander Krull, "Towards Structured Noise Models for Unsupervised Denoising," *Computer Vision–ECCV 2022 Workshops*, pp. 379-394, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] C. Tian, Y. Xu, W. Zuo, B. Du, C. W. Lin, and D. Zhang, "Designing and Training of a Dual CNN for Image Denoising," *Knowledge-Based Systems*, vol. 226, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] S. Patil, M. Sid-Ahmed, and M. Shridhar, "Noise Reduction in Images Using Statistical Filtering," *ICASSP '82 IEEE International Conference on Acoustics, Speech, and Signal Processing*, Paris, France, pp. 1142-1145, 1982. [CrossRef] [Google Scholar] [Publisher Link]

[14] Marc P.J. Acheroy, "Use of the Discrete Cosine Transform for The Restoration of an Image Sequence," *Medical Image Processing*, vol. 593, pp. 142-149, 1986. [CrossRef] [Google Scholar] [Publisher Link]

[15] R.H. Park et al., "A Fast Noise Reduction Technique of Binary Images from an Image Scanner," *Visual Communications and Image Processing '88: Third in a Series*, vol. 1001, pp. 53-60, 1988. [CrossRef] [Google Scholar] [Publisher Link]

[16] J. Rainer Kramm, and H. Uwe Keller, "An FFT Method to Optimize the Removal of Coherent Noise in Small and Large Images," *Image Processing II, SPIE*, vol. 1027, pp. 180-184, 1989. [CrossRef] [Google Scholar] [Publisher Link]

[17] Igor V. Kozintsev, Shu Xiao, and Kannan Ramchandran, "Graphical Statistical Modeling of Wavelet Coefficients and its Applications," *Wavelet Applications in Signal and Image Processing VIII, SPIE*, vol. 4119, pp. 806-820, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[18] Vasily Strela, Javier Portilla, and Eero P. Simoncelli, "Image Denoising Using a Local Gaussian Scale Mixture Model in the Wavelet Domain," *Wavelet Applications in Signal and Image Processing VIII*, vol. 4119, pp. 363-371, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[19] Alan H. Baydush, and Carey E. Floyd Jr, "Bayesian Image Estimation of Digital Chest Radiography: Interdependence of Noise, Resolution, And Scatter Fraction," *Medical Physics*, vol. 22, no. 8, pp, 1255-1261, 1995. [CrossRef] [Google Scholar] [Publisher Link]

[20] Qing Lu, and Tianzi Jiang, "A New Bayesian Approach to Image Denoising with a Combination of Mrfs and Pixon Method," *Proceedings 15th International Conference on Pattern Recognition*, Barcelona, Spain, vol. 3, pp. 726-729, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[21] Yunmei Chen, B.C. Vemuri, and L. Wang, "Image Denoising and Segmentation Via Nonlinear Diffusion," *Computers and Mathematics with Applications*, vol 39, no. 5-6, pp. 131-149, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[22] Y.M. Hawwar and A.M. Reza, "Nonlinear Filtering in the Wavelet Transform Domain," *Proceedings 2000 International Conference on Image Processing*, Vancouver, BC, Canada, vol. 3, pp. 266-269, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[23] Michael Elad, Bahjat Kawar, and Gregory Vaksman, "Image Denoising: The Deep Learning Revolution and Beyond-A Survey Paper," *SIAM Journal on Imaging Sciences*, vol. 16, no. 3, pp. 1594-1654, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Walid El-Shafai et al., "Traditional and Deep-Learning-Based Denoising Methods for Medical Images," *Multimedia Tools and Applications*, vol. 83, pp. 52061-52088, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Hewa Majeed Zangana, and Firas Mahmood Mustafa, "From Classical to Deep Learning: A Systematic Review of Image Denoising Techniques," *Journal Ilmiah Computer Science*, vol. 3, no. 1, pp. 50-65, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Saeed Izadi, Darren Sutton, and Ghassan Hamarneh, "Image Denoising In The Deep Learning Era," *Artificial Intelligence Review*, vol. 56, no. 7, pp. 5929-5974, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[27] Yinan Chen et al., "A High-Quality Self-Supervised Image Denoising Method Based on SDDW-GAN and CHRNet," *Expert Systems with Applications*, vol. 258, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[28] Haoyang Jin et al., "Adaptive Noise-Aware Denoising Network: Effective Denoising for CT Images with Varying Noise Intensity," *Biomedical Signal Processing and Control*, vol. 96, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[29] Jialiang Zhang et al., "DEGAN: Decompose-Enhance-GAN Network for Simultaneous Low-Light Image Lightening and Denoising," *Electronics*, vol. 12, no. 14, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[30] Rajdeep Kumar et al., "A Novel Framework for Satellite Image Denoising and Super Resolution Using CNN-GAN," *Recent Trends in Artificial Intelligence and IoT*, pp. 78-88, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Shaobo Zhao et al., "Dual-GAN Complementary Learning for Real-World Image Denoising," *IEEE Sensors Journal*, vol. 24, no. 1, pp. 355-366, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[32] Shreya Priyadarshini Roy et al., "Denoising of Underwater Images with Regulated Autoencoders," *Journal of Computer Science*, vol. 20, no. 6, pp. 670-681, 2024. [Google Scholar] [Publisher Link]

