A Review on Medical Image Generation Generative Adversarial Networks (GANs)

Shrina Patel
U & P U Patel Department of Computer Engineering, C S Patel Institute of Technology, Charotar University of Science and Technology, Changa-Gujarat, India
shrinapatel310@yahoo.com

Dr. Ashwin Makwana
U & P U Patel Department of Computer Engineering, C S Patel Institute of Technology, Charotar University of Science and Technology, Changa-Gujarat, India
ashwinmakwana.ce@charusat.ac.in

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***Abstract*— This review focuses on the way GANs can be applied in the medical image generation and how they can be helpful in diagnostics, training or data augmentation. Through GANs, it is possible to create artificial images for synthetic medical image generation because the current data collected in the healthcare field lacks sufficient large amount of data amount and diverse image quality, however, there are apparent problems in the production of high quality and diverse, and strongly interpretable synthetic images. The work examines several structures based on GANs and compares them, pointing out the challenges that need to be addressed when generating realistic images of severe medical conditions. Some of these are to increase GAN dimensions to improve model complexity and expand the training data to include therapeutic relevance. Thus, this review contributes to the identification of the state of AI-based medical image synthesis.**

Keywords*— Deep Convolutional GAN (DCGAN); Conditional GAN (cGAN); CycleGAN; StyleGAN; Self-Attention GAN (SAGAN).

I. Introduction

The modern health care system largely relies on medical imaging for diagnosis, treatment planning, and assessment and monitoring of a wide range of medical disorders [1, 2]. With the advent of AI, especially GANs, medical image production has undergone a sea change [3]. GANs play a crucial role in the creation of synthetic medical images for data augmentation, denoising and missing modality synthesis but obstacles such as, instability of training persist. This field is rich in potential application of machine learning techniques, especially GANs with their great potential toward improving the accuracy of diagnosis and advancing medical research because it demonstrates the ability to produce real and high-quality medical images [4,7]. The current work will delve into the impact that these revolutionary technologies bring to the medical imaging field by focusing on the latest developments and applications of AI-enhanced methods for the production of medical pictures using GANs.

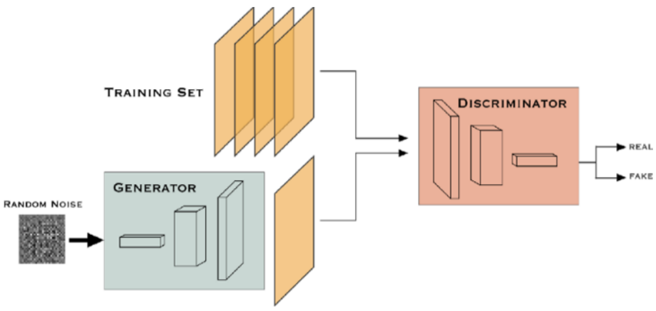

Fig. 1. Process of GAN[12]

In Figure 1, there is an introduction of an alternative strong force in medical image synthesis known as the Generative Adversarial Network. On this model of AI has a discriminator alongside a generator through competitive learning that produces still very realistic images [8,12]. GANs are helpful in medical imaging to meet the scarcity of the data and also due to patients' private information restrictions in some cases. This implies that since GANs can generate many diverse realistic images, it is possible to create the image datasets on any given medical condition differently; this also make the improvement of the machine learning algorithms for any given medical condition to be improved.

In addition to data constraint overcomes, GANs have more extensive uses in the area of medical image generation [14,16]. The AI-enhanced technique is promising to create efficient training datasets for medical image analysis and improve the operational performance and sustainability of deep-learning models. Furthermore, as the GANs worked to generate the pathological images naturally, doctors and researchers can know the difference of presenting the disease [17,18]. Practical image analysis enhancing generalizability and durability of the deep-learning models. In addition, GANs are used in developing pathological images naturally, which helps doctors and researchers to understand the variation of manifestation of a disease [19,20]. As with the other skills of this doctor, this one is especially valuable when training other medical people, to improve the criteria for diagnosis, and to make the different kinds of treatment more personalized. However, there is optimism that as GANs advance much further and are implemented appropriately in clinical routines, AI generated medical images can shift the paradigms formulated in diagnostic medicine and even improve patients' outcomes [21,25].

