Multimedia Tools and Applications (2024) 83:58181–58199
https://doi.org/10.1007/s11042-023-17468-2

A comprehensive review of image denoising in deep learning

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Received: 24 May 2023 / Revised: 28 September 2023 / Accepted: 3 October 2023 /
Published online: 20 December 2023

Abstract
Deep learning has gained significant interest in image denoising, but there are notable distinctions in the types of deep learning methods used. Discriminative learning is suitable for handling Gaussian noise, while optimization models are effective in estimating real noise. However, there is limited research that summarizes the different deep learning techniques for image denoising. This paper conducts a comprehensive review of techniques and methods used for image denoising and identifying challenges associated with existing approaches. In this paper, a comparative study of deep techniques is offered in image denoising. The study conducted a comprehensive review of 68 papers on image denoising published between 2018 and 2023, providing a detailed analysis of the field's progress and methodologies over a period of 5 years. Through its literature review, the paper provides a comprehensive summary of image denoising in deep learning, including machine learning methods for image denoising, CNNs for image denoising, additive white noisy-image denoising, real noisy image denoising, blind denoising, hybrid noisy images, state- of-the-art methods for image denoising with deep learning, salt and pepper noise, non-linear filters for digital color images. The main objective of this paper is to provide a comprehensive overview of various approaches used for image denoising, each of which has been explored and developed based on individual research studies. The paper aims to discuss these approaches in a systematic and organized manner, comparing their strengths and weaknesses to provide insights for future research in the field.

Keywords Image denoising · Deep learning · Blind denoising · Salt and pepper noise · Hybrid noisy images

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1 Introduction

Image denoising is an essential task in image processing that aims to remove noise from images while preserving their underlying structure and details [1]. With the growing availability of high-resolution digital images, there has been an increasing need for more effective and efficient denoising methods. In recent years, deep learning-based approaches have shown remarkable performance in image denoising tasks, surpassing traditional handcrafted methods [11]. Deep learning-based image denoising techniques utilize convolutional neural networks (CNNs) to learn the mapping between noisy and clean images [16]. These networks are trained on large datasets of paired noisy and clean images, with the goal of minimizing the difference between the network's output and the corresponding clean image. One of the key advantages of deep learning-based denoising methods is their ability to learn complex non-linear relationships between noisy and clean image patches. This allows the network to capture both local and global image structures and patterns, leading to more accurate and visually pleasing denoising results. Various deep learning-based denoising models have been proposed in the literature, such as the standard CNN model, the residual network (ResNet) model, and the generative adversarial network (GAN) model. The standard CNN model learns a direct mapping from noisy to clean images, while the ResNet model utilizes skip connections to learn residual mappings between noisy and clean images, resulting in more efficient training and improved denoising performance. The GAN model incorporates a generator network that produces denoised images and a discriminator network that distinguishes between real and fake images, leading to improved denoising performance [65, 66] and more realistic image generation [40, 42]. In summary, image denoising [67, 68] is a crucial task in image processing, and deep learning-based methods have shown remarkable performance in this area. With ongoing research efforts and advancements in deep learning techniques, we can expect to see even more accurate and efficient denoising methods in the future.

Deep learning's use of image denoising has enormous implications for computer vision and image processing. This review consolidates knowledge and methods created thus far by analyzing and synthesizing existing research, offering a thorough overview of the state-of-the-art in deep learning for image denoising. Such a review is a useful tool for practitioners and business professionals as well as researchers who want to stay current on the most recent developments. They are able to determine the best deep learning-based methods for image denoising, which eventually results in better performance across a range of industries, including digital photography, surveillance, and medical imaging. Additionally, this evaluation can provide as a springboard for further investigation, generating fresh ideas and methods in the area of deep learning-based image denoising.

1.1 Organization of the survey

In this survey, Section 2 contains the brief discussion about wind power deterministic forecasting methods, wind power probabilistic forecasting methods, short-term forecasting, immediate-short-term forecasting, long-term forecasting, DNN for feature extraction, DBN for feature extraction, CNN for feature extraction, SNN for feature extraction, GA for model configuration, PSO for model configuration, and CS for model configuration. Section 2.11 contains the research gaps and Section 2.12 contains the problem statement. Section 3 wraps up this study.

2 Literature review

Some of the recent research works related to image denoising in deep learning were reviewed in this section.

2.1 Image denoising

In 2019, Gupta et al. [1] have proposed an improved non-local mean filter to suppress speckle noise in ultrasound images. The filter combines the functions of a non-local mean filter and a bilateral filter, resulting in improved image quality. The filter's performance is analyzed using peak signal-to-noise-ratio (PSNR) and structural similarity (SSIM) parameters. In 2019, Awad [2] have proposes a method for denoising images corrupted by Gaussian, impulse, or mixed noise. The method consists of a cascade of stages that remove abnormal values and noisy components. The proposed method is faster and provides better performance in terms of PSNR and visual quality compared to existing methods, particularly for mixed Gaussian and impulse noise. In 2019, Randhawa et al. [3] have used despeckling of ultrasound images, which is first tested on synthetic images degraded by speckle noise with different noise variances. Symlet 8 is found to be the best wavelet filter, and the optimal value of thresholding parameter 'β' is selected. The proposed method outperforms existing methods and is also tested on liver ultrasound images with improved results. In 2020, Shin et al. [4] have used a neural denoising framework that incorporates "noise-separable orthogonal transform features (OTFs) into the CNN-based image denoising process. Wavelet and PCA are chosen as the orthogonal transforms, which help restore image details and reduce artifacts. The denoising process is guided by concatenating OTFs from the image denoised by existing methods, resulting in improved performance compared to single-input networks. In 2020, Helou and Süsstrunk [5] have developed a blind and universal deep learning image denoiser for Gaussian noise removal based on fusion denoising with a Gaussian image prior assumption. The approach shows generalization strength to unseen noise levels and improves state-of-the-art color and grayscale image denoising performance on both seen and unseen noise levels. The network can denoise images without needing to know the noise level at test time.

