2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)
Amity University, Noida, India. Sep 3-4, 2021

2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO) | 978-1-6654-1703-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICRITO51393.2021.9596487

A Review on Generative Adversarial Networks used for Image Reconstruction in Medical imaging

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***Abstract*— In computer vision, Because of its capacity to generate data, generative adversarial networks have gotten much interest. Generative Adversarial Network (GANs) opens different ways to overcome difficulties in medical image investigations like de-noising of the captured image, reconstruction of captured medical image, segmentation of the captured medical image, synthesis of the captured image, detection and classification of processed medical image. GANs great potentials in image restoration or reconstruction for different anatomy open a new research area. However, image reconstruction for specific anatomy is still facing the challenge. This article consists of a recent literature review on the applications of GAN for the reconstruction of medical images. Different reconstruction methods in the field of medical imaging were explored in this paper thoroughly. We have studied the foremost relevant publications.**

Keywords*— Generative adversarial network, GAN model, Medical imaging Anatomy, Reconstruction.

I. INTRODUCTION

Development in machine learning leads to new trends and provide a platform for researchers to deploy their interest. Medical imaging is critical for disease diagnosis and therapy assistance. In medical imaging, the reconstruction process is the fundamental component. The primary goal of image reconstruction is to provide a clinical ready high-quality image at low cost and less risk to the patient. Image restoration started in 1990. Earlier, the models are typically mathematical and mostly handcrafted, designed by human knowledge. Later the model is designed, which are both handcrafted plus data-driven models. Around 1999 these models are created. These models are learning-based handcrafted models. After handcrafted models, the next step is to derive knowledge from the properties of the data. Many deep learning algorithms employ this principle, in which the network picks up information from the data set. In medical imaging, the convolutional neural network is the most widely used model. With the help of filters, CNNs convert the input to feature input for the next layer. CNN comes in lamplight after the advancement in computing technology. Around 2012, with the introduction of CNN, deep learning comes into action. CNN's such as AlexNet, ResNet, and generative adversarial networks have been introduced and used for image reconstruction. These models are called deep learning models or data-driven models. With the introduction of new models, the community has noticed and transformed the existing handcrafted models into the new learning-based model. So for deep learning is the best choice in medical imaging. The year 2012 marks the beginning of deep learning within machine vision. The vulnerability and potential of deep learning, due to which researchers started using deep learning in medical imaging. [11] Deep learning has the potential of image interpretation, image classification, object detection, segmentation, registration. These are some applications in medical imaging such as neurological pathology (brain diseases), retinal fundus pathology, chest pathology, breast cancer, cardiac pathology, abdominal and musculoskeletal pathologies. The massive amount of labelled data set is the main obstacle in the path of deep learning to be the best in class in numerous tasks of medical imaging and standard computer image processing. In this article, the main focus is on Adversarial generative networks and their application in the reconstruction of medical images. Compared to different methodology, Reconstruction of a medical image using GAN produces the detailed image in the indigenous form. In GAN, a pure training methodology employed for

balancing generator, that gives a network to create minimally damaged or corrupt image and differentiator discovers prediction of legitimacy [3].

II. GENERATIVE ADVERSARIAL NETWORKS

GANs was proposed by Ian Goodfellow in 2014. This concept of GAN is relatively new with continuous progress [3].With the aid of deep learning approaches like CNNs, generative adversarial networks are a generative model for creating new images. It is an unsupervised learning technique of machine learning. The inspiring force for GANs is the game theory called the zero-sum game. It is a plan within which two models are trained at the same time by the adversarial method. It's a generative modal made up of both a generator and a discriminator. Figure 1 shows this model. In GAN generator is made up of a neural network. The input to the neural network is a random noise for basic GAN and transforms it into a sample from the model distribution [3]. The discriminator is a neural network that distinguishes between output data point (fake) from the generator and training data samples (real) [13]. The basic GAN models consist of G the generator, D the discriminator, $P_z(z)$is the input noise, $P_g(x)$ is generated distribution over the data set x.θ_d and θ_g are the parameters of discriminators and generator respectively. G(Z; θ_g) is the mapping between input random noise to generative parameters, where G is a generator with multilayer perceptron. Whereas D(x; θ_d) is the binary output or we can say a classifier. The generator is minimizing function and D is the maximizing function.