The scope of this review focuses on how the GAN-improved approach to generating medical pictures is described with reference to both revolutionary possibilities and current problems, as well as the moral issues concerned with the introduction of GAN in the healthcare industry. Altogether, review develops a coherent comprehensive study towards a state of culmination of the present scenario of AI aided imaging in medicine and to delineate possible trends of research and development in the future.

II. Literature Review

With regards to medical picture augmentation and synthesis, the literature investigated provides a critical evaluation of Generative Adversarial Networks (GANs). The set of breast ultrasound pictures provided by Al-Dhabyani et al. (2020) [1] is a valuable data source for medical image analysis to diagnose and classify breast lesions. In the research by Anaam et al. (2021) [2], the authors explain that using GAN image augmentation improves a limited dataset based on HEp-2 cell imagery. Arvidsson et al. (2019) [3], while looking for augmentations to enhance broad applicability in Gleason grading, mentioned ways some strategies enhance classification more than others. Using the multimodal brain tumor picture segmentation dataset provided by Menze et al. (2015) [4], several medical images can be suggested for both individual and multiple uses. In addition to using noise-to-image and image-to-image GANs, Han et al. (2019) [5] enhances the brain MR images for the detection of tumors, while adopting the same idea in 3D CT imaging to synthesize lung nodules, as proposed in Han et al. (2019) [6]. GANs are useful for medical imaging applications.

For orthopedic imaging development, Darabi (2024) [7] provides a dataset derived from computer vision for bone fracture diagnosis. The second dataset, concerning ophthalmology and helpful for training models, is the Diabetic Retinopathy Detection dataset initiated by Dugas et al. (2024) [8]. For instance, to demonstrate that synthetic data is effective for medical image analysis, Frid-Adar et al. (2018) [9] use GAN-based synthetic augmentation to enhance CNN performance in classifying liver lesions. To show how GANs can enhance the distinction accuracy of diagnostic AI models, Fujioka et al. (2020) [10] use them to detect satellite abnormalities in breast ultrasound (USP) images.

To improve vascular segmentation models, HaoQi and Ogawara (2020) [11] use conditional GANs to generate images from retinal fundus imagery. To improve the categorization of medical pictures, Arora et al. (2019) [12] discuss the effects of image enhancement using DCGANs. For instance, in the use of GANs across different modalities of medical imaging, Park et al. (2023) [13] focus on classification enhancement for endoscopic images. In order to improve training, Xu et al. (2020) [14] use rotation-invariant data to augment microorganism images with the aid of a new GAN training framework. Yang et al. (2019) [15] apply GANs to enhance data in X-ray images used to detect prohibited items outside the health domain.

Mudavathu et al. [16] proposed an ACC GAN model for dataset augmentation, discussing the generality of the proposed model. In 2019, Karim et al. [17] developed an approach for medical image translation using GANs to improve cross-domain medical imaging assignments. For lesion classification in radiology and ophthalmology, Kermany et al. (2018) [18] presented labeled views of chest X-rays and OCT scans. In an attempt to address intra-class imbalance, Huang et al. (2019) [19] proposed a GAN-based approach for enhanced augmentation, particularly for medical data, which typically presents this problem.

For enhancing diagnostic models, Liang & Huang (2021) [20] apply an adaptive CycleGAN to generate synthetic images of malaria blood cells. For vision-based tasks of classifying photos of blood cells, Ma et al. (2020) [21] demonstrate performance improvements by integrating DCGANs with ResNet. For diagnostic imaging enhancement, Mahapatra et al. (2019) [22] propose progressive GANs for medical image super-resolution. An illustration of the precision of modern GAN designs in medical imaging is the work of Negi et al. (2020) [23], where Wasserstein GANs are used for breast ultrasound lesion segmentation. Bana and Nishant (2021) [24] explore GANs for COVID-19 diagnosis based on audio data, adding a new application of GANs to medical data beyond images. For annotated biomedical data, Dimitrakopoulos et al. (2020) [25] present a spatially constrained GAN for data augmentation.