In 2021, Sun et al. [6] have used novel deep learning denoising framework dynamic PET image denoising, named DeepRED denoising, which enhances quantitative accuracy via the introduction of deep image prior (DIP) combined with Regularization by Denoising (RED). The encoder-decoder architecture uses skip connections to combine hierarchical features and the network input can be random noise or other prior images. The proposed method outperforms conventional methods, including GF, NLM, BM3D, DIP, and SGLD, in terms of noise versus bias performance, based on simulated and real patient data. In 2022, Zin et al. [7] have proposed a local image denoising method using the learned linear filter from RAISR for super-resolution. This method efficiently recovers high-frequency components lost in conventional local processing and achieves comparable performance to nonlocal denoising methods like BM3D, with a lower computational cost. The proposed algorithm is a rapid and high-accurate denoising method for Gaussian noise removal. In 2023, Li et al. [8] have used a hybrid image denoising model based on traditional image processing techniques. The model combines the BM3D algorithm, WNNM, NSST, and gradient domain guided filtering to obtain a denoised image with enhanced texture details. An adaptive iterative NSST algorithm is also proposed to address problems with thresholding. Experimental results show the proposed method outperforms several deep learning denoising methods in terms of PSNR and SSIM. In 2023, Zhang and Zhou [9] have developed a self-supervised image denoising method using Context-Aware Transformer, which overcomes the limitations of CNNs by incorporating a dual-branch structure. The proposed Denoise Transformer includes CADT units and SNE block for secondary noise extraction, and is capable of directly learning the noise distribution information through residual learning. The method achieves competitive PSNR/SSIM performance on real-world SIDD benchmark and has a competitive performance, especially on blurred textures and low-light images, without additional knowledge about noise level or type.

2.2 Image denoising with machine learning and deep learning techniques

2.2.1 Deep learning

In 2019, Park et al. [10] have presented a denoising method for low-dose CT images without paired training data using a generative adversarial network (GAN). The GAN is optimized by minimizing a weighted sum of two losses: Kullback-Leibler divergence and `2 loss. The proposed method preserves fine anomalous features and performs comparably to a method using paired datasets. In 2019, Cui et al. [11] have proposed an unsupervised deep learning method for PET image denoising using prior high-quality images from the same patient. The network is trained to learn intrinsic structure information from the noisy image and output a restored PET image. The proposed method outperforms several reference methods based on contrast-to-noise ratio improvements in both computer simulations and clinical data evaluations. In 2020, Wang et al. [12] have developed FastDerainNet, a deep residual learning algorithm for removing rain streaks from single images. It utilizes the share-source residual module (SSRM) and image decomposition to modify the loss function, simplifying the training process. FastDerainNet is trained on a synthetic dataset and achieves superior results in comparison to other state-of-the-art methods in terms of de-raining and detail preservation, as demonstrated by experiments on both synthetic and real-world images.

In 2021, Tian and Song [13] have proposed a new method for Magnetic Resonance Image (MRI) denoising using Generative Adversarial Networks (GANs). The method uses a Convolutional Neural Network (CNN) as a discriminator to distinguish between real and fake image pairs. The generator, which is based on convolutional encoder-decoder networks, is trained using adversarial learning to remove noise from noisy MRI images. In 2022, Bayhaqi et al. [14] have used the Optical Coherence Tomography (OCT) in smart laser osteotomy requires high-quality images for accurate tissue classification and feedback. Traditional frame-averaging denoising methods are time-consuming and susceptible to motion artifacts. To overcome these limitations, a deep-learning-based denoising method was developed, which achieved similar image quality to frame-averaging and improved tissue classification accuracy. This method shows promise as a pre-processing step for real-time tissue classification in smart laser osteotomy.

2.2.2 Deep and machine learning

In 2023, Sereethavekul and Ekpanyapong [15] have developed a deep learning-based data recovery system, called License Plate Recovery GAN (LPRGAN), that uses a Generative Adversarial Network (GAN) principle for adaptive lightweight license plate image recovery. Unlike existing image restoration systems, our system has self-awareness and a fail-safe mechanism that reduces workload overhead and improves efficiency. The LPR-GAN has an encoder-decoder style aided by dual classification networks, which is suitable for problem-characteristic learning.

Figure 1 depicts the denoising performance of the proposed model. The figure consists of two subfigures: (a) displays the noisy images, while (b) illustrates the corresponding denoised images obtained.

2.3 CNN for image denoising

In 2019, Hashimoto et al. [16] have proposed A new method for dynamic PET image denoising using the deep image prior (DIP) approach. This approach does not require prior training datasets as CNN structures can solve inverse problems such as denoising. The proposed method was found to perform better than other post-denoising methods in terms of contrast-to-noise ratio in both computer simulations and real data. In 2019, Wang et al. [17] have proposes a method for removing mixed noise, specifically Gaussian mixture noise and Gaussian-impulse noise, by integrating traditional variational methods and deep learning-based algorithms. The proposed method can automatically classify the noise type and level for each pixel by iteratively estimating the noise parameters. The deep learning method is used to learn the natural image prior and enforce regularization, which significantly improves the quality of the restored images. Numerical experiments show that the proposed method achieves state-of-the-art results for mixed noise removal. In 2020, Zhang et al. [18] have developed the Memory-Based Latent Attention Network (MLANet) to address the limited capability of hierarchical feature utilization in deep convolutional neural network-based image restoration. MLANet employs a memory-based latent attention block (MLAB) that utilizes global and local features through a multi-kernel attention module. MLANet achieves state-of-the-art performance on image super-resolution, denoising, and compression artifact reduction tasks. In 2021, Lan et al. [19] have proposed a novel deep residual convolutional neural network (DRCNN) for image denoising, which utilizes skip connections between convolutional layers to reduce path length of gradient transfer and alleviate the vanishing-gradient problem. DRCNN outperforms several state-of-the-art algorithms and achieves satisfactory denoising performance. CNN with deeper and thinner structures is more flexible to extract image details and has achieved impressive performance on image denoising. In 2021, Rawat et al. [20] have developed a novel complex-valued convolutional neural network-based model, CVMIDNet, for medical image denoising, which uses residual learning to subtract noise from noisy images. Performance comparison with four state-of-the-art models and its real-valued counterpart shows that CVMIDNet outperforms them in terms of peak signal to noise ratio and structural similarity index for different levels of additive white Gaussian noise in chest X-ray images. The results suggest that CVMIDNet has the potential to be a valuable deep learning model for medical image denoising. Convolution neural network structure is shown in Fig. 2.