The training is frequently practiced by gradient-based techniques. Unlike deep learning, Generative adversarial training is a new concept with significant recent research. This paper focuses on the usage of GANs in the medical industry for reconstructive work. We start with a quick overview of GANs concepts. It is followed by work done analysis in the medical image using GANs and also includes work done for different pathologies. Summarize it with work analysis on image reconstruction using GANs.

$$\text{MinMax}(D,G) = E_{x\ Pdata(x)}[\log D(x)] + E_{z\text{-}Pz(z)}[\log(1 - D(G(z)))]$$

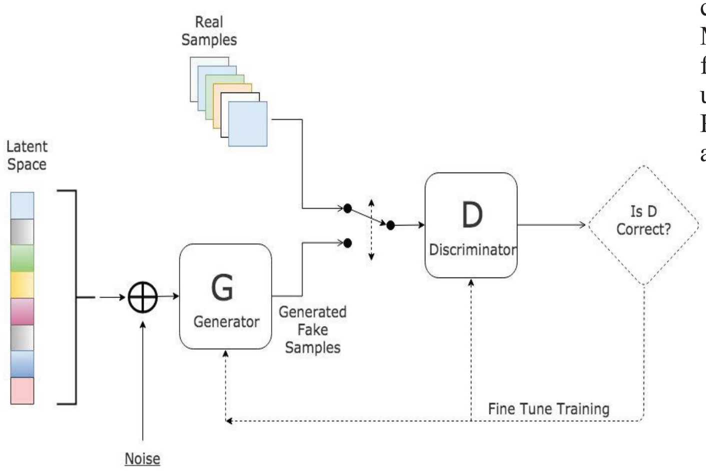


Fig. 1. vanila GAN

III. Some GAN model used in medical imaging

A. *InfoGAN*

InfoGAN was proposed in 2016 [21].In this case, the input data is divided into two vectors, z and c. z are incompressible, and c, known as the idle code and will focus on the huge organized semantic highlights of the genuine information distribution. The objective function of infoGAN is $minmax V_I\ (D,\ G) = V\ (D,\ G)\ \text{-}\lambda L V_I\ (c,\ Q)$ where lower bound is L_I and V (D, G) is function which called as an objective function of GAN [21].

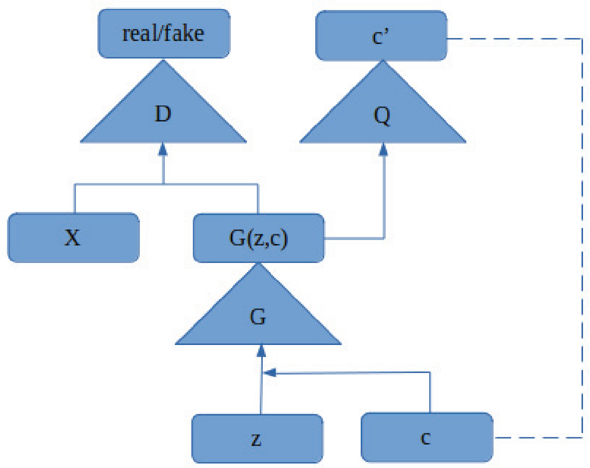


Fig. 2. InfoGAN

B. *cGAN*

The Vanilla GAN has not had any management for the particular image formation, Mirza and Osindero (2014) planned a new model called conditional GAN to assimilate extra data such as category marked data within the image generation method. In GAN, there's no management over modes of the info to be generated [9]. The conditional GAN changes that by adding the label as a further parameter to the generator and hopes that the corresponding image is generated. The conditional GAN improves the generated image but also helps in training stability. Generated image features are preserved using conditional GAN. Some other conditional GAN models are Markovian GAN proposed by Markovian [13]. The VGG19 network serves as the foundation for MGAN [22].The cGAN algorithm is often used to convert one image to another. Proposed models like Pix2Pix are used [17]. Pix2Pix model uses U-Net-based architecture.