The related work summarize that GANs are beneficial for several purposes in medical image synthesis and augmentation, addressing data limitations, optimizing model performance, and supporting a wide range of applications across various medical imaging domains and modalities. Thus, one could conclude that using GANs is highly helpful when dealing with the challenges of medical image analysis and interpretation.

TABLE I. FEATURES, PARAMETERS, APPLICATIONS

Author(s)	Features	Parameters	Applications
[1] P. K. Darabi	Bone fracture detection	Image augmentation, classification models	Detecting bone fractures using a computer vision
[2] E. Dugas et al.	Diabetic retinopathy detection	GANs for image synthesis, classification	Computer detection of diabetic retinopathy from retinal images
[3] H. C. Park et al.	Endoscopic image classification	Data augmentation, GAN-based synthesis	Computer visions for the diagnosis of diseases through endoscopic images
[4] H. M. Anaam et al.	HEp-2 cell image augmentation	GAN-based data augmentation	HEp-2 cell image enhancement for classification and diagnosis
[5] Z. Liang et al.	Malaria blood cell image synthesis	Cycle-consistent GANs, adaptive networks	Medical image synthesis on malaria blood cell for research purposes
[6] A. Negi et al.	Breast ultrasound lesion segmentation	Wasserstein GAN, UNET model	The sheer size of breast ultrasound lesion segmentation
[7] P. Dimitrakopoulos et al.	Annotated data augmentation	Spatially constrained GAN	Medical image analysis based on data augmentation
[8] L. Ma et al.	Blood cell image classification	DC-GAN, ResNet	Deep learning for classification of blood cell images
[9] H. Xu et al.	Environmental microorganis	GAN-based data augmentation	Microorganism image enhancement for

	m image augmentation		environmental analysis
[10] H. G. HaoQi and K. Ogawara	Retinal fundus image synthesis	CGAN-based image generation	Synthesizing retinal images for medical application and vessel boundary detection.
[11] T. Fujioka et al.	Anomaly detection in breast ultrasound images	GAN-based anomaly detection	Mammoet archives abnormal patterns identified in breast ultrasound images
[12] W. Al-Dhabyani et al.	Dataset of breast ultrasound images	Image annotation, classification models	The creation and use of a breast ultrasound image dataset
[13] C. Han et al.	Brain MR image augmentation for tumor detection	Noise-to-image GAN, image-to-image GAN	MRI of brain with augmentation for tumor identification
[14] C. Han et al.	Lung nodule detection	3D conditional GANs	Effect of augmented 3D CT image in the detection of lung nodule.
[15] H. Arora et al.	Image augmentation through DCGANs	DC-GAN, image transformation	GANs for medical image augmentation of datasets
[16] J. Yang et al.	X-ray image augmentation	GAN-based data augmentation	Image enhancement for object detection using x-ray images
[17] A. Karim et al.	Medical image translation using GANs	CycleGAN, image-to-image translation	Clinically relevant image translation for better diagnosis
[18] L. Huang et al.	Image augmentation using GANs	Intra-class imbalance resolution	The second is GAN-based image augmentation for balanced training in medical imaging
[19] N. Arvidsson et al.	Augmentation techniques for Gleason grading	GAN-based and non-GAN-based methods	Application of augmentative technique in imaging of prostate cancer to facilitate Gleason grading
[20] D. Mahapatra et al.	Medical image super-resolution	Progressive GAN, image resolution	Enhanced analysis of medical images through super-resolution.
[21] M. Frid-Adar et al.	Liver lesion classification enhancement	GAN-based synthetic augmentation	Those are synthetic image generation to enhance the identification of liver lesion.
[22] K. D. B. Mudavathu et al.	Image dataset augmentation	Conditional GANs	Generating new examples for a range of medical image data sets.
[23] D. Kermany et al.	Optical coherence tomography and chest X-ray data	Image classification models	Categorization of OCT and chest X-ray images.
[24] N. Y. Nishant et al.	Sound-based COVID-19 diagnosis	GAN-based data generation	Data generation through GAN for diagnosis of the COVID-19 by using sound.
[25] B. H. Menze et al.	Brain tumor segmentation	Multimodal image data, GAN-based methods	Segmentation of medical images for the diagnosis of brain tumor.