In 2021, Gurrola-Ramos et al. [21] have developed RDUNet, is a residual dense neural network for image denoising based on densely connected convolutional layers. It uses local residual learning to avoid the vanishing gradient problem and global residual learning to predict the residual noise of the corrupted image. The algorithm achieves competitive results compared with state-of-the-art networks for image denoising without requiring prior knowledge about the noise level. In 2022, Meng and Zhang [22] have proposed a gray image denoising method using ConvNet with symmetric and dilated convolutional

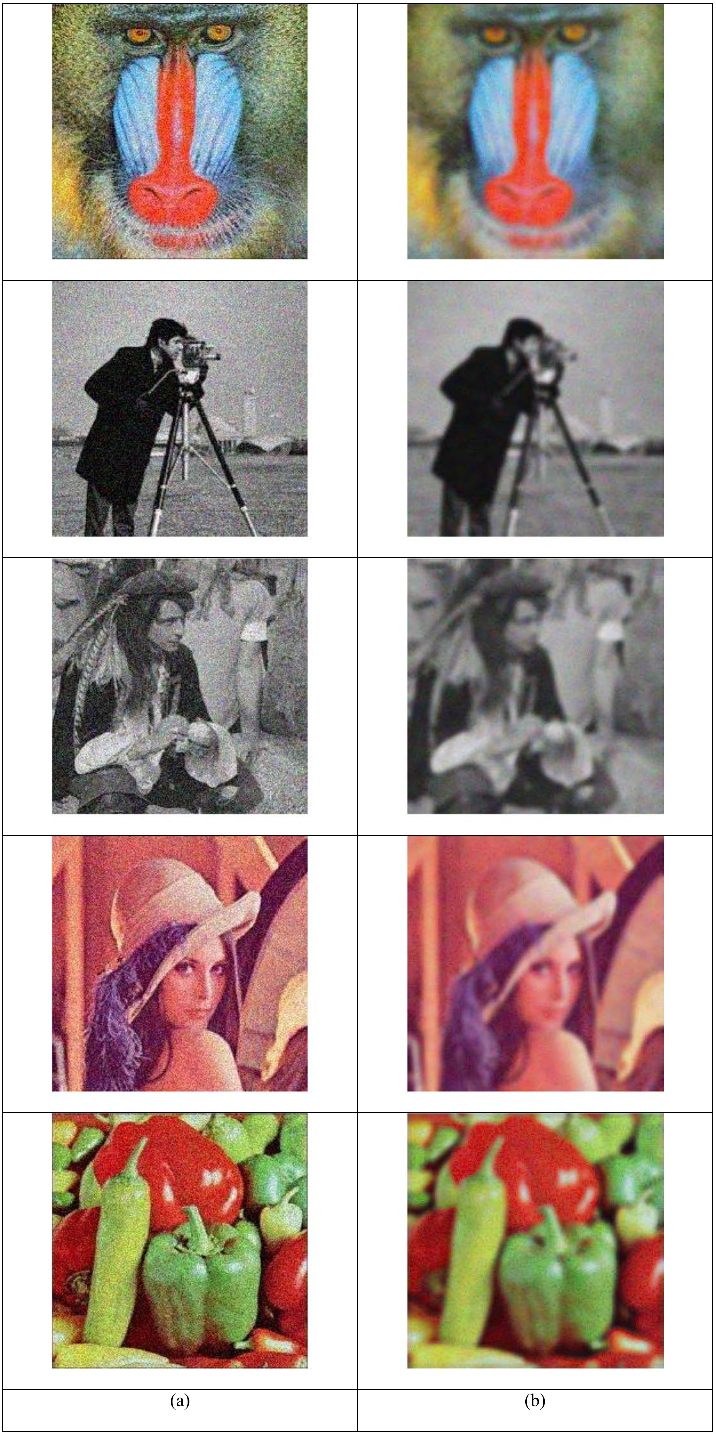

Fig. 1 **a** Noise images. **b** Denoised images

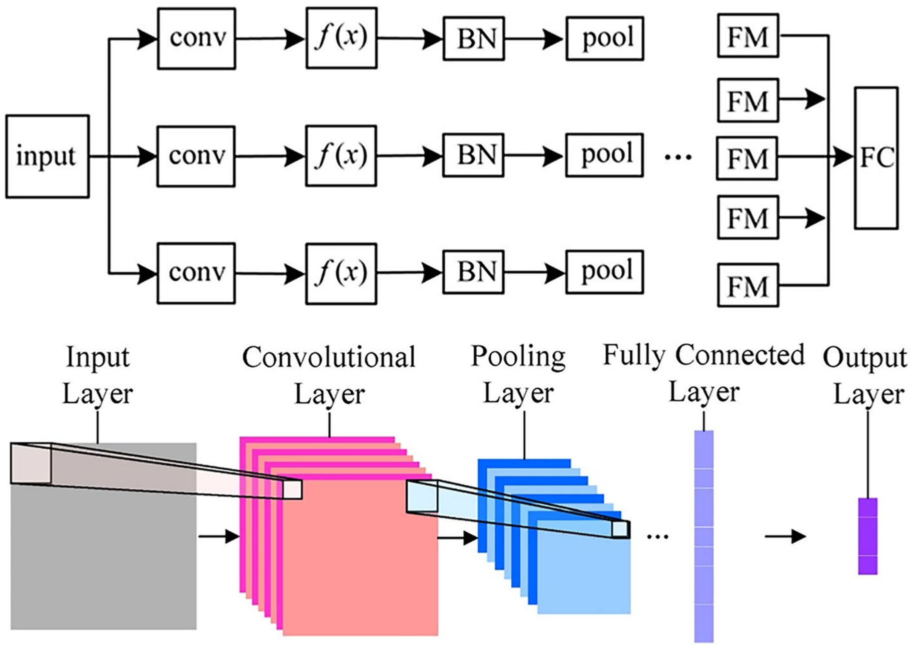

Fig. 2 CNN – Image denoising

residual network, and leaky ReLU and ReLU dual-functions. Achieved better objective and subjective results compared to other methods in high noise level environments. Provided comprehensive discussion of related work and future directions in image denoising. In 2022, Zhang et al. [23] have proposed a robust deformed CNN for image denoising that utilizes relations between surrounding pixels to extract noise features. The CNN contains a deformable block, an enhanced block, and a residual block, which work together to enhance learning ability and memory capacity. Experimental results show that our model outperforms other denoising methods. In 2022, Lee et al. [24] have developed a region adaptive denoising network that adjusts the denoising strength based on image regions. A texture map is generated using a classification network on the DCT domain, and denoising is performed independently for texture and non-texture regions. The proposed method outperforms existing methods in both objective scores and subjective image quality. In 2023, Holla et al. [25] have proposed the EFID network uses parallel image and edge processing blocks to recover edges and fine structures while smoothing out noise in AWGN-corrupted images. It requires only one trained model for all levels of degradation, making it more efficient than other state-of-the-art networks. The EFID network outperforms other models in terms of noise removal and detail preservation, with a smaller parameter size and faster processing time.

2.4 Additive white noisy-image denoising

In 2018, Shi et al. [26] have examined stochastic resonance (SR) in a bistable system with time delay, driven by multiplicative white noise and additive color noise. The effective potential function is deduced, and the mean first-passage time (MFPT) and signal-to-noise ratio (SNR) are analyzed. The study concludes that adjusting the intensity of additive color noise is more effective than regulating multiplicative white noise for controlling SR, and the asymmetric parameter has a non-monotonic effect on SR. In 2018, Khmag et al. [27] have developed a patch-based method for estimating the noise level in natural images contaminated with additive white Gaussian noise. The proposed method uses principal component analysis (PCA) to estimate the noise level from selected patches and applies it to a blind image