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Deep Generative Adversarial Networks For Noise Reduction in Medical Images: A Review

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Abstract

Imaging is a vital component of the diagnostic and early detection processes for many medical disorders. However, the noise in the images can sometimes interfere with the accuracy of the diagnosis. Speckle noise, Poisson noise, salt and pepper noise, and Gaussian noise are a few instances of these disturbances, which are produced by imaging techniques and reduce diagnostic accuracy as well as image quality. Noise reduction methods, such as spatial filtering and transformational domain filtering, have a lot of problems when dealing with various kinds of noise. With the growth of deep learning, especially generative adversarial networks, the capabilities of image noise reduction are even superior to those of traditional techniques. This study compares the efficacy of GAN techniques with traditional de-noising techniques and illustrates the effects of various noise sources on medical imaging. Besides that, it describes how the GAN accomplishes the noise reduction task in medical imaging by discussing its advantages, uses, and efficiency in comparison to other techniques. The study's outcomes revealed a new approach to using GAN to filter out the noise in medical images and the possibility of utilizing this technique in real-world cases to generate accurate diagnosis and analysis. But, in addition to that, it serves as a passageway to more in-depth research that focuses on medical image enhancement and patient healthcare.

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1. Introduction

Medical imaging has several clinical applications, such as early diagnosis, monitoring, treatment evaluation, and condition assessment. There is no doubt that medical imaging, particularly positron emission tomography (PET), computed tomography (CT), magnetic resonance imaging (MR), mammography, ultrasound, X-rays, and so on, is valuable for the early detection, diagnosis, and treatment of disorders. This idea has become evident over the past few decades [1].

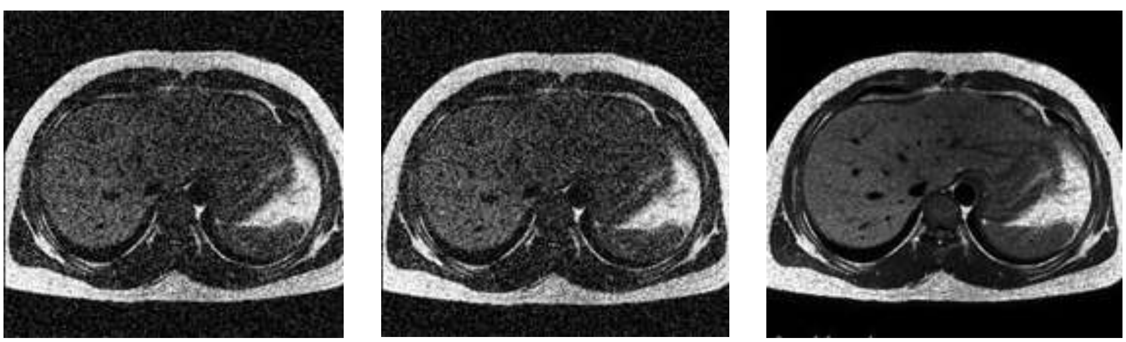
This device can be sensitive to various types of noise, so the image degradation and the difficulty of diagnosis will be significant [2]. Interfering signals from electronic equipment and surroundings, as well as human factors, can result in noise and blurry images, which are common [3]. Normally, there are different noise levels and types of noise. They may be from many sources that might have similar or different frequencies [4]. Denoising the image is an important requirement for medical imaging pre-processing that will make the image clean from noise and keep the sharp structures such as corners and edges. Computed tomography (CT), magnetic resonance imaging (MR), and ultrasound (US) are the three most widely used medical imaging modalities. These approaches can sometimes be contaminated by deleterious noises such as Poisson, Gaussian, salt & pepper, and speckle [5]. Four methods of image quality assessment (IQA) metrics—Root Mean Squared Error (RMSE), Peak Signal

Noise Ratio (PSNR), Mean Absolute Error (MAE), and Structural Similarity Index (SSIM)—have opted to implement different types of denoising filtering methods, such as bilateral, non-local means, hybrid median, Gaussian, Wiener, and anisotropic diffusion [6]. Nevertheless, traditional techniques frequently focus on and eliminate a certain type of noise, which has disadvantages, including ineffectiveness in managing various noise levels. Recently, all conventional methods for broad photo denoising have been exceeded by models based on deep neural networks, especially generative adversarial networks.