[33] Savvas Karatsiolis, and Christos N. Schizas, "Conditional Generative Denoising Autoencoder," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 10, pp. 4117-4129, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[34] Nahla Elazab Elashkar, and Mahmoud Maghraby, "Autoencoder-based Image Denoiser Suitable for Image of Numbers with High Potential for Hardware Implementation," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 44, no. 2, pp. 234-246, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[35] Feng Gu et al., "Denoising Image-Based Experimental Data Without Clean Targets Based on Deep Autoencoders," *Experimental Thermal and Fluid Science*, vol. 156, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[36] Rini Smita Thakur et al., "Nature-Inspired DBN Based Optimization Techniques for Image De-noising," *Intelligent Systems with Applications*, vol. 18, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[37] Dharmalingam Muthusamy, and S. Sathyamoorthy, "Deep Belief Network For Solving The Image Quality Assessment In Full Reference And No Reference Model," *Neural Computing and Applications*, vol. 34, no. 24, pp. 21809-21833, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[38] Wencong Wu et al., "Dual Residual Attention Network For Image Denoising," *Pattern Recognition*, vol. 149, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[39] Vedat Acar, and Ender M. Eksioglu, "Densely Connected Dilated Residual Network for Image Denoising: DDR-Net," *Neural Processing Letters*, vol. 55, no. 5, pp. 5567-5581, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[40] Jan-Ray Liao, Kun-Feng Lin, and Yen-Cheng Chang, "Residual Dense Network with Non-Residual Guidance For Blind Image Denoising," *Digit Signal Processing*, vol. 137, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[41] Ian Goodfellow et al., "Generative Adversarial Networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139-144, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[42] Pascal Vincent et al., "Extracting and Composing Robust Features with Denoising Autoencoders," *Proceedings of 25th International Conference on Machine Learning*, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[43] Geoffrey E. Hinton, Simon Osindero, and Yee-Whye Teh, "A Fast Learning Algorithm for Deep Belief Nets," *Neural Computing*, vol. 18, pp. 1527-1554, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[44] Kaiming He et al., "Deep Residual Learning for Image Recognition," *Proceedings IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770-778, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[45] Kannadhasan Suriyan et al., "Performance Analysis of Peak Signal-To-Noise Ratio and Multipath Source Routing Using Different Denoising Method," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 1, pp. 286-292, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[46] Manasa Nadipally, "Optimization of Methods for Image-Texture Segmentation Using Ant Colony Optimization," *Intelligent Data Analysis for Biomedical Applications*, pp. 21-47, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[47] Yancheng LI et al., "RED-MAM: A Residual Encoder-Decoder Network Based on Multi-Attention Fusion for Ultrasound Image Denoising," *Biomedical Signal Processing and Control*, vol. 79, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[48] Ning You et al., "Research on Image Denoising in Edge Detection Based on Wavelet Transform," *Applied Science*, vol. 13, no. 3, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[49] Sreedhar Kollem, Katta Ramalinga Reddy, and Duggirala Srinivasa Rao, "A Novel Diffusivity Function-Based Image Denoising for MRI Medical Images," *Multimedia Tools and Applications*, vol. 82, pp. 32057-32089, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[50] Lianmin Zhou et al., "Multi-Scale Network Toward Real-World Image Denoising," *International Journal of Machine Learning and Cybernetics*, vol. 14, no. 4, pp. 1205-1216, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[51] Anwar Shah et al., "Comparative Analysis of Median Filter and Its Variants For Removal of Impulse Noise From Gray Scale Images," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 3, pp. 505-519, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[52] Gemma Corona et al., "A New Method To Solve Rotated Template Matching Using Metaheuristic Algorithms and The Structural Similarity Index," *Mathematics and Computers in Simulation*, vol. 206, pp. 130-146, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[53] K.V.N. Kavitha, Ashok Shanmugam, and Agbotiname Lucky Imoize, "Optimized Deep Knowledge-based No-Reference Image Quality Index for Denoised MRI Images," *Scientific African*, vol. 20, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[54] Fuyong Wang, and Yun Zai, "Image Segmentation and Flow Prediction of Digital Rock with U-Net Network," *Advances in Water Resources*, vol. 172, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[55] Jinchun Qin, Hongrui Zhao, and Bing Liu, "Self-Supervised Denoising for Real Satellite Hyperspectral Imagery," *Remote Sensing*, vol. 14, no. 13, pp. 1-24, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[56] Ramya Murugesan, Nandhagopal Nachimuthu, and G. Prakash, "Attention Based Deep Convolutional U-Net with CSA Optimization for Hyperspectral Image Denoising," *Infrared Physics & Technology*, vol. 129, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[57] Zhiyuan Zha et al., “Hyperspectral Image Denoising Via Nonlocal Rank Residual Modeling,” *Proceedings 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Rhodes Island, Greece, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[58] Dabing Yu et al., “DSTrans: Dual-Stream Transformer for Hyperspectral Image Restoration,” *Proceedings 2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, Waikoloa, HI, USA, pp. 3739-3749, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[59] Risheng Huang et al., “Robust Hyperspectral Unmixing with Practical Learning-Based Hyperspectral Image Denoising,” *Remote Sensing*, vol. 15, no. 4, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[60] Jiale Zhang et al., “Xformer: Hybrid X-Shaped Transformer for Image Denoising,” *arxiv*, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[61] Kelum Gajamannage, Yonggi Park, and Alexey Sadovski, “Geodesic Gramian Denoising Applied To The Images Contaminated With Noise Sampled From Diverse Probability Distributions,” *IET Image Process*, vol. 17, no. 1, pp. 144-156, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[62] Xin Su, Zhi Zhang, and Fang Yang, “Fast Hyperspectral Image Denoising and Destriping Method Based on Graph Laplacian Regularization,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[63] Hao Liang et al., “Variational Bayesian Deep Network For Blind Poisson Denoising,” *Pattern Recogniion*, vol. 143, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[64] Ahmed Almulihi et al., “Oil Spill Detection in SAR Images Using Online Extended Variational Learning of Dirichlet Process Mixtures of Gamma Distributions,” *Remote Sensing*, vol. 13, no. 15, pp. 1-20, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[65] Leonid I. Rudin, Stanley Osher, and Emad Fatemi, “Nonlinear Total Variation Based Noise Removal Algorithms,” *Physica D: Nonlinear Phenomena*, vol. 60, no. 1, pp. 259-268, 1992. [CrossRef] [Google Scholar] [Publisher Link]

