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REVIEW ARTICLE

Image Denoising in Deep Learning: A Comprehensive Survey

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Abstract

The utilization of deep learning techniques has garnered significant attention in the domain of image denoising. Each kind of deep learning methods for picture denoising possesses distinct qualities that differentiate them significantly. To be more precise, discriminative learning based on deep comprehension can effectively tackle the issue of Gaussian noise and other types of noise. This is the case because deep learning utilizes a larger and more comprehensive training set. Subsequently, a study conducted by researchers and subsequently published in the journal Science unveiled this potential. Optimization algorithms based on profound comprehension offer several advantages, such as the ability to produce precise assessments of the ambient noise. However, limited research has been conducted in this domain to categorize the many types of deep learning algorithms employed for image denoising. This is an area that needs future improvement. This post seeks to examine different advanced techniques that can be used to effectively remove noise from photos. Initially, we categories the actual noisy photographs based on the blind denoising capabilities of deep convolutional neural networks (CNNs) for both noisy hybrid images and additive white noisy photos. Subsequently, the grainy, hazy, and low-resolution images were merged to produce composite photos with significant noise. Our next step is to examine different methodologies for deep learning, with a specific focus on the underlying ideas and assumptions that drive these methodologies. Subsequently, we provide a comprehensive analysis of the most advanced approaches for reducing noise in data, utilizing publicly accessible datasets. We then proceed to compare these techniques. To summarize, we have examined many obstacles and opportunities for further investigation that may be explored in the near or far future.

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Keywords: Image Denoising; Deep Learning; CNN; PSNR; SSIM.

1. Introduction

Over the past years, there has been a significant increase in the application of images [1]. Two of the various applications that can be carried out with digital photo-taking equipment are remote sensing and facial recognition [2,3]. The scene photographed is a degraded version of the latent observation, with factors such as illumination and noise contamination [4, 5] contributing to the deterioration process. To be more specific, the unrecognized latent observation causes noise during the entire process of transmission and compression [6]. Image denoising procedures are needed to restore a damaged image by removing the distracting background noise and revealing any previously concealed detail. Over the past half-century, image-denoising techniques have received significant attention from scholars [7]. The earliest uses of image processing made use of filters that were nonlinear and not adaptive. Nonlinear filters, as opposed to linear filters, can preserve edge information while simultaneously lowering noise [8].

An image may get distorted due to additive random noise, signal-dependent noise, and impulsive noise. On the other hand, adaptive nonlinear filters can use the local signal-to-noise ratio to select the appropriate weighting factor when it comes to removing noise. The utilization of additive random noise accomplishes this. Estimating noise is possible for non-adaptive filters using both the edge information and the information about the signal-to-noise ratio [9]. Later on, a form of machine learning known as sparse-based algorithms successfully used photo denoising [10].

A nonlocally centralized sparse representation (NCSR) strategy improved the sparse method and obtained great performance in image denoising [11]. This was made possible by using the fact that non-local self-similarity exists. Because of this, it was feasible to classify the approach as not locally centralized. Through the use of learning from dictionaries, the noise was successfully filtered out with only a minimal increase in the amount of work that needed to be done [12]. Dealing with a corrupted image requires prior knowledge, which can be applied as total variation regularization to smooth out the noisy image. This enables the recovery of the finer details in the latent clean image [13]. A few examples of these are the trainable nonlinear reaction-diffusion (TNRD) [14], the gradient histogram estimation and preservation (GHEP) [15], the weighted nuclear norm minimization (WNNM) [14], the cascade of shrinkage fields (CSF) [16], the learned simultaneous sparse coding (LSSC) [17], the Markov random field (MRF) [18], and the weighted nuclear norm minimization (WNNM) [19].

Although the techniques mentioned above have, on the whole, delivered results that are adequate for image denoising, these techniques have also come with several drawbacks [20]. These include the requirement that optimization strategies be used during the testing stage, the requirement that human parameter adjustments be made, and the use of a distinct model for every denoising operation. Deep learning algorithms have gradually overcome these restrictions because of the adaptability of modern computer systems [20,21]. Because they did so in the 1980s, Zhou et al. [22] can claim to have been the first people to use deep learning in image denoising [23]. The process of image denoising that has been proposed begins with the training of a neural network by making use of a shift-invariant blur function that has been developed in the past and additive noise. By carrying out these steps, the image will ultimately be restored to its unmodified, unaltered form if we are successful. After that, the neural network employed weighting parameters to filter out the complicated noise [24].