denoising algorithm that combines undecimated wavelet-based denoising algorithms and PCA. The proposed algorithm outperforms conventional noise estimators in terms of image quality and processing speed. In 2018, Chen and Rui [28] have presented a method for reducing the high-dimensional Fokker-Planck-Kolmogorov (FPK) equation to a one- or two-dimensional partial differential equation for nonlinear stochastic systems excited by additive white noise. The proposed method employs the concept of equivalent drift coefficient and the path integral solution to solve the reduced FPK-like equation. The effectiveness of the proposed method is demonstrated through response analyses of various systems. In 2019, Dytso et al. [29] have addressed the problem of estimating the norm of a n-dimensional Gaussian vector in the presence of additive Gaussian noise. The optimal estimator and the corresponding minimum mean square error (MMSE) are derived. Additionally, it is shown that in the large vector size regime, the MMSE normalized by n converges to zero as n approaches infinity.

In 2020, Soverini and Söderström [30] have developed two frequency domain algorithms for identifying finite impulse response (FIR) models in the presence of additive white noise, and compares them with time domain algorithms through Monte Carlo simulations. The first algorithm is based on theoretical results for the dynamic Frisch scheme, while the second maps the FIR identification problem into a quadratic eigenvalue problem. Both methods resemble existing time domain algorithms. In 2020, Akinlar et al. [31] have proposed a new approach for modeling epidemic diseases using fractional white noise, which allows for more accurate and efficient modeling compared to deterministic differential equations. A new SIRS model is developed and perturbed to the fractional-stochastic systems, and chaotic behavior is studied at steady-state points. Numerical solutions are obtained using trapezoidal and Euler methods, and the SIRS model is associated with fractional Brownian motion using Wick product. This is a novel contribution to the field as there has been no previous consideration of SIRS-type models with fractional white noise or Wick product settings.

2.5 Real noisy image denoising

In 2018, Zhang et al. [34] have developed a fast and flexible denoising CNN that can handle a wide range of noise levels and spatially variant noise with a single network. It works on down sampled sub images, achieving a good trade-off between inference speed and denoising performance. Extensive experiments show that FFDNet outperforms state-of-the-art denoisers in both synthetic and real noisy image denoising tasks. In 2019, Zhao et al. [35] have developed the Pyramid Real Image Denoising Network (PRIDNet) to tackle the challenge of blind denoising on real-world noisy images. It consists of three stages: noise estimation, multi-scale denoising, and feature fusion. The PRIDNet achieves competitive performance in comparison to state-of-the-art denoisers in terms of both quantitative measures and visual perception quality. The code is publicly available on GitHub.