III. System Methodology

TABLE II. DATASETS

Section	Dataset	Description
Brain Imaging	BraTS 2020	Magnetic resonance imaging (MRI) images in three dimensions using the NIFTI protocol. The set includes T1ce, T2-weighted, T2-Native, and T2-FLAIR images.
Chest Radiographs	Chest X-Ray Pneumonia	There were 5,863 X-ray images in JPEG format, which were divided into two categories: normal and pneumonia. Guangzhou Women and Children's Medical Center pediatric patients, ranging in age from one to five years old.
Retina Imaging	Diabetic Retinopathy Detection	Magnified pictures of the retina. There are five levels of DR: no DR, mild, moderate, severe, and proliferative. A total of 88.29 gigabytes.
Bone Fracture	Fracture Multi-region X-Ray Data	Pictures sorted according to the most common kinds of bone fractures, including those of the elbow, fingers, forearm, shoulder, and wrist. Tagged with segmentation masks and bounding boxes.
WBC Cell	ALL_IDB1 and ALL_IDB2	108 pictures with about 39,000 blood components. ALL-IDB2 incorporates cropped photos of normal and blast cells from ALL-IDB1.
Dermatology	ISIC 2019	25,331 pictures from Dermoscopy were sorted into nine different categories, including melanoma, basal cell carcinoma, melanocytic nevus, and more.
Breast Ultrasound	Breast Ultrasound Images Dataset	680 pictures taken by 600 female patients (ranging in age from 25 to 75). Pictures labeled as Nebulous, Cancerous, or Normal.
Mammography	DDSM Mammography	55,890 examples for training, with 14% as positive and 86% as negative. Images saved in tfrecords format that have been pre-processed from the DDSM and CBIS-DDSM datasets.
Cardiac Imaging	Cardiac Nodule Chest X-ray	Nodules detected on chest X-rays. Examined by twenty radiologists for severity.

A. *Deep Convolutional GAN (DCGAN)*

Here, a discriminator along with a generator are two basic components of a model as termed in DCGAN. The generator obtains a noise vector, and with the help of transposed convolutional layers up sample the image [7, 8]. The discriminator, which is also a convolutional neural network (CNN), looks at these images, and decides whether they have been generated by the generator model or not. As for the architecture, it is crucial to note that several important improvements were introduced in DCGAN [9,11].

- To reduce the dimensionality appropriately, the discriminator employs stride convolutions.
- For this purpose, in order to decrease the variance of the network during training, batch normalization is used on both the discriminator and generator parts of the network.
- Activation Functions: Unlike the output of the network which uses Tanh activation function, the rest of the generator employs ReLU activation.
- That is why; to produce more diverse images, the generator will receive a random noise vector as the input.

B. Conditional GAN (cGAN)

Conditional GANs come as a more general form of the traditional GAN design to provide this added conditional information. The discriminator analyses and takes into account both the picture and the conditional data while the generator takes in account a vector of noise and some conditional input like class labels [7,9,11].

- Controlled image generation is made possible via conditional input, which causes the generator to produce images depending on the provided conditions, like class labels.
- The general layout is similar to a Vanilla GAN, except it has more input channels to handle conditional data.

C. CycleGAN

CycleGANs use symmetric architectures made of two discriminators, and two generators. Two generators are utilized to map images from one domain into another. There is one transform, G_AB which does the first trans- formation and the second, G_BA, which performs the inverse. D_A and D_B are discriminators which verify the validity of produced images for the respective domain[7][11].