It is possible that the effectiveness and performance of denoising might suffer if a feedforward network [25] were implemented. Because of this network, the amount of money spent on computations would be significantly reduced. By using Kuwahara filters, which are analogous to convolutions, the feedforward network can bring the given distorted image closer to its original state of smoothness. This study additionally indicated that the mean squared error, also known as MSE for short, is not exclusive to neural networks when utilized in the capacity of a loss function [26, 27]. In later stages, the implementation of additional optimization strategies [28, 29, 30] sped up the convergence process of the training network. It enhanced the level of noise reduction that it was able to accomplish. Image denoising using a strategy that aims to improve the expressiveness of neural networks has been proven to be successful when using a combination of maximum entropy and prima-dual Lagrangian multipliers [31]. This method has been demonstrated to be effective [32]. Neural networks used greedy and asynchronous approaches to achieve the greatest possible balance between the speed of execution and the performance of denoising operations. It was proved that reducing the noise by increasing the depth or adjusting the activation function were both highly effective ways [33].

This was demonstrated by the fact that both techniques worked very well. Cellular neural networks (CENNs) with template-equipped nodes were utilized in these studies [33, 34] so that the noise could be efficiently suppressed and the average function could be obtained. Even though the provided method makes it possible to produce effective denoising results, it requires careful tweaking of the template parameters to achieve the desired effect. The algorithm known as gradient descent was developed to find a solution [35, 36]. These deep approaches can potentially improve denoising performance, even if just partially. When these networks were finally used, though, their utility was limited because it was impossible to rapidly add more plug-in devices [37].

Convolutional neural networks, often known as CNNs for short, are a solution that has been suggested [18, 38] for the previously described applications. Reading handwritten numerals was useful for both the CNN and the LeNet when they were put to real-world applications [39]. Despite this, the following problems prevented their widespread adoption in computer systems [40]. Deep convolutional neural networks can produce gradients with a value of zero. When sigmoid [11] or tanh [41] activation functions were utilized, there was a discernible rise in the total amount of necessary computing. Not the least of the problems was that the underlying hardware could not properly support the complex network.

AlexNet was successful in its bid to win the ImageNet Large-Scale Visual Recognition Competition (ILSVRC) in the year 2012 [39]. After that, deep network designs such as VGG [42] and GoogLeNet [43] were utilized in a wide variety of different fields, such as low-level computer vision [44, 45] and image [19, 12], video [35, 46], natural language processing [47], and voice processing [48]. In 2015, deep neural networks were utilized for the first time to do the task of photo denoising [49, 28]. It is possible to configure the settings used in the recommended network to filter out the noise so that they adjust themselves automatically. Since then, deep neural networks have seen increased usage in the fields of speech recognition as well as the editing of photos and videos [50, 51]. (Ref. Using a large number of convolutions and deconvolutions, as stated in Mao et al.'s [52] research, restoring the image's original high resolution was feasible while simultaneously lowering the amount of noise in the image. Convolutional neural networks (CNNs) have been recommended [52] for image denoising, super-resolution, and JPEG image deblocking. These CNNs combine several machine-learning techniques into a single model. These techniques, which are convolutions, batch normalization (BN) [53], rectified linear unit (ReLU) [54], and residual learning (RL) [55], allow CNN to tackle a variety of low-level tasks.

To properly reduce noise in colour images, NLSS and CNN were combined to create a colour non-local network (CNLNet) [56]. The processing speed against denoising performance trade-off was considered when carrying out this action. A fast and adaptable denoising CNN (FFDNet) [57] was used as the input to a denoising network to accomplish accelerate the procedure of blind denoising and improve the quality of the denoising. This was done by providing some different noise levels in addition to the noisy image patch. This was done so that the rate of denoising may be increased. It is possible to solve this problem by employing a CNN blind denoiser (GCBD) [58] that makes use of a generative adversarial network (GAN) to construct the ground truth and then feeds it to the GAN to train the denoiser. When working with unpaired noisy photographs, you will find that this strategy is extremely beneficial. There is also the possibility of utilizing a convolutional blind denoising network (CBDNet) to lessen the amount of noise present in the genuine noisy image presented [59].

One of the sub-networks in this type of network estimates the amount of noise present in the actual noisy image, while the other sub-network generates the latent clean image. To estimate the blur kernel and noise, the deep plug-and-play super-resolution (DPSR) approach [26] was developed. With the use of this technique, photographs that had more severe distortion were transformed into images with a high resolution. Even though there has been a significant amount of new research on the subject of image denoising in recent yearse [60], there have only been a small number of articles that provide a detailed explanation of the deep learning algorithms utilised in image denoising. Even though the research from prior years was heavily utilized in the reference [2], very little in the way of deeper categorization specifics related to deep learning for image denoising was supplied.