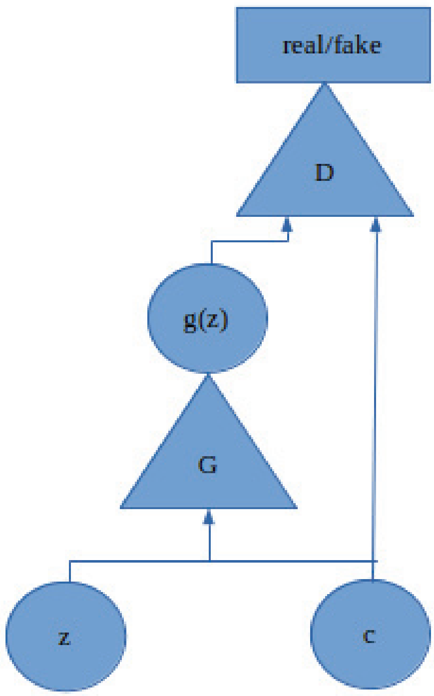


Fig. 3. cGAN

C. *DCGAN*

Deep Convolutional GAN (DCGAN) was proposed by Radford in 2015 [23]. In DCGAN the generator and discriminator both employ the deep convolutional network and exploit hierarchic feature learning [23]. It's made up of a convolution layer with fully connected layers with no max pooling. This GAN architecture uses batch normalization and leakyReLU activation function to improve training.

D. *WGAN*

Wasserstein-GAN was proposed by Arjovsky et al.2017. They use Wasserstein distance as a divergence measure. It's an associate extension of GAN in which alternated training method is used for better approximation. WGAN is practically very easy to implement but has a problem of slow optimization.

E. *LSGAN*

In 2017 Mao proposed a new model called Least Squares GAN which has similarities with WGAN but there is a change in loss function to circumvent vanishing gradient.

F. *CycleGAN*

In 2017 For image translation Zhihao and others introduced the cycleGAN [18]. cycleGAN model provides the mapping between one domain to another domain. Without paired example, cycleGAN can automatically train from one image to another image conversion. The training process used in the particular model is unsupervised.

IV. Application of GAN in Medical Imaging

Using two aspects, we can apply GANs in medical imaging. One is the generative aspect, where G generative learns and generates a new image. Second is discriminator D, in which discriminator is thought to be learned previously from the traditional image and then employed as a detector when exposed images with abnormality [1]. GANs can be applied in

- classification
- detection
- segmentation
- reconstruction
- image synthesis
- registration

Figure 4 shows various GAN publications in the medical image field and figure 5 show the various applications of GAN in medical imaging.

Medical imaging several different modalities that allude to a technique and procedures used to take pictures of different sections of the human body for indicative and treatment purposes, making it one of our most impressive assets accessible to successful care about patients. Like we have Magnetic resonance imaging, computed tomography, Histopathology, RF Imaging, X-ray, Ultrasound sonography, Dermatoscopy, Positron Emission Tomography, Mammography. Figure 6 show GAN implementation in different modalities. About 50 percent of work is done on image synthesis that is cross-modality. Generation of the image of one modality to another modality is the one that is implemented the most like CT to MR. Synthesis of MR is common because of the long acquisition time. Because of the publicly accessible MR dataset, it is the most commonly utilized medical imaging modality. Dataset of different anatomy are available publicly but not for each anatomy figure 7 shows work done according to different anatomy. Figure 7 shows most of the work is done in brain imaging, skin and eye because of publicly available datasets like BRATS2017, ISIC2018, DEIVE.