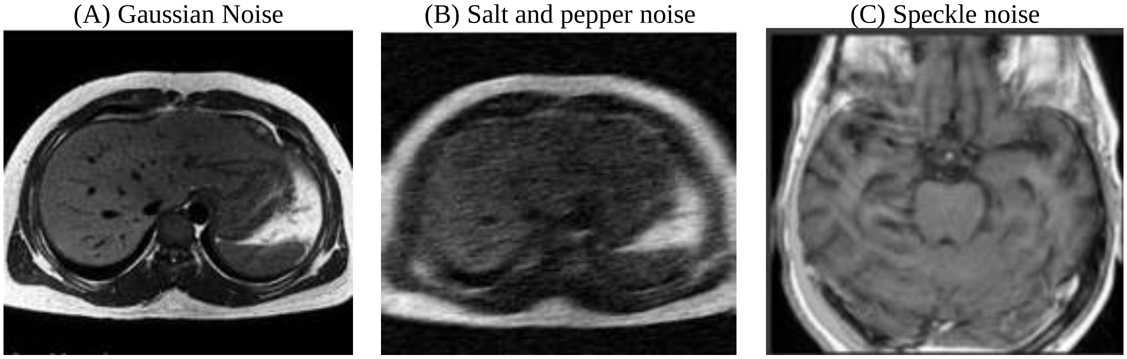
Image noise causes an inconsistent variation of contrasts in the images. Different types of noise can affect images. Regular sources like particles or thermal vibrations, as well as the distinct radiation of warm objects, can produce Gaussian noise. Exponential sound waves can also contribute to the production of Gaussian noise. Speckle noise is a complex phenomenon that distorts image value by introducing backscattered wave presence. It also makes it harder for the viewer to pick out minute features in the picture during investigative checks. It derives from several microscopic, scattered reflections across internal organs. The term "salt-and-pepper noise" is often used to describe information drop noise [7].

The following is a list of the most common types of noise found in medical images:

- *Gaussian Noise:* may also be referred to as enhancer noise. Electronic circuit noise, temperature-related sensor noise, and inadequate lighting all contribute to Gaussian noise. [8][9], as shown in Figure (1A).
- *Salt and Pepper Noise:* Impulse noise is the kind of noise in an image that shows the highest values in white pixels and the lowest values in black pixels. The noise will replace the value of the image pixels when it is detected by the camera's sensor [10], as shown in Figure (1B).
- *Speckle Noise*: Speckle Noise it is also called a multiplicative noise, it is a granular noise that by nature exists which affects the accuracy of the medical images [11], as shown in Figure (1C).
- *Poisson Noise*: Electronic noise, known as Poisson noise, is a type of uncertainty associated with light intensity. This happens in an image when there aren't enough energy-carrying particles, such as electrons, for there to be detectable differences [12], as shown in Figure (1D).
- *Blurred Noise*: External influences and light intensity are the causes of blurred noise. When an object moves, it is misrepresented by many pixels. Furthermore, it's unclear where the pixel value boundaries are. When there is picture blurring, it becomes challenging to identify objects [13], as shown in Figure (1E).
- *Motion Artifacts Noise*: These artifacts occur as a result of two reasons. first, internal factors such as the patient's heartbeats and breathing. second, the motions that come from outside of the patient’s body(motion of the devices or equipment during the image capturing) [14]. They appear as blurring, streaking, or ghosting effects on the image, as shown in Figure (1F).



(A) Gaussian Noise (B) Salt and pepper noise (C) Speckle noise



(D) Poisson Noise (E) Blurred Noise (F) Motion Artifacts Noise

Figure (1): the most prevalent kinds of noise that are present in medical images[11].

2. Research Methods

Image pre-processing, often know Image pre-processing, often known as image denoising, comes before image processing. It is a series of adjustments made to the image to enhance its visual quality by lowering or eliminating noise. It is a series of adjustments made to the image to enhance its visual quality by lowering or eliminating noise [15].