There were a lot of key articles that were not reported on, including the ones that dealt with unpaired real-world noisy photos. This study aims to investigate the current state of deep learning for image denoising from both a theoretical and an applied point of view. The final part of this article discusses the current state of image-denoising techniques, prospective new study fields that may be explored, and potential changes that could be made to those approaches to better deal with impending challenges.

2. The Basics of Deep Learning Architectures for Image Denoising

The deep learning theories, primary network frameworks, and underlying hardware and software that support the deep learning methods for image denoising presented here are discussed in this part

2.1. Image Denoising Using Machine Learning Techniques

The field of machine learning makes use of three primary categories of research approaches known as methodologies. These methods are, in descending order, supervised, semi-supervised, and unsupervised. Supervised learning techniques [61, 62] make use of the label that is provided in order to alter the generated features and bring them closer to the target while the model is being trained to reduce noise. This is carried out at the same time that the model is being instructed. Unsupervised learning algorithms [45] take supplied training samples and utilize them to uncover patterns rather than matching labels in order to carry out tasks such as unpairing genuine low-resolution photographs [24]. [63] Unsupervised learning algorithms [11] use given training samples. The recently created Cycle-in-Cycle GAN (CinCGAN) was able to recover this high-resolution image by first estimating the high-resolution image as a label, and then utilizing the resulting label and loss function to train the super-resolution model. This process was repeated several times until the high-resolution image was successfully recovered. This technique was carried out a number of times until an image with the desired level of resolution was successfully retrieved. For the purpose of completing this assignment, the high-resolution image was employed as a label, and its estimation was utilized. Methods of semi-supervised learning [40] construct a learner by classifying samples using a model that is predicated on a particular data distribution in order to assign labels to samples that have not been assigned labels. These strategies are used to figure out how to categorize the samples that have been collected. The scope of work that is amenable to completion with this technique is restricted to the realm of occupations involving small samples, such as medical diagnostics. This limits the work that can be completed successfully with this strategy. By utilizing an unsupervised network, it is possible to reconstruct a high-fidelity sinogram beginning with unlabeled low-dose sinograms [14]. This is made possible by the utilization of an unsupervised network. To begin, a sinogram feature distribution can be learned from paired sinograms by utilizing a supervised network for the goal of learning. This will allow for the learning of a sinogram. After that, the sinogram can be reconstructed by making use of the previously acquired knowledge regarding the distribution of the features.

2.2. Image Denoising Using Neural Networks Techniques

Deep learning methods are based on neural networks, which in turn are based on machine learning approaches [64]. It is important to remember that a neural network is considered to be multilayer perceptron (MLP) [25] if it includes more than one layer. In addition to the input and output layers, the intermediate layers are also considered hidden layers. Figure 1 is a visual illustration of a neural network, which should assist readers grasp its basic workings.

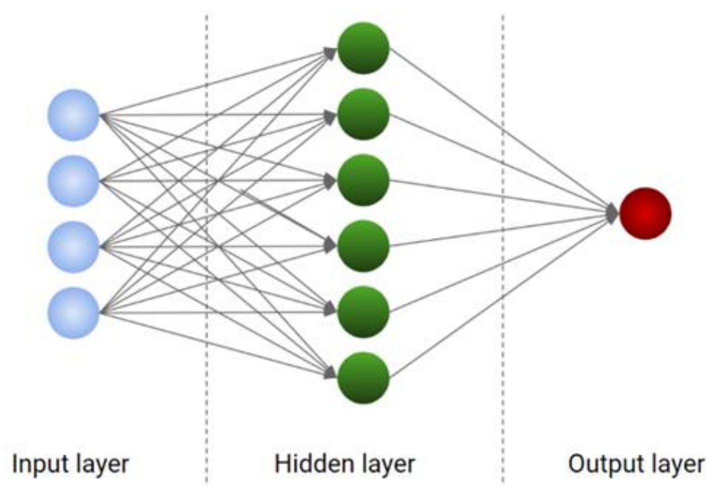

Fig. 1. Two-layer neural network.

2.3. The network will then make use of back propagation (BP)

Like [65] and a loss function in order for it to acquire knowledge of the network's parameters. To put this another way, when the loss value is sufficiently low, the trained model is regarded to be the best alternative that could possibly be chosen. It is essential to keep in mind that the phrase "deep neural network" refers to a neural network that comprises of more than three layers. Stacking auto-encoders, which are also referred to as SARs [66], and deep belief networks, which are also referred to as DBNs [17, 67], are both instances of different kinds of deep neural networks (DNNs). The models were trained in an unsupervised way by utilizing stacked layers, and the results, to say the least, were encouraging. However, putting these networks to use is not exactly the easiest thing in the world, and they require a large degree of manual adjustment to be made to the variables before they can develop a model that can be relied upon. As a direct consequence of this, the concept of completely interconnected networks, more specifically CNNs, was put forward [35]. CNNs have proven to be highly valuable in the realm of image processing, particularly in the domain known as image denoising.