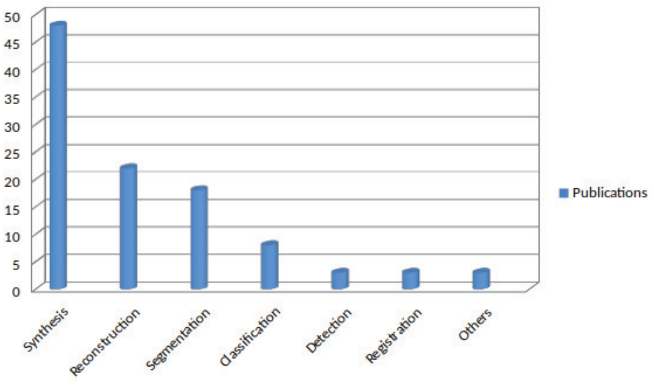
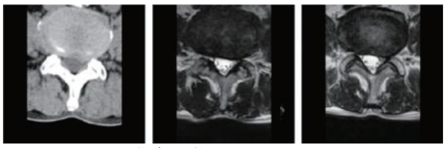


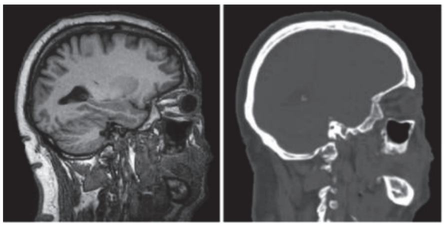
Fig. 4. GAN publications in Medical Image.

A. *Reconstruction of medical image*

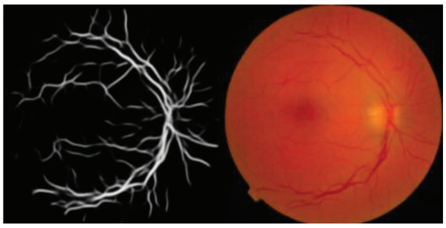
The constraints in medical imaging like radiation hazardous to patients because x-rays can cause mutation in genes and there is the tendency of causing carcinoma in relation to radiation dosage. Reduction in the radiation dosage can amplify the noise and introduce the artifacts in the image to be reconstructed, which hampers the diagnostic details [11] [1].In order to obtain a high-resolution image, MRI does have some limitations, and there is a need for extended capturing time [12]. Some other possible limitations, such as small graphical coverage and movement artifacts, lead to lower image quality. Some other artifacts like foreign bodies present in the patients causing confusion to the examiner as they resemble the pathological findings. These physical limitations deteriorate the quality of the clinical image that is to be interpreted due to misinterpretation [12]. Table 1 shows the analysis of recent reconstruction work done on medical imaging. Fast MRI medical Imaging without sacrificing the details is the main problem. Fast MRI acquisition is highly desirable with reduced motion artifacts. Reconstruction of the image is possible using GAN because of its image generation capability with realism in generated images. DAGAN architecture was used earlier for MR reconstruction. In this method, three-loss functions are used perceptual loss, adversarial loss, pixel-wise loss. After DAGAN, 3D super-resolution strategies with 3D convolutional layers are used.



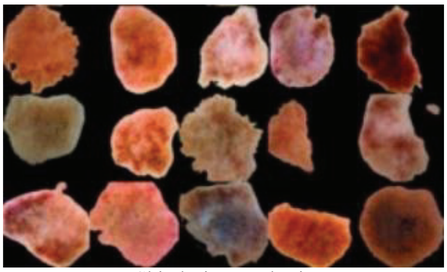
Spine CT to MRI



MRI to CT



Normal retinal fundus into Super resolution image



Skin lesion synthesis

Fig. 5. Applications of GAN in Medical Imaging.

V. Discussion

In this paper, we have displayed various GAN-based models and GAN ability in medical image reconstruction. Evidence suggests that GAN can be successfully used for different anatomy with different modalities. Most of the work is done in the case of image synthesis. Some anatomy like skin, spine are less common because of the less availability of dataset. In the case of reconstruction, images are reconstructed because they include some artifacts and distortion in the image. So the reconstruction of different anatomy for MRI and CT is needed. In recent years, the application of GAN is Increasing significantly in various fields. We have various modalities in which we can apply GAN but MRI is considered the one which is investigated the most in GAN. The application of GAN in the MRI modality is the reduction in acquisition time. As we know that there is a need for a significant period spent on the acquisition [12]. So in minimizing the acquisition time, we can apply GAN for MRI modality. It will be beneficial to the patient as well as for the operator.