2.5.1 Deep learning

In 2016, Zhu et al. [32] have proposed a method for scheduling complex multi-cluster tools in semiconductor manufacturing, with the aim of increasing their productivity. The system is modeled using resource-oriented Petri nets, and necessary and sufficient conditions for the existence of a one-unit periodic schedule are derived. An optimal one-unit periodic schedule is then found using algorithms with polynomial complexity. The proposed method is illustrated with industrial examples, demonstrating significant reduction in cycle time compared to existing methods. In 2018, Xu et al. [33] have used a method for real-world noisy image denoising using external and internal priors. External priors are learned from clean natural images, and internal priors are learned from the given noisy image with the aid of the external priors. The priors are formulated as orthogonal dictionaries for efficient reconstruction. Experimental results show that the proposed method outperforms state-of-the-art denoising methods on several real-world noisy image datasets.

In 2019, Chen et al. [36] have developed the Deep Boosting Framework (DBF) integrates deep learning with boosting for real-world image denoising. The DBF replaces handcrafted boosting units with convolutional neural networks, including a lightweight Dense Dilated Fusion Network (DDFN) that addresses gradient vanishing and promotes efficiency. Extensive experiments show that the proposed method outperforms existing models on synthetic and real-world noise. A new Real-world Image Denoising (RID) dataset is introduced, and a one-shot domain transfer scheme is proposed to address domain shift. The proposed method has the potential for generalization to other image restoration tasks and applications. In 2020, Song et al. [37] have used a new model called GMSNet for real-world image denoising, which uses multi-scale context, residual connection, and feature reuse to achieve superior performance. A revised method of noise synthesis is also introduced to generate synthetic denoising datasets, leading to further improvements in model performance. The results show that GMSNet outperforms previous state-of-the-art methods on multiple benchmarks, achieving PSNR over 40dB and SSIM over 0.96 on the sRGB track of the DND benchmark. Real noisy – image denoise are shown in the Fig. 3.

2.6 Blind denoising

In 2019, Chen et al. [38] have proposed a blind CNN model for random-valued impulse noise (RVIN) denoising. The model includes a flexible noise ratio predictor to choose the appropriate DnCNN for denoising. The proposed method achieves state-of-the-art performance in terms of both execution efficiency and restoration results. In 2019, Jin et al. [39] have addressed the challenge of channel estimation in mmWave massive MIMO systems through the use of a modified convolutional blind denoising network (CBDNet). This CBDNet includes a noise level estimation subnetwork, non-blind denoising subnetwork, and asymmetric joint loss functions for robust blind channel estimation across a large range of signal-to-noise ratios (SNRs). The proposed CBDNet outperforms traditional channel estimators, compressive sensing techniques, and deep CNNs in terms of normalized mean squared error while reducing offline training costs. In 2019, Zhu et al. [40] have used the BDGAN is an end-to-end method for image blind denoising based on a conditional GAN, which can generate clean images directly without requiring a precise noise level. This approach outperforms discriminative learning-based and non-blind denoising methods, and has been shown to achieve favorable results in blind denoising performance and visual object detection. In 2020, Goncharova et al. [41] have developed a new method to improve