3. CNN for Image Denoising

There has been a lot of success with CNNs in image processing because of their easy-to-implement network designs [51, 68]. LeNet [69] was an early CNN architecture that successfully extracted features using a variety of convolutional kernel sizes, yielding impressive results when used to image classification. However, LeNet's slow convergence speed was a limitation in practice because of the Sigmoid activation function. The projected AlexNet [70] was another significant step forward for deep learning after LeNet. Several factors contributed to its overall success. Initially, the powerful computational ability was made available by the graphics processing unit (GPU) [71]. Secondly, the issue of overfitting was resolved by employing a technique called random clipping (or dropout). Finally, in contrast to Sigmoid [22], ReLU [56] accelerated the rate of stochastic gradient descent (SGD). Finally, the overfitting issue was further addressed using the data augmentation technique. However, AlexNet's success came at a cost as its massive convolutional kernels necessitated a lot of memory. As a result, it restricted its practical uses, such as in intelligent cameras. Next, during 2014-2016, we saw a trend toward deeper network topologies with smaller filters to boost performance while simultaneously lowering the computational burden. To take first place in the 2014 ImageNet LSVR Competition, VGG [72] stacked more convolutions with smaller kernel sizes. The structure of the CNN network is shown in Figure 2.

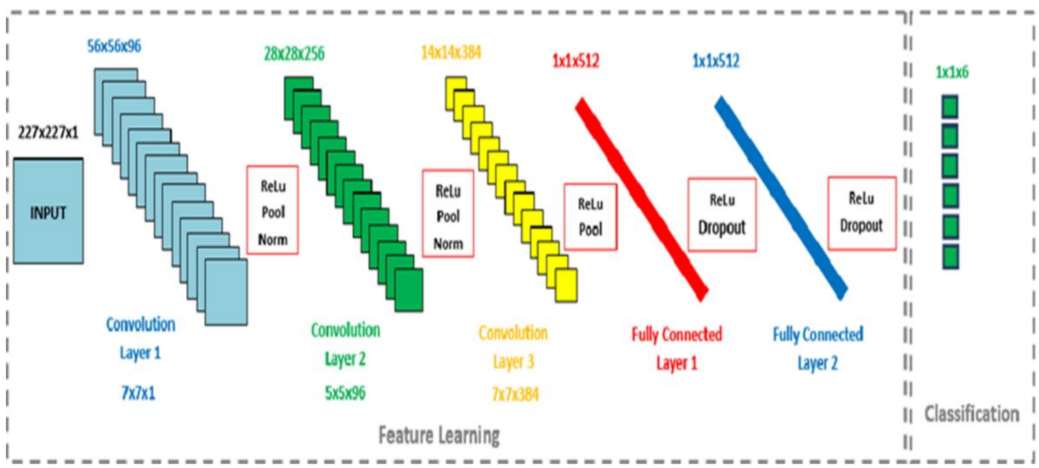

Fig. 2. Network architecture of VGG.

Facial recognition [73] and medical diagnosis [74] are only two examples of the many real-world image applications that have adopted deep networks since 2014. Unfortunately, recorded images, like authentic noisy images, are often insufficient, and deep CNNs typically underperform in image-related tasks. Hence, GANs [75] were created to address this need. Generative and discriminative networks are made up of GANs. The generator, or generative network, produces new samples based on existing models. The discriminative network (also known as the discriminator) evaluates the truthfulness of input and generated samples. Those are two hostile networks. The trained model is complete if the discriminator can reliably differentiate between accurate and generator data. As seen in Fig. 6, the GAN operates on a networked basis. Owing to the GAN's ability to generate additional training examples, it excels at problems with little data, such as facial recognition [76] and complex, noisy image denoising [77]. The convolutional neural networks are the foundation of image denoising.