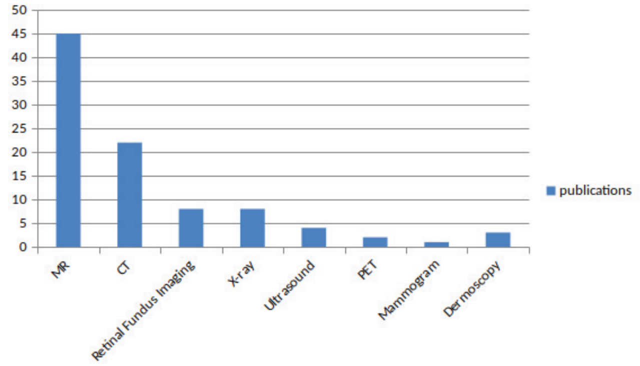


Fig. 6. GAN implementation in different modality.

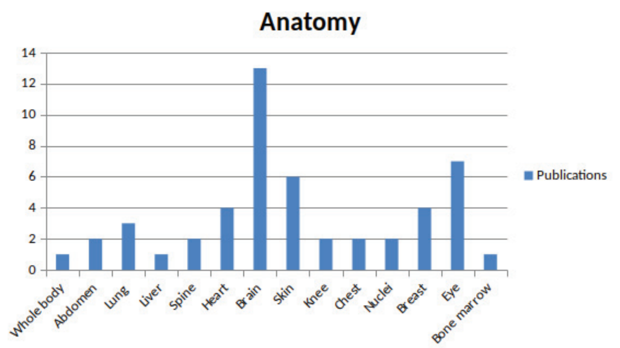


Fig. 7. work done according to different anatomy.

TABLE I. Reconstruction work done in medical imaging

Analysis		
Sno	**Publications**	**Method/Anatomy/Modality**
1.	Lee et al., 2020	• Lumbar spine CT to MRI [19] • 2D fully-convolutional • Preliminary study
2.	Armanious et al., 2020	• Medgan is a framework [7] • Image to image model • Loss function adversarial loss percep- tual loss, style transfer losses, content loss • Casnet which is inspired Resnets. • U net based architecture
3.	Q.Yang et al.,2018	• CT may cause heath problem in form of cancer. • 2D fully-convolutional [20] • Use perceptual loss function • Used pre-trained deep CNN like VGG
4.	Yang et al.,2018	• GAN based learning architecture DA-GAN use U-NET architecture [5] • Conditional model • Used Content loss consist of pixel wise image domain MSE loss, fre-quency domin MSE loss and a percep- tual loss.
5.	Wang et al.,2018	• 3D cGAN framework used [2] • U-NET architecture • Conditional input of PET medical image
6.	Chen et al.,2018	• Restoring HR image from single LR [4]. • Deep learning approach mdcsrn using GAN • Divide a single densenet into small shallow block called multi level densely connected structure
7.	Sekuboyina A. Et al.,2018	• A butterfly-formed system that works on spine image [8] • Method is on 2D with different rep- resentations. • The btrfly network is consists of an arm. we can say to view.
8.	Wolterink et al.,2017	• Convert low dose CT image into a reduced noise image. • Data set is obtained from 28 patient's for cardiac CT • GAN with both the generator and the discriminator is a CNN. • Combine two-loss function voxel and adversarial loss [1].
9.	Mahapatra.et al.,2017	• Normal retinal fundus into Super-resolution image • Gans are used for image super resolution using resnet. • Loss function contain content loss and generative loss and balance by a factor [6].

VI. Future Challenge

Despite many positive applications of GAN in medical imaging, there is a certain challenging factor that requires resolution. In the image reconstruction process and process of image synthesis, mostly traditional shallow reference matrices like MAE, SSIM has been used for quantitative assessment only but not for the visible quality of the processed image. For example, during reconstruction, pixel-wise loss results in the creation of a blurry image. It looks tough to specify this range in horizontal differentiation of Generative Adversarial Network-based work mostly. This problem can be alleviated by using downstream work like classification and segmentation for enhancing the standard of the generated image.

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