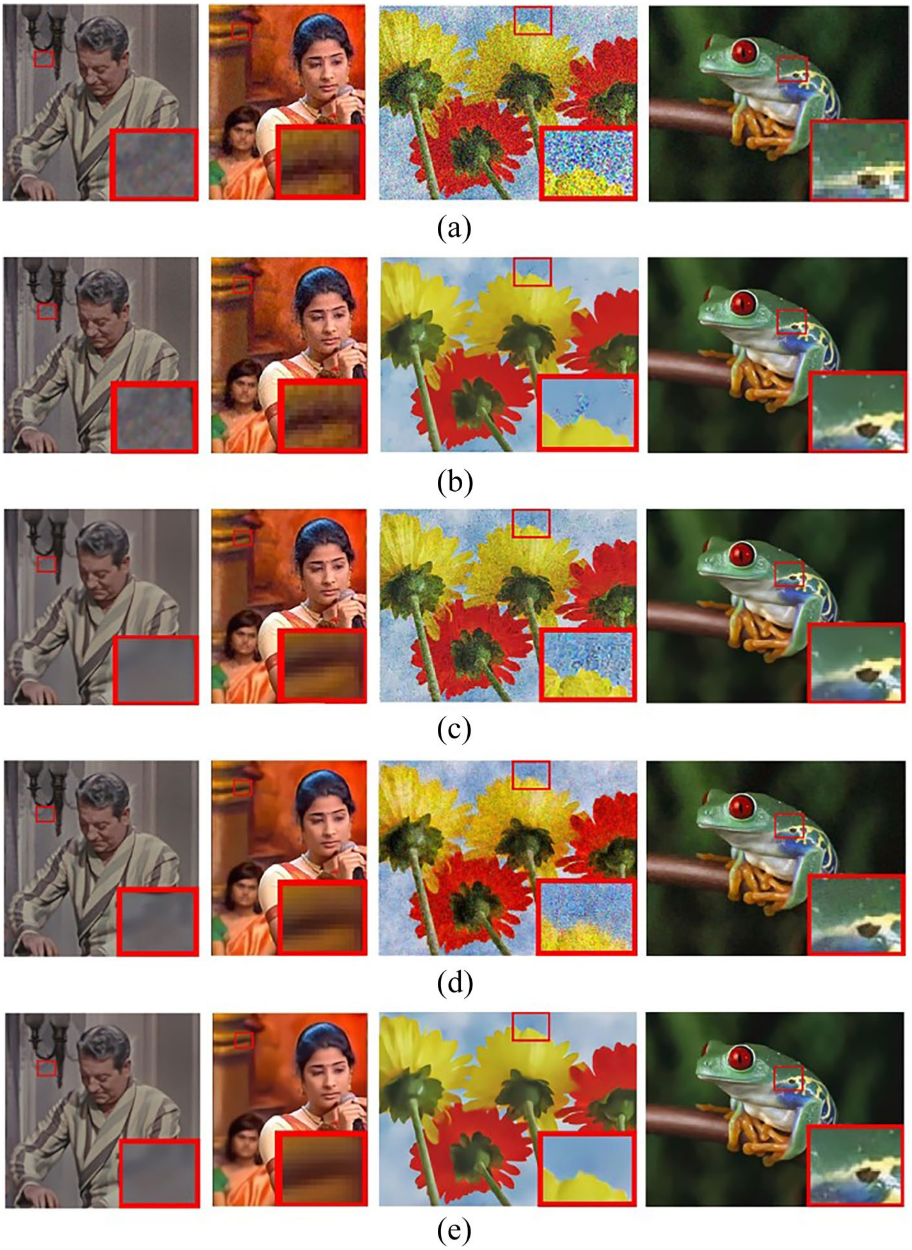

Fig. 3 Real noisy – Image denoise

self-supervised denoising for microscopy. Due to limitations in usable light, microscopy images often have high levels of noise. While self-supervised methods have emerged as an option, they can produce high-frequency artifacts and inferior results compared to supervised approaches. This new method incorporates knowledge of diffraction-limited microscopy images and includes a convolution with a point spread function to eliminate high-frequency artifacts and achieve results close to traditional supervised methods.

In 2021, Vo et al. [42] have developed the HI-GAN is a hierarchical generative adversarial network designed for blind denoising of real images. It addresses the issue of balancing between removing noise and preserving details, which is often encountered by deep convolutional neural networks and GANs. The HI-GAN comprises three generators that handle different aspects of image denoising, including restoring high-frequency features, eliminating instability caused by the discriminator, and boosting reconstruction performance. The proposed method outperforms other state-of-the-art denoisers in terms of both quantitative metrics and visual quality. In 2021, Yuan et al. [43] have proposed a novel denoising model called Partial-DNet for hyperspectral images (HSIs) with inconsistent and mixed noises. The model estimates the noise intensity of each band and uses a channel attention mechanism to generate feature maps. A multiscale neural network is then employed to extract spatial-spectral joint features. Experimental results demonstrate the effectiveness of the proposed method in removing noise from both simulated and real HSI data sets, with higher PSNR index and classification accuracy compared to other state-of-the-art denoising methods.

2.7 Hybrid noisy images

In 2018, Routray et al. [44] have presented an efficient hybrid image denoising method based on SVM classification. The noisy image is divided into overlapping patches and local features are extracted using SIFT. SVM is then used to classify the patches into texture and flat patches. Texture patches are processed using GHP and flat patches using sparse-based denoising method with K-SVD. The denoised image is obtained by merging the results of the two processes. Experiments on standard noisy images show that the proposed method outperforms existing denoising methods in preserving edges and textures. In 2018, Nourani and Partoviyan [45] have proposed a hybrid denoising-jittering data pre-processing approach to improve the performance of Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models for multi-step-ahead rainfall-runoff modeling. The approach involves wavelet-based denoising to smooth hydrological time series, followed by the addition of small normally distributed noises with varying standard deviations to form different denoised-jittered training data sets. The proposed approach, which combines denoising and jittering techniques, was evaluated for the Milledgeville and Pole Saheb stations in the USA and Iran, respectively. The study found that the proposed approach improved the performance of the ANN and ANFIS models for single-step-ahead rainfall-runoff modeling, as well as for multi-step-ahead modeling for both watersheds. In 2019, Das et al. [46] have used the Early Started Hybrid Denoising Technique for medical images, a modified Haar wavelet transform and image fusion to enhance brain images obtained using PET and CT scans. The proposed algorithm shows improved denoising parameters and image quality, with better PSNR, UIQI, and MI results for the fused images. The study focuses on hybrid techniques for medical image denoising and shows promising overall performance for brain images. Figure 4 depicts the hybrid image denoising.

In 2020, Abubakar et al. [47] have developed a hybrid denoising algorithm for division-of-focal plane (DoFP) polarization images, combining BM3D and KSVD methods. The algorithm enhances the grouping step in the second round of collaborative filtering by purifying the 'Semi-Filtered' image using KSVD before the second round. Extensive

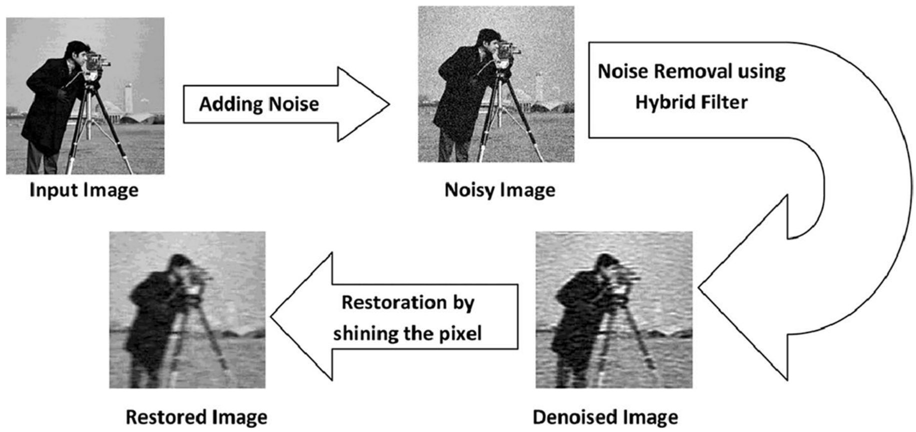

Fig. 4 Hybrid image denoise

experiments show that the proposed algorithm outperforms state-of-the-art denoising algorithms for DoFP polarization images in terms of visual quality and quantitative metrics. In 2020, Golbaghi et al. [48] have presented a hybrid image denoising method that combines the Rudin-Osher-Fatemi and fractional-order total variation models. The proposed method utilizes the advantages of both models and proves the existence and uniqueness of the presented model after introducing an appropriate norm space. The finite difference method is employed for numerically solving the obtained equation and the results demonstrate the efficiency of the proposed model, yielding good visual effects and a better signal-to-noise ratio. In 2021, Kaur et al. [49] have explored the use of a hybrid approach for denoising EEG signals in depression using Variational Mode Decomposition (VMD) and wavelet transforms. The presence of artifacts in EEG signals can lead to degraded performance in neuro engineering applications, making it necessary to carefully deploy noise-reducing algorithms. The proposed approach, which combines VMD with either discrete wavelet transforms or wavelet packet transform, effectively removes artifactual components without completely rejecting them. Simulations on artificially contaminated and real databases of depression demonstrate the effectiveness of the proposed technique using performance parameters such as SNR, PSNR, and MSE. This artifact removal system could serve as a crucial pre-processing stage for clinicians and prevent delays in the diagnosis of depression signals.