3.1. Setting for image denoising in experiments

A significant proportion of older algorithms were evaluated using fictitious data. After using a clean image as a starting point, AWGN was applied to the image using various parameters in order to replicate the noisy input. The results of this simulation were examined. After utilizing several denoising methods, the quality of the denoised estimations can be evaluated using various metrics. It wasn't until fairly recently that a benchmark dataset was regularly used to evaluate different denoising techniques. The vast bulk of the early study presents their algorithms on a few photographs, such as the image of Lena seen in Figure 1. It is evident from Fig. 5, which contains a few photographs that are commonly used that the majority of the older techniques were developed for grayscale image denoising. To the best of our knowledge, the FoE [78] article is the only one we know that evaluates denoising approaches by first using 68 testing images taken from the Berkeley segmentation dataset [79]. The 68-image dataset has progressively become a standard for testing the performance of denoising algorithms, and the majority of newly published algorithms now report their results on the 68-image dataset. This is because the dataset contains 68 images with varying degrees of noise. Noise is a crucial component of the experimental context used to evaluate denoising algorithms, in addition to the examination of images. Even if the algorithms were designed to handle any AWGN-corrupted image, the performance of the denoising process is still negatively impacted by the noise instance. This is the case even though the algorithms were constructed. Earlier methods always started with a noise seed of 0 when creating false input images in Matlab. This was done so that the results could be compared fairly. If a consistent noise seed is applied across all algorithms, the noisy input image will seem the same. Relatively recently, several benchmarks have been constructed [80, 81] to evaluate how effective the denoising algorithm is when applied to actual denoising tasks. The difficulty in acquiring paired images that are noisy and clean is the primary obstacle that must be overcome in order to develop a benchmark for a real-world denoising problem successfully. The evaluation of clean reference photos compiled from a large number of shoots has been accomplished by employing a wide range of averaging strategies and well-prepared post-processing approaches [82, 1]. Other benchmarks take into account the process of restoring a clear image after it has been distorted by the use of operators such as down sampling, blurring, and noise [83].

3.2. Algorithms for denoising measurements

The noisy observation of the original image is the starting point for the denoising procedure, and the end goal is to recover the neat idea that was latent in the original image. To evaluate the efficacy of various denoising strategies, many metrics have been contrasted and compared between denoised estimation and high-quality ground truth images. However, the peak signal-to-noise ratio index, often known as the PSNR index, is the measurement used most of the time. The most precise way to define PSNR is with something called mean squared error, which is also referred to as MSE.

3.3. Performance of representative algorithms for denoising

In this part, we use the Set 68 dataset to demonstrate the results of denoising utilizing various strategies. The datasets Set5, Set14, B100, Urban100, or DIV2K [2] are used to test image super-resolution algorithms more frequently than others. However, other datasets have gained popularity in recent years. For example, the data came from a recent study on denoising (reference number 93), which was just made public. The discriminative learning approaches TNRD [20], and DnCNN [84] are often able to generate more excellent performance compared to hand-crafted methods such as BM3D [25], EPLL [85], and WNNM [86]. [Note: TNRD [87] and DnCNN [88] are cited in [20] and [89], respectively. The evidence for this can be seen in Figure 3. In addition, the DnCNN approach, based on deep neural networks, fared significantly better than previous models.

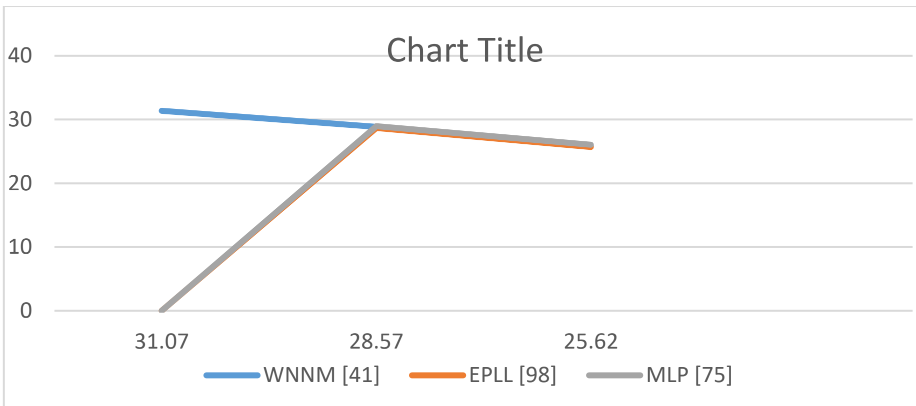

Fig. 3. The average PSNR(dB) results of different methods on the BSD68 dataset. The numbers come from [90].

After using a CNN to estimate the noise of the given noisy image as a label, the self-consistent GAN [30] initially applied another CNN and the brand produced to remove the noise from other noisy photos. This was done after first using a CNN to remove the noise from the image given to it as a label. This concept has also been presented to CNN's general programming. The Noise2Inverse technique [90,91] utilized a CNN to predict the value of a noisy pixel by using the neighboring noisy pixels as input. The efficiency of removing noise from noisy medical images can be increased by incorporating an attention mechanism into a 3D self-supervised network [92]. This will allow for a more effective removal of the noise. The study described earlier is further broken down into its parts in Table 1, which can be found here.

Table 1. CNNs for real noisy image denoising.