In this paper, two important techniques in the field of medical imaging and its applications, especially noise removal or reduction, were addressed. These techniques are Traditional and Deep Learning-Based.

2.1 Traditional Techniques

One common technique for removing damaged or noisy pixels from an image is called spatial domain filtering [16]. It is a series of mathematical procedures that modify every pixel in the image plane. Here, we use the window filtering technique on every pixel within the image by applying mathematical-based filtering algorithms to the pixels. Additional classifications of spatial filters include linear and non-linear [17]. One type of linear filter is the mean filter. However, the edges become blurry, which is a disadvantage [18]. The median filter is a non-linear technique for spatial filtering [19] (as shown in Figure 2).

In research studies, an enormous amount of attention was paid to the second class of image-denoising algorithms, or transform domain filtering. To efficiently filter through this new form and extract additional information from the signal, in contrast to the original form, it can be thought of as a series of filtering procedures that deal with the image in other contexts (other domains), like the frequency domain.

A brief description of the common traditional techniques is summarised as follows:

- **Filtering Methods** [20]**:** The mean, median, and Gaussian filters are the ones that are most often used. The neighbourhood average is used by the mean filter to replace each pixel value. The neighbourhood median is used by the median filter to replace each pixel value. A weighted average that considers the neighbourhood is applied using the Gaussian filter.
- **Wavelet Transforms**: Wavelets are mathematical techniques that separate the source signal into several frequency components and analyse each one separately. The wavelet transform's (WT) basis functions are scaled based on frequency [21].
- **Anisotropic Diffusion**: is a method for lowering image noise without significantly altering the image's content; these elements are usually borders, lines, or other information that are crucial to understanding the image [22].
- **Non-Local Means**: This is created using the mean filter. The image input is divided into sub-images, and the distance between the sub-images is calculated. These weights are then used for the evaluation of the image's pixel values to eliminate noise [23].
- **Dictionary Learning**: is a method for processing images that is used to eliminate noise [24]. whereby the algorithm acquires knowledge of a dictionary of basis functions, or "atoms," that are capable of representing image patches sparsely and efficiently eliminating noise from the image. For the technique to function, patches must first be extracted from the image. Next, a dictionary of atoms that best represent the patches must be learned. After the dictionary is learned, it may be used to reconstruct the imagery by mixing the patches to create the final image and determining which patch in the dictionary has the sparsest representation.