- Tasks like style transfer and domain adaptation, which do not have paired images (input-output), are well-suited to CycleGANs for unpaired image-to-image translation.
- Enforcing consistency between translations, the Cycle Consistency Loss function makes sure that when a picture is converted from domain A to B and back to A, the finished image looks like the original.

D. StyleGAN

This model is based on a mapping network with a synthesis network combined in StyleGAN that provides a unique way of image synthesis by separating style (texture) from content (shape). Beyond this, StyleGAN2 also improves training stability and the quality of generated images.

- Distinction between Form and Function: Being generated from the input noise, vectors representing style are used to regulate the style of the requisite synthesis network layers. This grants fine detail on how the produced photographs should look like.
- Images That may Be Customized: StyleGANs are quite fit for use in situations where high levels of realism with customizable outputs are required because the user could maybe change the style or format of the outcomes generated.

E. Self-Attention GAN (SAGAN)

SAGAN brings enhancements to the basic structure of GAN; self-attention mechanisms are employed. To allow the model to be aware of the relationship faraway pixels have the model uses self-attention layers in both discriminator and generator.

- Self-attention a technique used by the model to consider images' long-range dependencies solves the problem of global consistency and coherency.
- Self-attention application further improves SAGAN's performance in generating enormous, detailed images of superior quality.

As their special emphasis lies to some extent in image management, training stability as well as output quality, these GAN deviations imply a variety of choices in producing image related work.

IV. Differetial Analysis

TABLE III. Dataset Vs GAN Used

Medical Dataset	GAN Used
Brain Imaging [1,8,12] X-Ray, CT, MRI	CDAGAN, DCGAN, cGAN,
Chest Radiographs [7] X-Ray, CT, MRI	DCGAN, cGAN, Cycle-GAN
Retina Imaging [11] Microscopy	DCGAN, cGAN, Cycle-GAN
Bone surface [9] X-Ray, MRI	DCGAN, cGAN
Blood Cell Analysis [4,5,6] Microscopy	DCGAN, cGAN, Star-GAN
Dermatology [18, 22] Microscopy	DCGAN, cGAN, Style-GAN
Breast Ultrasound Imaging [10] X-Ray, CT, MRI, PET	Cycle-GAN
Mammography X-Ray, CT, MRI	DCGAN, cGAN
Cardiac Imaging [7] X-Ray, CT, MRI	WGAN, AGAN

TABLE IV. Strengths and Limitations of GANs

GAN Architecture	Strengths
Self-Attention GAN (SAGAN) [1]	1. Preserves the contextual features at long ranges with the images. 2. Improved image coherence.

StyleGAN [4,5,6,18,22]	1. High quality and highly customizable image generation. 2. The distinction between form and material.
Conditional GAN (cGAN) [7,9,11]	1. This work offers periodically protected image construction with conditional information. 2. Used for transference from one image to the other.
CycleGAN [7,11]	1. With a focus on single images, the unpaired image-to-image translation works can be defined. 2. Can be used in domain adaptation and style transfer.
Deep Convolutional GAN (DCGAN) [7,8,9,11]	1. Sustainable training for image generation. 2. Well-defined architecture. 3. Suitable for considering realistic images.

CONCLUSION

In this review, introduced the fields of Deep Learning with emphasis on GANs, as well as discussed their application in tackling critical issues in medical imaging including image enhancement, generation of synthetic images for purposes of image translation, segmentation, augmentation and diversification of datasets. Originally used for generating natural images, GANs are indispensable for processing vital one-dimensional medical information but it's interpretability, robustness, and practical admissibility are still questionable. For other simplifications and the performance boost of GANs, attention mechanisms and transfer learning can be used. Few studies should be devoted to improving interpretability and generalization abilities in clinical use in the future, as well as addressing ethical issues such as bias or violation of privacy. The further studies will focus on the assessment of the multiple synthesizing approaches, real-time GAN processes, and the ways of their implementation in clinical practice. Advancements in medical imaging, including: ultrasound, MRI, and PET will also need interdisciplinary work from computer scientists and health care leaders for better patient outcomes.

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