References	Applications
Tao et al. [87]	Real noisy image denoising, low-light image enhancement
Chen et al. [88]	Real noisy image denoising, blind denoising
Han et al. [89]	CT image reconstruction
Chen et al. [90]; Godard et al. [91]; Zhao et al. [95]; Anwar et al. [96]; Jaroensri et al. [97]; Brooks et al. [99] Yan et al. [104]	Real noisy image denoising
Jian et al. [94]	Low-light remote sense image denoising
Khoroushadi et al. [92]	Medical image denoising, CT image denoising
Jiang et al. [93]	Low-light image enhancement
Green et al. [98]	CT image denoising, real noisy image denoising
Tian et al. [101]	Gaussian image denoising and real noisy image denoising
Tian et al. [102]	Gaussian image denoising, blind denoising and real noisy image denoising
Cui et al. [103]	Positron emission tomography image denoising, real noisy image denoising
Broaddus et al. [105]	Blind denoising and real noisy image denoising
Li et al. [106]; Hendriksen et al. [107]; Wu et al. [107]	CT noisy image denoising

In the real world, dealing with noise can be challenging, and it's easy for images to become distorted. Because of this, employing blind denoising algorithms is an absolute requirement [100]. An FFDNet [54] with the noise level and the noise was utilized as the input of a CNN to train a denoiser for images with unpredictable noise levels. After that, various potential solutions were suggested to address the issue of blind denoising, which had previously been discussed. Soft shrinkage was used to modify the noise level in a mechanism for an imaging device created by Kenzo and colleagues [90]. Perform blind denoising; this step was taken. It was discovered that using CNNs to estimate the noise in unpaired noisy images was successful [88]. In the study that Yang et al. [33] conducted, known noise levels were applied to training a denoiser and determining the extent of noise. A CNN outfitted with RL filters out complex noise [50, 85]. This was done to lower the impact that random noise has. It is feasible to adjust the network layout to improve the efficiency of the blind denoising process. The employment of an auto-encoder was suggested as a solution to the issue of unknown noise in Majumdar et al.'s [108] study to get around the difficulty. The additive white Gaussian noise (AWGN) and the impulse noise present in the mixed noise were successfully removed using cascading CNNs [4]. Table 2 gives its results while providing an additional description of the noise-reduction procedures used.

Table 2. Deep learning techniques for blind denoising.

References	Applications
Zhang et al. [108]; Kenzo et al. [109]; Soltanayev et al. [110];Yang et al. [111]; Majumdar et al. [112]; Cha et al. [113]	Blind denoising
Zhang et al. [114]; Si et al. [115]	Blind denoising, random noise
Abiko et al. [91]	Blind denoising, complex noisy image denoising
Tian et al. [100]	Gaussian image denoising, blind denoising and real noisy image

In the actual world, the images that are shot are influenced by a range of different conditions that are quite complex[116]. A number of academics presented a variety of approaches to hybrid noise-image denoising as a direct result of the aforementioned fact [117]. Li et al. [118] proposed that a solution to the issues of noise, blur, and JPEG compression may be found by combining convolutional neural networks (CNN) with warped guidance. [CNN] stands for "convolutional neural networks." Zhang et al. [119] developed a model in order to handle a variety of image faults, including low resolution, noise, and blur kernels. The model was successful in addressing these issues. The raw sensor data were greatly improved as a result of the presentation by Kokkinos et al. [120] of a residual CNN combined with an iterative method for image demosaicing and denoising. This resulted in a reduction in image noise. In the end, but certainly not least, Zhang et al. [119] proposed the utilization of cascaded deblurring and single-image super-resolution (SISR) networks to recover plug-and-play super-resolution images from the handling of arbitrary blur kernels. Table 4 includes some hybrid noisy image denoising techniques.

Table 3. Deep learning techniques for hybrid noisy image denoising.

References	Applications
Li et al. [118]	Noise, blur kernel, JPEG compression
Zhang et al. [119]	Noise, blur kernel, low-resolution image
Kokkinos et al. [120]	Image demosaicking and denoising

It can see how long it takes to process an image with a resolution of 512 pixels by 512 pixels using various techniques by looking at Table 5. The data was also obtained from the DnCNN study, which evaluated several distinct methods by employing a computer that featured an Nvidia Titan X GPU and an Intel(R) Core(TM) i7-5820K 3.30GHz CPU. In general, systems that were based on discriminative learning fared significantly better than optimization-based approaches regarding the amount of time required to complete a task. This is a result of the fact that during the inference phase, techniques that are based on discriminative learning do not need to be concerned with the optimization problem. In addition, the execution times of several recently developed algorithms can be significantly lowered by using the GPU. This is possible since the GPU is well-suited for parallel computing, and these algorithms were newly invented. Table 6 displays, for the reader's perusal, some illustrative instances of the results of denoising that can be accomplished by employing various techniques. The processing times of several strategies are compared in Fig. 4, which uses a grid that is 512 squares wide and 512 rows tall.