2.8 State-of-the-art methods for image denoising with deep learning

In 2018, Manjón and Coupe [50] have proposed a new method for MRI denoising that combines deep learning with classical noise reduction techniques. The method follows a two-stage strategy, with the first stage based on a patch-based convolutional neural network and the second stage using a rotationally invariant non-local means filter. The proposed approach outperforms related state-of-the-art methods in all studied cases. In 2018, Gondara and Wang [51] presented a novel approach to multiple imputation for handling missing data, which is a major issue across various domains. The proposed model is based on overcomplete deep denoising autoencoders and is capable of handling different types of data, patterns of missingness, proportions of missingness, and distributions. Results from real-life datasets demonstrate that the proposed model outperforms current state-of-the-art methods under varying conditions while improving end-of-the-line analytics. In 2019, Tassano et al. [52] have introduce a fast and efficient video denoising algorithm based on a convolutional neural network. Our approach outperforms other patch-based methods while requiring significantly lower computing times. Our algorithm also has a small memory footprint and can handle a wide range of noise levels with a single network model. These desirable properties make it a practical solution for video denoising applications. Experimental results demonstrate that our method compares favorably to other state-of-the-art algorithms in terms of both visual quality and objective metrics.

In 2019, Davy et al. [53] have used a new CNN-based video denoising approach which incorporates non-local self-similarity into the network via a non-trainable layer. This layer finds similar patches in a 3D spatio-temporal search region and gathers their central values into a feature vector assigned to each pixel. The CNN is then trained to predict a clean image based on this information, achieving state-of-the-art results. This is the first successful application of CNNs to video denoising, outperforming previous non-local patch-based methods. In 2019, Liu et al. [54] have proposed an approach to automatically optimize network structures for medical image denoising using a Genetic Algorithm-based network evolution approach. The approach expedites the evolutionary process through an experience-based greedy exploration strategy and transfer learning. The resulting method, called EvoNets, outperforms state-of-the-art methods consistently at various noise levels in denoising computed tomography perfusion (CTP) images.

2.9 Salt and pepper noise

In 2019, Thanh et al. [55] have proposed an improved version of the BPDF filter for high density salt and pepper noise removal. The original BPDF filter is effective for low and medium noise levels, but not for high density noise. The proposed method is evaluated against BPDF and DAMF filters and shows better performance on high and very high noise levels. In 2019, Fu et al. [56] have developed an image denoising algorithm for salt and pepper noise. The algorithm uses a generative model on a patch as a basic unit to locate the noise and classify patches using a generative clustering method. Finally, a non-local switching filter is used to remove the noise. The proposed algorithm effectively denoises salt and pepper noise of various densities and outperforms state-of-the-art algorithms in terms of visual quality and peak signal-to-noise ratio. In 2020, Thanh et al. [57] have proposes a two-stage filter for high-density salt and pepper noise removal in images. The filter is effective for low to high-density noise, and its performance is evaluated using peak signal-to-noise ratio and structural similarity metric. The proposed method is compared with state-of-the-art denoising methods, and it successfully removes super-high-density noise above 90%. The study highlights the importance of image restoration for enhancing image quality and facilitating post-processing tasks. Figure 5 depicts the salt and pepper noise images.

In 2020, Thanh et al. [58] have developed an adaptive total variation (TV) regularization model for salt and pepper noise removal in digital images. The model is based on L1 fidelity and a proposed estimation for regularization parameter based on salt and pepper noise characteristics. The model is implemented using the primal dual gradient method and evaluated through full-reference image quality assessment metrics on different synthetic and real images. The results are compared with other salt and pepper denoising methods, demonstrating artifact-free edge-preserving restorations. In 2021, Liang et al. [59] have

Fig. 5 Salt and pepper noise

used a fully convolutional neural network with a new type of layer called a median layer to denoise images contaminated by salt-and-pepper noise. By adding median layers into widely used fully convolutional deep neural networks, an end-to-end network is developed that removes extremely high-level salt-and-pepper noise without any non-trivial preprocessing tasks. The network outperforms state-of-the-art methods with limited training data and significantly boosts the signal-to-noise ratio when inserted into a simple fully-convolutional network with the L2 loss. Experimental results demonstrate the effectiveness of the proposed approach.

