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Generating Medical Chest X-Ray Images using Generative Adversarial Network

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Abstract*:* Generative adversarial networks (GANs) have opened up new possibilities for medical imaging applications. Specifically, GANs can generate high-quality data without labeled data by competing between generator and discriminator networks. The Gans networks are becoming a standard by improving results in various medical tasks like image registration, reconstruction, augmentation, and translating images between images. In this paper, we propose a new GAN architecture to enhance the chest x-ray dataset for unsupervised pneumonia identification. We demonstrate how the proposed GAN works well with generated medical images as augmented data. Medical imaging data is expensive to label and scarce because of patient privacy issues; furthermore, the data is difficult to collect. The loss output resulted in the discriminator equaling 2.222 and the generator loss equaling 1.160 this means the generator succeeded in creating x-ray images that the discriminator unable to distinguished where they were real or fake. In contrast to approaches that depend primarily on transfer learning, we construct our model from scratch. Our primary emphasis is on image creation. The Nividia GeForce RTX 2060-equipped PC on which the suggested system was built was programmed in python 3.7.

Keywords: *image generation, generative adversarial network, Data augmentation, Chest X-ray, deep learning.*

1. Introduction

The ability to acquire high-resolution pictures of many anatomical features-such as the bones, brain, lungs, kidneys, and visceral organs-is crucial in medical imaging. Privacy considerations, along with the high costs and lengthy processes involved in acquiring labeled for medical images, contribute to the dearth of labeled medical data that is appropriate for use in image classification tasks [1]. The field of computer vision has witnessed a significant surge in interest surrounding generative adversarial networks, primarily attributed to their remarkable capability to generate data without the need for explicit modeling of the probability density function. Rich features in an image are constantly in high demand for medical image analysis. Typically, the diagnosis will be best served if the picture's fine features are preserved and the image is provided in high quality. For automated analysis of a medical picture, certain conditions must be met, such as high-quality photos, low maintenance, high-level characteristics, and so on. An image translation framework that can convert images from one modality to another has the potential to be very promising as it eliminates the need for multimodality scanning of the patient, resulting in time and cost savings[2][3]. Effective models for applications such as picture generation in deep learning techniques necessitate substantial volumes of data for training. Medical imaging data is somewhat scarce compared to other domains of computer vision, mostly due to privacy restrictions and considerations. Furthermore, supervised learning is limited to use only data that has been labeled. Medical image annotation is a costly and time- consuming process, resulting in a limited number of labeled medical images available for illness classification tasks. An example of an unsupervised framework is the generative adversarial network (GAN), which has successfully achieved accurate and reliable cross-modality picture creation[4].

Generative adversarial networks acquire knowledge about the underlying data distribution by employing adversarial techniques. The GAN is a highly successful model that has emerged in recent years and has gained significant attention in the field of artificial intelligence. Due to its exceptional performance, GAN has garnered significant attention since its proposal. The significance of GAN lies not only in its ability to function as high- performing generative model, but also in its profound impact on all facets of deep learning, leading to the emergence of novel research avenues and diverse applications[5][3].

The contribution to this paper is as follows:

- Novel images were produced with enhanced resolution closely resembling the original images, hence facilitating the augmentation of a restricted dataset pertaining to a novel pandemic.
- All layers of the generator employ the ReLu activation function, until the last one uses the tanh activation function.
- For all layers of discriminator use LeakyReLu activation until the last one, using the sigmoid activation function.

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2. RELATED WORK

The field of medical research has witnessed ongoing advancements, particularly in the realm of synthetic data generation, which has garnered significant interest. The proposal of incorporating realistic medical images in healthcare aims to enhance the diversity and quantity of existing training data, thereby enhancing the robustness of deep learning models. In recent decades, there has been a notable surge in research conducted within the medical field pertaining to disease categorization. This upward trend underscores the growing significance and continued relevance of this area of study [6]. The Generative adversarial networks (GANs) were first introduced from Ian good well et al in 2014. Good well developed two networks, a discriminator and a generator, are employed in a minimax game to discover the Nash equilibrium between them [7].

A survey on the utilization of generative adversarial networks in the field of medical applications was published by Salome Kazeminia et al. The present survey provides a summary of the application of GANs in the field of medical image processing. The authors discuss the various uses of GANs in tasks such as image segmentation, reconstruction, synthesis, detection, classification and registration [8].

Radford et al. pioneered the concept of deep convolutional generative adversarial networks that employ deep convolutional networks for the models of discriminator and generator after they implemented other alterations to vanilla GAN framework [9].