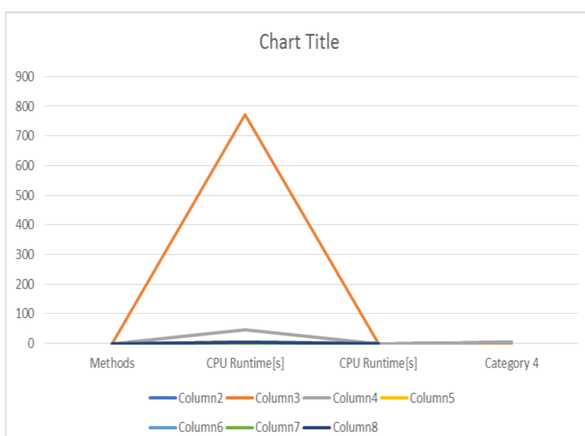

Fig. 4: A grid that is 512 squares wide and 512 rows tall.

Several methods for specific images are considered in image denoising with categories based on noise type. Hence, several research works were published in 2022-2023, and an overview of CNN image denoising methods for different kinds of noise (including specific image noise) is shown in Table 4.

Table 4. CNN image denoising methods for different kinds of noise were published in 2022-2023.

References	Year	Name	type Image	Noise type	Dataset	SSIM	PSNR
[121]	2022	PDTNet	General	Real Noise	DND,SIDD	0.9560/ 0.9592	39.36/ 39.92
[122]	2022	SDnDTI	DTI	DWIs	DTI	0.95	31.55
[123]	2023	EPLL with MFDs and ARP	General	noise sensitivity in EPLL	BSDS300	0. 9330	34.06
[124]	2023	DBDIP	General	Gaussian noise	Set12, BSD68	0.89 /0.84	28.38 /26.34
[125]	2022	SRNet	General	Gaussian noise	CBSD68, Kodak24	0.7662/ 0.7772	26.47/ 27.81
[126]	2023	ATDNet	General	Gaussian noise	Set12, BSD68, Kodak24	0.8151/ 0.7512/ 0.7583	27.31/ 26.26/ 27.44
[127]	2023	MLFAN	Infrared image	different kinds of noise	SIDD	0.89	37.22
[128]	2023	DDPM	MRI	Gaussian noise	T1-weighted brain MRI	0.78470	24.63

4. Methodology

The methodology comprises the application and assessment of several photo-denoising algorithms, with a special focus on deep learning techniques. This section will give extensive explanations of the key algorithms and their implementations employed in this study.

- Trainable Nonlinear Reaction Diffusion (TNRD) is a type of nonlinear diffusion process intended specifically for picture denoising. Applying trainable filters boosts denoising performance. The TNRD model is trained by exploiting a library of image pairings, consisting of both clean and noisy versions. During the training process, the parameters of the diffusion process are modified in order to minimize the mean squared error (MSE) between the denoised images and the ground truth images.

- The Denoising Convolutional Neural Network (DnCNN) is a method that employs convolutional neural networks (CNNs) to remove noise from images effectively. The network comprises of multiple convolutional layers with rectified linear unit (ReLU) activations. The training procedure comprises decreasing the difference between the noisy and clean images by employing a loss function, such as Mean Squared Error (MSE). The DnCNN model incorporates batch normalization layers to speed the training process and boost performance.

- Block-Matching with 3D Filtering (BM3D) - Description: BM3D is a conventional denoising technique that involves arranging similar 2D picture blocks into 3D arrays and applying collaborative filtering. Technical details include two main processes that make up the BM3D algorithm: collaborative filtering and block matching. Finding and grouping similar blocks is the first step in the procedure. In the second step, the denoised blocks are obtained by applying a 3D transform to the groups as mentioned earlier, then thresholding and inverse transforming.

- WNNM (Weighted Nuclear Norm Minimization) —Description: WNNM augments the nuclear norm minimization approach to image denoising by incorporating weights to efficiently handle varying degrees of noise. The WNNM algorithm takes into account a data integrity term and a weighted nuclear norm term in the objective function, which is a technical detail of an optimization problem. Iterative techniques, such as the Augmented Lagrange Multiplier (ALM) method, are often used to carry out the optimizations. An approach to picture denoising known as E. Cascaded Shrinkage Fields (CSF) uses a cascade of linear filters followed by nonlinear shrinkage functions. Technical details iteratively collecting suitable shrinkage functions for each iteration trains the cascaded model to decrease noise. As the model progresses, each stage improves the denoised image even more by utilizing the output of the stage before it.