2.10 Non-linear filters for digital color images

In 2018, Wang et al. [60] have presented an improved filter for color image denoising by combining the advantages of non-local means and bilateral filters. The proposed method adds texture information to weights to compare patch similarity, resulting in better performance for reducing Gaussian and mixture noise. Non-local means filter is effective in preserving edges and details of the original image. In 2018, Tsoutsanis et al. [61] have proposed a modification to the bounds limiter for higher-order Monotone-Upstream Central Scheme for Conservation Laws (MUSCL) numerical schemes on unstructured meshes in the finite-volume (FV) framework. The modified limiter utilizes all the spatial information provided by all the elements in the reconstruction stencil. Numerical results show that the proposed extended bounds limiter outperforms cell-based or vertex-based bounds implementations in terms of accuracy and mesh sensitivity on smooth and discontinuous test problems of the Euler equations on unstructured meshes. In 2019, Punarselvam and Suresh [62] have proposed a non-linear filtering technique to test a Finite Element Analysis (FEA) model of the human lumbar spine. The FEA model is generated to simulate the biomedical properties of two vertebrae (L4 and L5) and an intervertebral disc. Different non-linear filters and edge detection techniques are used to segment the edges of the spine model, with the results compared. The study finds that the median filter produces improved segmented output results. The behaviour of the spine model is analyzed using ANSYS simulation tool in terms of various parameters like equivalent elastic strain, total deformation, and principal stresses. The proposed spine model is also implemented in MATLAB to test various filters and edge detectors. In 2020, Manju and Sneha [63] presented a study on the application of two filters, Wiener filter and Kalman filter, for removing noise from Electrocardiogram (ECG) signals. ECG signals are crucial for detecting heart problems, but are often corrupted by noise. Performance parameters such as Mean Square Error (MSE), Percentage Root Mean Square Difference (PRD), Signal to Noise Ratio (SNR), Power Spectral Density (PSD), Spectrogram, and Magnitude spectrum are used to evaluate the effectiveness of the filters. The results of the study indicate that the Wiener filter is the better option for denoising ECG signals. In 2021, Kaur et al. [64] have highlighted the importance of preserving traditional cultural artwork and how modern image processing tools can aid in restoring their quality. Noise removal and image enhancement are crucial steps in image processing, which can be achieved through various filters and techniques. The paper proposes a combination of the non-linear median filter with three different histogram equalization techniques (CLAHE, BBHE, and DSIHE) for image quality improvement. MATLAB is used for implementation and quality assessment is done using reference and non-reference quality metrics such as AMBE, PSNR, NMSE, CPP, BRISQUE, and PIQE.

2.11 Research gap/challenges

The problem of image denoising is prevalent in various fields, including medical imaging, surveillance, and computer vision. The challenge is to effectively remove noise from images while preserving the important details, which is crucial for accurate analysis and interpretation". However, traditional denoising methods often result in loss of image details and may not effectively handle complex noise patterns. As such, there is a need to explore and develop advanced denoising techniques, particularly in the context of deep learning. Despite recent advances in deep learning-based image denoising, there are several challenges that remain. One challenge is developing models that can handle diverse and complex noise patterns, such as non-Gaussian noise or mixed noise types. Another challenge is improving the speed and efficiency of denoising algorithms, particularly for real-time applications. Additionally, overfitting and generalization issues can arise when training deep learning models on limited datasets. Some potential ideas for future research in deep learning-based image denoising include developing novel architectures that combine multiple denoising techniques, exploring unsupervised and self-supervised approaches to training denoising models, and investigating the use of generative adversarial networks (GANs) for denoising. Additionally, there is a need to evaluate and compare the performance of different denoising techniques on diverse datasets and noise types to gain a better understanding of their strengths and limitations.

2.12 Problem statement

Image denoising is a crucial problem in computer vision, particularly for image processing applications. Image noise can be introduced in images due to various reasons, such as low light conditions, high ISO settings, or sensor limitations. This noise can reduce the visual quality of images, making it difficult to extract meaningful information from them. Therefore, it is essential to develop efficient and accurate image denoising techniques to remove unwanted noise and improve the quality of images [1]. In recent years, deep learning techniques have shown promising results in image denoising tasks. Convolutional neural networks (CNNs) have been widely used for this purpose, as they can automatically learn features from the input images and remove noise by exploiting the redundancy in the data. However, designing an effective deep learning-based image denoising model requires addressing several challenges, such as selecting an appropriate network architecture, training on diverse and representative datasets, and avoiding overfitting. Moreover, there is a trade-off between denoising accuracy and computational complexity. While deeper and more complex models can achieve higher denoising accuracy, they may require more computational resources and longer training times. Therefore, it is essential to develop efficient and scalable deep learning-based image denoising models that can balance the trade-off between accuracy and complexity [20]. In summary, image denoising is a critical problem in computer vision, and deep learning-based techniques have shown great potential in addressing this problem. However, designing efficient and accurate deep learning models for image denoising requires addressing several challenges related to network architecture, dataset selection, and computational complexity.

3 Conclusion

Image denoising had seen a considerable increase in interest in deep learning, but there were important differences between the various deep learning techniques employed. While optimization models were successful in estimating true noise, discriminative learning was suitable for handling Gaussian noise. There was, however, no research that compared the various deep learning methods for picture denoising. In this study, a thorough analysis of methods and strategies for picture denoising was carried out, highlighting problems with current methods. A comparison of deep image denoising approaches was presented in this paper. The study reviewed 68 publications on image denoising published between 2018 and 2023 in-depth, offering a thorough appraisal of the field's advancement and approaches during a 5-year period. The paper provided a thorough overview of image denoising in deep learning through its literature review, covering machine learning methods for denoising, CNNs for denoising, deep learning techniques for additive white noisy-image denoising, deep learning techniques for real noisy image denoising, blind denoising, hybrid noisy images, state-of-the-art methods for image denoising with deep learning, salt and pepper noise, and non-linear filters for digital images. This paper's primary goal was to present a thorough review of the many methods for picture denoising, each of which has been investigated and created based on separate research projects. The goal of the work was to compare the merits and shortcomings of different methodologies in order to provide information for next field research. For future work, it is crucial to address the challenge of handling real-life noise types beyond those studied thus far. Another important area to explore is training deep models without relying on paired image data, which remains an open problem. Additionally, there is potential to extend the methodology of image denoising to diverse applications beyond its current scope.

Data availability All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real world data with appropriate permissions.

Declarations

Data sharing Not applicable.

Conflict of interest The authors declare that we have no conflict of interest.

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