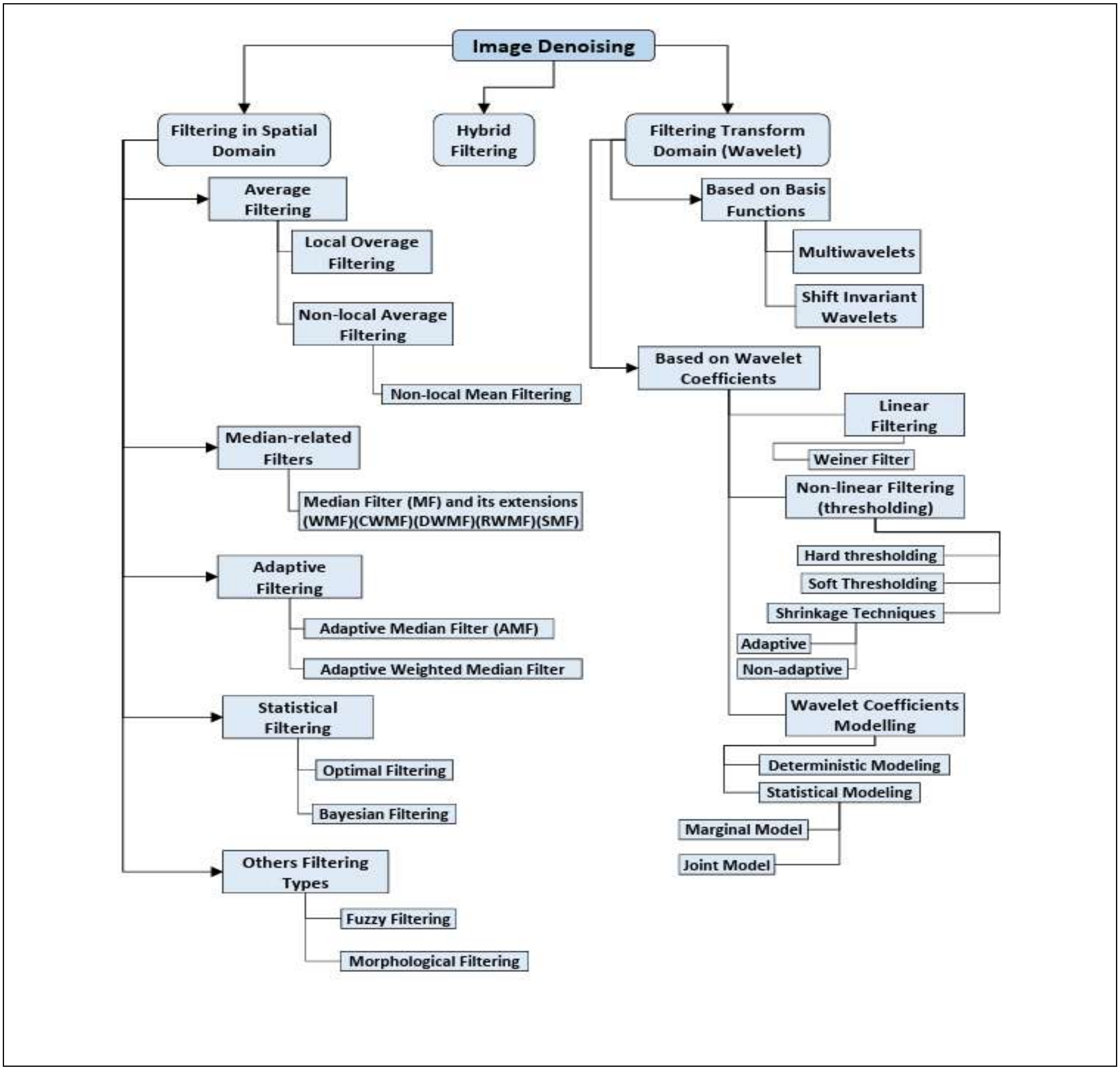


Figure (2): Image Denoising Approaches.

3. Deep Learning-Based Denoising Techniques

Various deep-learning architectures are used for denoising medical images, each with its unique advantages and disadvantages [25][26]. These are some of the most prevalent:

3.1 Convolution Neural Networks (CNN)

Image denoising is dominated by CNN-based techniques, which have demonstrated good results in eliminating artificial noise [27]. The pooling layer and the convolutional layer make up CNN's most crucial architecture. The fundamental part of a CNN is called a convolutional layer, which combines linear operations (convolution) and nonlinear operations (activation function) to primarily extract features [28].

For image-denoising applications, especially medical image-denoising, CNNs have been frequently employed. Thakur [29] examined and categorised many CNN methods for image denoising in recent work. They also looked at well-known datasets that are used to assess CNN image denoising techniques. Modern CNN image denoising techniques were shown in graphical form for certain techniques and provided detailed explanations for others. The authors explained the goals and guiding principles of CNN techniques and suggested a study of image denoising using CNN.

The use of CNNs for medical image denoising has also been investigated in several other papers. As an example, it was proposed to simultaneously represent the medical image and the noise using a two-stage deep convolutional neural network [30]. A novel convolutional neural network architecture based on the wavelet domain was suggested by another study [31] for the purpose of medical image denoising. Another study [32] examined the model in the context of a deep framework, learning technique, and regularisation strategy to develop deep-feedforward convolutional neural networks for medical image denoising using a limited sample size. This study [33] suggested combining the traditional convolutional neural network (CNN) architecture with the potent self-attention processes from the Transformer to improve cardiac MRI segmentation in deep learning.