In order to train GANs to produce high resolution and high quality images, Karras et al. presented a novel approach. This method entails training with progressively larger discriminator and generator networks. In order to train the generator to produce higher resolution images, progan iteratively uses lower resolution photos to teach it. Generation of low resolution images is the initial step in the progressively add increasingly complicated details. A lot of the consistency in training comes from the incremental learning method [10].

H.Zhang et al. presented a StackGAN that utilizes a provided text description as input and generates high-quality images based on that description. The authors introduced stackGan as method to produced high-resolution, lifelike graphics measuring 256*256 pixels using textual descriptions. To make images that look almost exactly like genuine photos, stackgan uses a sketch refining technique to divide the complicated challenge into simpler ones. Stacked generative adversarial networks are used to accomplish this [11].

X.Chen et al. developed InfoGAN. The primary objective of InfoGAN is to facilitate the learning of GANs to create images with disentangled representations and the ability to manipulate certain attributes or features of the generated images without the need for supervision. Instead of solely employing a noise vector z as input, the authors partition the noise vector into two parts. The first part is the usual noise vector z, while the second part is novel “latent code vector”[12].

In their study, Kohlbeger et al. undertake the synthesize pathology images pertaining to cancer, incorporating natural out of focus characteristics. The objective of this synthesis is to evaluate general pathology images for any potential issues related to focus quality [13]. Likun Cai et al. present an innovative GAN value function based on the alpha divergence, a variant of the Kullback-Leibler divergence. The goal of this strategy is to make the Wasserstein GAN algorithm work better. Researchers test the suggested approach on the svhn, mnist, and celeba datasets [6]. The x-ray pictures that Abdul Waheed et al. produced for COVID-19 were created using the auxiliary classifier GAN (ACGAN) technique. The first step of the selection method was to identify all photos as "403" for COVID-19 and "721" for normal. Here, he used the vgg16 model, which had its training ground in both the original and supplemented datasets[14].

3. The generative adversarial network (GAN)

GAN is an acronym for generative Adversarial Network. A neural network is a specific sort of machine learning model that is specifically designed to mimic the structure and functionality of human brain. Neural networks in machine learning are occasionally called artificial neural networks (ANNs) due to this rationale. Deep learning, is a subfield of machine learning (ML), relies on this technology to identify intricate patterns in diverse input formats like images, texts and sounds [15].

The generator refers to convolutional neural networks (CNN), which are a specific sort of deep learning algorithm capable of analyzing an input image, distinguishing between the items present in it, and assigning significance to each object. Weights are the designated levels of significance. The primary objective of a generator network is to produce outputs that closely resemble authentic data[16].

The discriminator (classifier) is a type of neural network known as deconvolutional neural networks (DNN) these algorithms operate in an opposite manner compared to CNNs, with the goal of detecting the characteristics of an input that were either overlooked by the CNN or blended with other signals. A discriminator network is designed to determine the authenticity of a given output[17] .

A data generation model called GAN uses an adversarial game between two players to generate a generative model from a basic data set. They represent a generator and a discriminator. The generative models aim to acquire a probability density function from a given training set and thereafter produce additional samples that are randomly selected from the same distribution. GANs produce synthetic data that closely mimics real data by competing two neural networks, namely the generative and the discriminator. The generative attempts to accurately represent the actual distribution of data in order to create fresh samples. The discriminator, however, often functions as a binary classifier, aiming to accurately differentiate between genuine and counterfeit generated samples [18].

Concurrently, training networks are a hallmark of the GANs neural network, one for image production and the other for classification. The adversarial training scheme has gained significant traction in both academic and industrial domains due to its efficacy in generating novel image samples and its utility in mitigating domain shift. When data is noisy, machine learning and neural networks are more likely to incorrectly identify objects. Misclassifying photographs becomes more likely when additional noise is introduced due to a slight increase. Is it possible to develop a method for neural networks to recognize new patterns, like sample training [16].

4- X-ray dataset

The x-ray imaging data used in the experiment was sourced from [19] with the goal of training the image, the dataset has been partitioned into three files: "train," "test," and "val," as shown in figure (1). Pneumonia and typical instances each have their own subdirectory of photos. The 5863 x-ray pictures included in the.jpg file have been classified as either normal or pneumonia-positive. The study utilized anterior posterior chest x-ray images obtained from retrospective cohorts of pediatric patients aged 1 to 5 years old at guangzhou women and children's medical centre in guangzhou. The chest x-ray imaging was conducted as part of the patients' stranded clinical care. There is an obvious imbalance in the training folder data, and it is possible to overfit the neural network by training it to classify the data into two groups [19].