[66] Jian Wang et al., “A Protocol Layer Trust-Based Intrusion Detection Scheme for Wireless Sensor Networks,” *Sensors*, vol. 17, no. 6, pp. 1-19, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[67] Minghua Wang et al., “l_0-l_1 Hybrid Total Variation Regularization and its Applications on Hyperspectral Image Mixed Noise Removal and Compressed Sensing,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 9, pp. 7695-7710, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[68] A. Buades, B. Coll, and J. M. Morel, “A Review of Image Denoising Algorithms, with a New One,” *Multiscale Modeling & Simulation*, vol. 4, no. 2, pp. 490-530, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[69] Yu Guo et al., “The Optimal Weights of Non-local Means for Variance Stabilized Noise Removal,” *Journal of Scientific Computing*, vol. 101, no. 2, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[70] Tugay Direk, “Image Denoising by Linear Regression on Non-Local Means Algorithm,” *Signal Image Video Processing*, vol. 18, no. 5, pp. 4457-4465, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[71] Dajun Sheng, “A Hybrid Image Fusion and Denoising Algorithm based on Multi-scale Transformation and Signal Sparse Representation,” *Scalable Computing: Practice and Experience*, vol. 25, no. 5, pp. 3500-3506, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[72] Hu Deng, Guoquan Liu, and Luoyu Zhou, “Ultrasonic Logging Image Denoising Algorithm Based on Variational Bayesian and Sparse Prior,” *Journal of Electronic Imaging*, vol. 32, no. 1, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[73] Xinzhao Zhou et al., “Research on Trenching Data Correction Method Based on Wavelet Denoising-Kalman Filtering Algorithm,” *Arabian Journal for Science and Engineering*, vol. 48, no. 2, pp. 1097-1117, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[74] Ning Cao, and Yupu Liu, “High-Noise Grayscale Image Denoising Using an Improved Median Filter for the Adaptive Selection of a Threshold,” *Applied Sciences*, vol. 14, no. 2, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[75] M. Senthamil Selvi et al., “Tomato Leaf Disease Detection using Image Processing,” *International Conference on Inventive Computation Technologies (ICICT)*, pp. 367-371, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[76] Tianqu Hu et al., “Adaptive Denoising of Photoacoustic Signal and Image Based on Modified Kalman Filter,” *Journal of Biophotonics*, vol. 16, no. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[77] Zongsheng Yue et al., “Variational Denoising Network: Toward Blind Noise Modeling and Removal,” *Advances in Neural Information Processing Systems 32 (NeurIPS 2019)*, vol. 32, 2019. [Google Scholar] [Publisher Link]