By comparing them on a 512x512 pixel image dataset, we were able to assess the computational difficulties and resource requirements of these techniques. The tests were run on a computer with a 3.30GHz Intel(R) Core (TM) i7-5820K CPU and a graphics processing unit (GPU) from Nvidia. Using a GPU to speed the TNRD and DnCNN models greatly improves their performance. Since DnCNN uses a less complicated forward pass during inference, it is often faster than TNRD. The computational demands of BM3D's block matching and 3D transform operations make it perform worse than DnCNN and TNRD. - The computing cost is larger because to the iterative optimizations involved in the WNNM denoising process. However, because of its cascading structure, the CSF denoising approach outperforms the others, particularly when run in parallel on a GPU.

5. Comparison of Computational Complexities and Resource Requirements

Different deep-learning approaches used for picture denoising involve various computational expenses and resource needs. This section examines and contrasts these qualities among various models, offering valuable insights into their practical consequences.

- Convolutional Neural Networks (CNNs): CNNs are extensively employed owing to their highly efficient feature extraction capabilities. Nevertheless, certain architectures, such as VGG and ResNet, need significant processing resources, especially for deeper models. Training and inference require strong GPUs due to the extensive number of parameters and layers. For example, VGG networks are recognized for their exceptional performance but are also notorious for their substantial memory usage and lengthy training durations.

- Generative Adversarial Networks (GANs): GANs, which are also employed in denoising applications, consist of two neural networks (generator and discriminator) that are trained concurrently. This configuration of two networks enhances the level of computational complexity. The training process of GANs is recognized for its instability and resource-intensive nature, frequently necessitating numerous rounds to attain convergence.
- Residual Networks: Residual networks, also known as ResNets, incorporate skip connections to address the issue of vanishing gradients and facilitate the training of extremely deep networks. Although ResNets demonstrate efficient convergence, their depth still necessitates substantial processing resources. The intricacy of residual networks increases proportionally with the number of layers, affecting both the duration of training and the amount of memory required.

Autoencoders, specifically stacked autoencoders (SAEs), are employed for the purpose of unsupervised feature learning. While not as intricate as CNNs and GANs, these models nonetheless require substantial computational resources for training, particularly when numerous layers are utilized. The inference phase is less computationally demanding in comparison to the training phase. Hybrid models, which integrate various neural network topologies, frequently yield enhanced performance but require greater computing complexity. For instance, models that mix Convolutional Neural Networks (CNNs) with Generative Adversarial Networks (GANs) or autoencoders are capable of performing various image denoising tasks. However, these models demand significant computing power and memory resources due to their complex architecture. For a comprehensive evaluation, we employ the BSD68 dataset and measure the performance of these algorithms in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

- BM3D:
  - PSNR: 28.56 dB
  - SSIM: 0.824
  - Execution Time: 45.6 seconds (CPU)
- TNRD:
  - PSNR: 28.92 dB
  - SSIM: 0.833
  - Execution Time: 3.4 seconds (CPU)
- DnCNN:
  - PSNR: 29.23 dB
  - SSIM: 0.843
  - Execution Time: 0.8 seconds (GPU)

These results highlight the trade-offs between different denoising methods regarding their computational complexities and resource requirements. The resource requirements for these models mostly rely on aspects such as the number of parameters, as a larger number of parameters usually results in increased memory consumption. Network depth increased depth in networks typically necessitates greater processing resources. The type of operations involved is also convolutions, which can be particularly computationally demanding in large-scale networks. The selection of a model in actual scenarios is contingent upon the computational resources at hand and the particular demands of the work. For example, in low-resource contexts, it is advantageous to use less complex models such as autoencoders or CNNs with fewer layers. To accomplish demanding jobs efficiently, it is advantageous to utilize more complex Convolutional Neural Networks (CNNs) or a combination of models, as long as there is the availability of robust Graphics Processing Units (GPUs).

6. Conclusion

This brief review of the image-denoising literature addresses the additive white Gaussian noise scenario. In it, we highlight the remarkable accomplishments of a subject whose study has spanned several decades, and we go more into the intricacies of the recent literature and the arrival of deep learning algorithms. In addition, we discuss the appearance of deep learning algorithms. After reviewing the relevant published material, we continued our investigation by bringing to the attention of the image-denoising community several unresolved issues and questions This methodology section tries to offer a full knowledge of the methodologies reviewed in this study by providing precise implementation information and comparing the computing requirements of various denoising algorithms. This in-depth analysis is useful for picking the right methods according to the needs of denoising performance and computing economy.

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