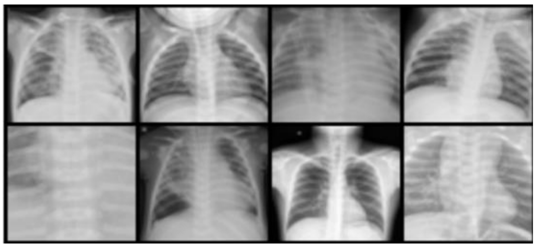


Fig (1) Training image[19]

5- Data augmentation

Data augmentation refers to the technique of creating more data samples to enhance the training of a model. Data augmentation is a valuable strategy that enhances the amount of information obtained from a limited dataset. Several writers have employed data augmentation strategies to acquire a broader range of data. This process involves applying

Various modifications to an image, such as flipping, cropping, scaling and rotating in order to alter it. Data modification aims to generate new instances of the class within the underlying category without any modifications.it can be employed in the process of training, testing or both. The utilization of a substantial volume of data enhances the performance of deep learning. Similarly, enhancing the detection performance of small objects can be achieved by augmenting the dataset with greater variety and quantity of small item examples[20]. Medical imaging data is expensive to label and scarce because of patient privacy issues; furthermore, the data is difficult to collect[5].

figure (2) show the first image rotated 30 degree counterclockwise, the second image rotated 30 degree clockwise and the last image crop to smaller size.

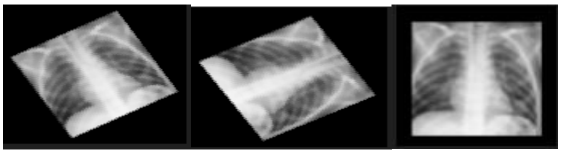


Fig (2) Traditional data augmentation

6- The proposed model

Using deep convolutional generative adversarial networks, the experiment improves regular x-ray images. Figure (3) shows the suggested GAN. The proposed system introduced a generator composed of 14 layers. The first image size (512*512) is input to the network, and the generator receives an input of a 100*1 noise vector, we used the NN-SVG online tool [21] for draw the proposed generative deep learning network as appears in figure (4). The first layer of the generator, as appeared in figure (4) contains the Transpose convolution operation, is performed using a kernel size (4*4), bath normalization and the RELU activation function. The second Transpose convolution operation is performed using a kernel size (4*4) generated image size (256*256) pixels, Bath normalization, and RELU activation function. The third transpose convolution is performed using a kernel size (4*4) generated (128*128) image size, batch normalization, and RELU activation function.

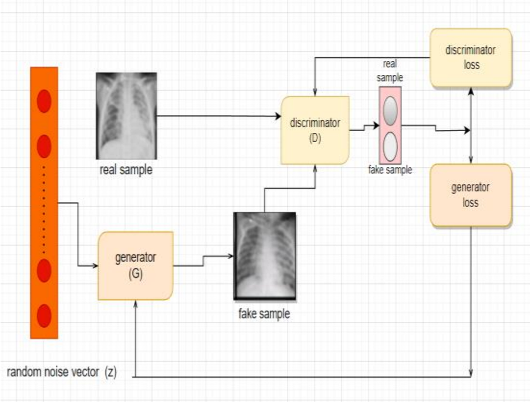


Fig (3) the proposed GAN

The fourth Transpose convolution has a kernel size of (4*4) generated (64*64) image size, the batch normalization operation, and the RELU activation function, ending with the tanh activation function. The discriminator is composed of 14 layers. The image size (64*64) is input to the network; the first operation is convolution is performed using a kernel size (4*4) LeakyRELU activation function,the second is convolution with a kernel size (4*4) that generated (128*128) pixel image size. Then there is the batch normalization operation and LeakyRELU activation function. The convolution operation generated an image (256*256) size. The batch normalization, Leaky RELU operation, and the last convolution operation with kernel size (4*4) that generated (512*512) image size and using the sigmoid function in the last layer.

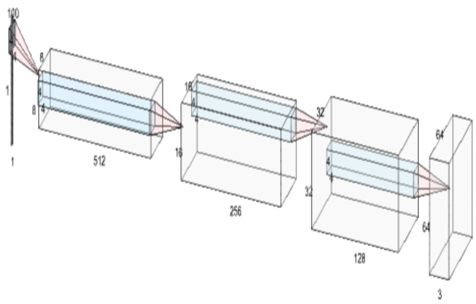


Fig (4) The proposed system generator architecture

6.1 THE GAN OBJECTIVE FUNCTION

In the suggested design, the generator aims to minimize the loss from the discriminator while also striving to make the fake distribution closely resemble the genuine distribution. The generator is given a 100x1 noise vector as input. Assume that z is a normal distribution-based random selection for the latent space vector. G(z) is a function that translates the latent vector z into the data space and is known as the generating function. The discriminator network, referred to as D(x), determines the likelihood that a given input x comes from the training data (genuine) rather than the generated data (false) produced by the generator distribution pz(z). The suggested method seeks to estimate the underlying distribution, referred to as p(data), from which the training data was formed. The estimating process enables the approach to produce synthetic samples, known as pg, that replicate the features of the predicted distribution. The GAN network trains a generator and discriminator together in a mini-max game, where the discriminator aims to maximize the loss function. The objective of D is to enhance the likelihood of accurately distinguishing between counterfeit and authentic photographs. The logarithm of the discriminator's output, LogD(x), is calculated while the generator aims to minimize the loss function [22]. Through the utilization of equation (1)