[78] Qian Zhao et al., “A Deep Variational Bayesian Framework for Blind Image Deblurring,” *Knowledge-Based Systems*, vol. 249, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[79] Jonathan Ho, Ajay Jain, and Pieter Abbeel, “Denoising Diffusion Probabilistic Models,” *Advances in Neural Information Processing Systems*, vol. 33, pp. 6840-6851, 2020. [Google Scholar] [Publisher Link]

[80] Chih-Wei Chang et al., “High-Resolution MRI Synthesis Using A Data-Driven Framework With Denoising Diffusion Probabilistic Modeling,” *Physics in Medicine & Biology*, vol. 69, no. 4, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[81] Kuang Gong et al., "PET Image Denoising Based on Denoising Diffusion Probabilistic Model," *European Journal of Nuclear Medicine and Molecular Imaging*, vol. 51, no. 2, pp. 358-368, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[82] Alicia Durrer, Philippe C. Cattin, and Julia Wolleb, "Denoising Diffusion Models for Inpainting of Healthy Brain Tissue," *Computer Vision and Pattern Recognition*, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[83] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Medical Image Computing and Computer-Assisted Intervention - MICCAI*, pp. 234-241, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[84] Karen Simonyan, and Andrew Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arxiv*, pp. 1-14, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[85] Yifan Zhou, and Yan Shing Liang, "Image Denoising with Machine Learning: A Novel Approach to Improve Quantum Image Processing Quality and Reliability," *arxiv*, pp. 1-9, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[86] Anitha Mary Chinnaiyan, and Boyed Wesley Alfred Sylam, "Deep Demosaicking Convolution Neural Network and Quantum Wavelet Transform-Based Image Denoising," *Network: Computation in Neural Systems*, pp. 1-25, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[87] Sai Kiran Guntupalli et al., "Quantum Generative Adversarial Networks for Image De-Noising," *Proceedings International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)*, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[88] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky, "Deep Image Prior," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 9446-9454, 2018. [Google Scholar] [Publisher Link]

[89] Alexander Krull, Tim-Oliver Buchholz, and Florian Jug, "Noise2void-Learning Denoising From Single Noisy Images," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 2124-2132, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[90] Joshua Batson, and Loic Royer, "Noise2Self: Blind Denoising by Self-Supervision," *Proceedings of the 36th International Conference on Machine Learning*, pp. 524-533, 2019. [CrossRef] [Google Scholar] [Publisher Link]