3.2 Generative Adversarial Networks (GAN)

When two networks—one for image creation and the other for discrimination—are trained concurrently, they form a special class of neural network models known as GANs [34]. Artificial neural networks and deep learning are the foundations of generative adversarial networks (GANs), which are methods for creating synthetic images [35]. Two artificial neural networks with different but mutually optimising objectives combine to form a GAN. The generator, one type of neural network, is designed to create artificial images that resemble real ones. The discriminator, the second neural network, is designed to discern between these artificial and authentic images [36].

there are several types of Generative Adversarial Networks:

1. Vanilla GAN :The traditional Generative Adversarial Network is the original proposed model from Goodfellow et al's 2014 paper [37]. In place of variational autoencoders for adversarial machine learning, the authors suggested the GAN model.
1. Conditional Generative Adversarial Nets (CGAN): The generative model's produced data may be altered by adding more data into this conditional model. Class labels and data from modalities suggested by Mirza et al. [38] are two examples of this data.
2. Deep Convolution Generative Adversarial Networks (DCGAN): "Unsupervised representation learning with deep convolutional generative adversarial networks" is the title of a 2015 article[39]. DCGAN speeds up and stabilises the training process by replacing a fully connected layer with a convolution layer that has a stride in place of an upsampling layer [40].
3. Wasserstein GAN (WGAN): WGAN is a GAN training alternative to the traditional kind. We show that this unique approach may lead to better learning stability, the elimination of mode collapse, and the acquisition of meaningful learning curves useful for debugging and hyperparameter searches[41]. The goal function of WGAN is to minimise the Wasserstein distance between the data distributions and the model[42].
4. Cycle-consistent Generative Adversarial Network (CycleGAN): The CycleGAN architecture was introduced by Zhu et al. [43] and allows image transfer across domains without requiring matching image datasets.
5. pix2pix: To translate images to images, Isola et al [44] suggested Pix2pix. Both the input and the intended output are required by the Pix2pix framework.
6. Information Maximizing Generative Adversarial Network (InfoGAN) :In 2016, Chen et al. presented the InfoGAN model, which stands for Information Maximising Generative Adversarial Network [45]. Very little complexity is added to the regular GAN model by the InfoGAN model.

4. Related Work

The GAN network has several uses. Among other uses, computer vision, image denoising, natural language processing, and medical image processing have all found success with the GAN.

Image denoising in medicine has been the use of Generative Adversarial Networks (GANs). For example, an unsupervised method for denoising medical images technique employing CycleGAN was suggested in a recent paper by Gu and Ye [46]. The study used patches of image data from a large sample of data to train the GAN. In a different research, a dual-channel denoising network based on GAN architecture was offered as a solution to the main issues with low-dose CT (LDCT) denoising, which include image blur and loss of detail structure.

Kaur and Dong [47] carried out an extensive assessment of image-denoising methods for medical pictures. The paper covers a range of methods, such as filtering, CNN-based, GAN-based, and transformer-based approaches, that may be used to eliminate noise from medical pictures. Additionally, the writers carried out an extensive assessment of the literature on cutting-edge techniques. In the conclusion, explainable AI (XAI) is highlighted as the significance of image denoising is suggested, summarising the results.

Using GANs for various purposes in medical imaging, such as synthesis and augmentation [48], segmentation [49], and classification [50], is covered in a number of studies. The use of the GAN technique to produce medical pictures that mimic authentic images from several medical modalities was covered by D. M. Vo et al. [51]. Diagnostic and therapeutic monitoring of the condition depends on the conversion of fundus pictures from yellow retinopathy to detailed retinal blood vessel imaging. The research aims to get rid of negative side effects such as fluorescein retinal imaging, dye injection, and quality improvement. He presented three new architectural designs, namely Fand2Ango, Attention2angio GAN, and calcium GAN. In the future, this research hopes to extend this work to other retinal and calcium imaging modalities. Researchers in [52] utilized GAN models to generate additional COVID-19 images, thereby enhancing the diagnosis and analysis of medical images. In some cases, it may be difficult to obtain a sufficient number of real medical images for COVID-19 due to their rarity or privacy restrictions. In the future, we can combine Ad CycleGAN with StyleGAN to improve the synthetic image resolution along with the image translation process. The accurate allocation of synthetic pattern locations is achieved by optimising the Ad CycleGAN using the Pix2Pix architecture. As a result, medical image segmentation may benefit from the expanded use of Ad CycleGAN.

An optimisation approach was used in the research [53] to reduce noise in images based on GAN. When the noise level was high, it performed typically better than the other approaches, even if it wasn't as effective as the others when the noise level was low. After reading this study, future research will focus on improving the denoising impact in low-noise settings to provide the best possible denoising effect across all noise levels. Zhong Y et al. [25] presented research on image noise removal. The generator network in the suggested model architecture is structured similarly to the SRDenseNet network, while the discriminator network uses similar methods and techniques, such as layer normalization and Leakyrelu, as the discriminator network in the SRGAN model. However, in this research, batch norm layers were replaced with layer norm layers due to the use of WGAN-GP technology. In addition to Gaussian noise, the suggested network can handle other kinds of noise. When faced with unknown actual noises, the model cannot perform correctly. This may be because the training data doesn't include enough ground-truth images to match real-noise images.

Competitive neural networks (GANs) were used by A. Makhlouf et al. [54] to eliminate noise from seismic images. We train neural networks on a collection of polluted or fuzzy images and their matching clean images to eliminate noise from seismic images. In the research, two types of GANs were utilized: Pix2Pix relies on conditional image translation to convert blurry images into corresponding clean copies. Pix2PixHD: This model generates high-resolution images and focuses on converting low-frequency data to high-frequency data. However, it needs to be further improved, mainly when referring to its application to real seismic data.

Kumar and Nachamai [20] presented a study of noise removal techniques from medical images using median, Weiner, and Gaussian filters and provided a comparative analysis of different filters for different types of noise. According to the research, the median effectively reduces Poisson and salt-and-pepper noise in grayscale images. Weiner works well at eliminating Gaussian noise and speckles. For unclear noise, the Gaussian is appropriate.

The use of noise reduction to enhance the quality of OCT retinal images was investigated in the research [55]. Even if the results show that the recommended strategy works better than the other existing techniques, DN-GAN has several disadvantages. In places with low pixel intensity, structural information may be discarded as noise due to the attenuation of incoming light, resulting in the loss of choroid information.

A study by I. Goodfellow et al. [56] found that lowering speckle noise in optical coherence tomography (OCT) images may increase disease detection and enhance image quality. The researchers proposed the MDGAN network, which consists of a discriminator network and a generator network. The generator network, including CMSM, SAM, and DBP, was designed by the researchers using the U-NET architecture as a basis. The DBP (Deep Back-Projection Layer) layer is used to enhance image quality or information in neural networks; CMSM (Cascade Multiscale Module) is a strategy to improve image processing; and SAM (Spatial Attention Mechanism) is a mechanism to focus on spatial information in photographs. Our long-term goal is to simplify the network architecture by using self-supervised deep-learning approaches for OCT image speckle reductions.

In his PhD thesis, Yu et al. [57] used a GAN model that relies on the attention mechanism to eliminate noise from OCT images. The proposed AttGAN fared better in denoising than both Unet and the conventional cGAN. Reference [58] presents research on using a GAN network to lower noise and enhance the quality of OCT images. A discriminator and a generator network make up the suggested architecture. The D-DBPN architecture served as the basis for the generator's design. with modifications inspired by the RRDB architecture, to enhance the precision and calibre of grainy, low-quality images. The proposed method may successfully denoise and super-resolve SD-OCT images while maintaining the bulk of edge information and image characteristics, especially for large-scale images. Nevertheless, there is some noise in the results.

Research on the removal of noise from OCT images impacted by speckle noise was provided by Jeong et al. [59]. The findings demonstrated that, in comparison to other denoising techniques, the suggested approach, SM-GAN, obtained the greatest values of PSNR and CNR.

Table (1) displays the most prominent previous studies that addressed the topic of removing noise from images.

Table (1): briefly reviews the most prominent previous studies that addressed the topic of removing noise from images

Reference #	technique used	(Methodology)		Dataset	Progress Ratio
[60]	Image Denoising using the GAN model by using Python programming	Gan model based on: - Generator: simplified U-Net structure. - Discriminator: image classification CNN.	Losses used in the training step: - Discriminator loss: binary cross-entropy. - Generator loss: content loss, using a VGG19 pre-trained model	Images are cropped in 256x256x3 dimensions, -COCO dataset is used as a train/test set. -BSD300 dataset is used as a second test set.	achieves good perceptual quality. A future extension could include developing a better structure for the Discriminator or changing it entirely to exploit a PatchGAN.
[54]	Using the GAN to remove noise from seismic images by training neural networks on a set of noise and clean images(GPU NVIDIA Tesla v100 with 16GB)	The researcher used two types of GAN. - Pix2Pix: this model is based on image translation, where blurry images are converted into corresponding clean copies. - Pix2PixHD: this model is based on the generation of high-resolution images		(10000 seismic patches pairs with 256 256 size)	results indicate that the generator can translate noisy data into clean data. However, it needs to be further improved
[56]	Using generative adversarial networks for image denoising in Python programming using pytorch (cuda 11.3)	This paper proposes a multiscale denoising generative adversarial network (MDGAN). the network is based upon a U-Net with skip connections. Specifically, in such an architecture, a cascade multiscale module(CMS), deep back-projection (DBP), and The spatial attention mechanism (SAM)		two different OCT datasets, the first dataset contains 17 retinal OCT image pairs acquired from normal and abnormal subjects. The second dataset contains five OCT image pairs	Results show that MEGAN is comparable to the best existing state-of-the-art methods, but it needs to reduce the complexity of the network architecture
[61]	using generative adversarial networks for image denoising in python programming using TensorFlow with NVIDIA K80 GPU	the GAN is Inspired by U-net, and employs a novel symmetrical encoder-decoder-based generator network. The encoder adopts convolutional neural networks to extract features, while the decoder outputs the noise in the images by deconvolution neural networks.		The data set used in this study is 100 images used for training, then use the same training set and add noise to it for training, but for verification use 10 images that are completely different from the training data	the proposed model provides a more efficient and universal image denoising method but there is still space to further enhance the experimental results.

5. Conclusions

The study makes a comparison of the effectiveness of GAN-based solutions with traditional noise-reduction techniques and examines the impact of different noise types on medical images. We designed the current paper to highlight GAN's contribution to noise reduction in medical imaging, elucidating its advantages, potential applications, and its superiority over other methods.

Here's a concise list of the main conclusions:

- GANs are effective in medical image enhancement. Studies have shown success in improving image quality, reducing speckle noise, and outperforming traditional denoising methods in tasks like OCT image enhancement.
- There are numerous designs available for GAN-based denoising. To eliminate noise, researchers have looked into attention processes, U-Net-based networks, and modified CNNs.
- Not perfect, but progress nonetheless: Even while GANs have produced positive results, more study is needed to:
- Increase the efficacy of the method
- Enhanced suitability for clinical settings
- Enhanced resilience to many forms of noise.

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شبكات التوليد التنافسية العميقة لتقليل الضوضاء في الصور الطبية

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المستخلص:

التصوير الطبي هو ركن أساسي في التشخيص والكشف المبكر للعديد من الأمراض. ولكن وجود الضوضاء (الشوائب) قد يؤثر سلباً على دقة التشخيص وجودة الصورة. وللضوضاء انواعٍ مختلفة نذكر منها: ضوضاء الحبيبات(Speckle noise) ، وضوضاء البوسون (Poisson noise)، وضوضاء الملح والفلفل(Salt-and-pepper noise) ، والضوضاء الغاوسية(Gaussian noise) وغيرها.

تواجه طرائق إزالة الضوضاء التقليدية، مثل التصفية المكانية وتصفية المجال التحويلي، صعوبة في التعامل مع أنواع الضوضاء المختلفة. لذا هناك حاجة للبحث عن طرائق جديدة تتوافق مع التطور الحاصل في مجال معالجة الصور الطبية. ومع تطور التعلم العميق، وخاصة شبكات التوليد التنافسية (Generative Adversarial Networks- GAN)، التي أثبتت قدرتها على إزالة ضوضاء الصور بكفاءة تفوق الطرق التقليدية. تقارن هذه الدراسة فعالية تقنيات GAN مع أساليب إزالة الضوضاء المعروفة، وتحلل تأثير مصادر الضوضاء المختلفة على الصور الطبية.