$$\text{Ming } \max D\ V(D,G)\ E_{x\sim P_{data}(X)}[\log D(X)] + E_{z\sim p_z(Z)}[\log(1-D(G(z)))] \qquad (1)$$

G endeavors to diminish the probability that D will classify its output as fake. Theoretical solutions exist for mini-max games, where the optimal strategy for the player, denoted as “pg“ is equal to the optimal strategy for the opponent, denoted as “pdata“. The discriminator assesses the probability of the inputs being real images (extracted from the training data) or synthetic images (generated data) based on probabilistic predications [23].

7. THE RESULT AND DISCUSSION OF THE EXPERIMENT

The proposed model possesses the capability to effectively extract the salient features present within the input images and then consolidate them into a single composite image. Continuous training has the capability to generate a multitude of synthetic images. The suggested GAN has the capability to produce novel images that have not been previously observed. The phenomenon under discussion is commonly referred to as variety in image production. In this context, the preference for GAN networks over traditional methods is seen. The utilization of methods for producing previously viewed is skin to the creation of artwork. We use a computer system equipped with windows 10 home, a AMD Ryzen 7 4800H with Radeon Graphics 2.90 GHz, and 16.0 GB of RAM to apply the suggested procedure. Google collab, Python, pytorch and tensorflow were employed as the software tools and programming languages in the execution of the suggested technique. Over the course of 2000 epochs of training, the GAN produced images that were visually similar to chest X-rays, with the quality of the generated images only increasing with time. Figure (4) is a comparison grid between genuine photographs (original data) and synthetic images (manufactured data). Typically, a loss function is used during training to bring a deep learning model to neural network convergence. Given that GANs need concurrent training of two neural networks. The output result: the loss for the discriminator is (loss_D = 1.223), Loss_D: 1.2223 Loss_G: 2.1597 D(x): 0.6463 D(G(z)): 0.0906 / 0.3155

the loss for the generator is (loss_G = 2.1597), and. D(G(z)) is the average discriminator output for the all fake batch D(z)=0.0906 .D(x) is the average output of the discriminator for the all real batch D(x) = 0.6463.The GAN demonstrates the capability to generate high resolution images that closely resemble the source images . That means the generator succeeded in creating x-ray images that the discriminator unable to distinguished where they were real or fake. By employing deep dense layers and optimizing hyperparameters as appeared in table (1) through data training for duration of (500) epochs. The batch size is set to (50). The reduction of learning rate to 0.0002 resulted in the generation of a high quality synthetic image. Furthermore, it exhibited superior performance compared to several GAN based methodologies in the generation of synthetic images. The resolution of image has significant importance in diagnostic models, as they heavily rely on the quality and resolution of medical images.

Table (1) The GAN hyperparameters

Hyperparameters	values
Optimizer for generator	adam
epochs number	500
batch size	50
learning rate	0.002
Size of z latent vector	100
Loss function	Binary cross entropy
Beta	0.55

Hyperparameters values

Optimizer for generator adam

epochs number 500

batch size 50

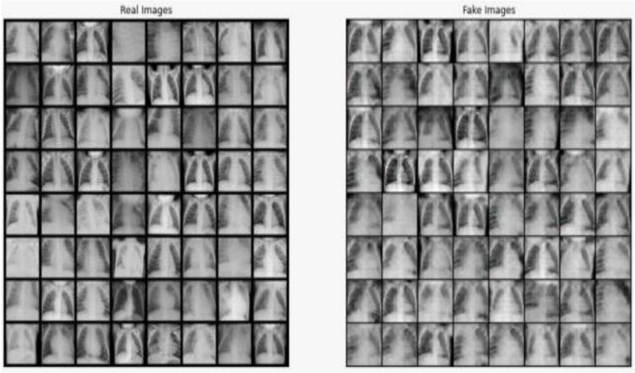
learning rate 0.002

Size of z latent vector 100

Loss function Binary cross entropy

Beta 0.55

We represent a visual representation consisting of a grid displaying authentic images (representing the original data) alongside fabricated images (representing the created images) in figure (5) bellow.



a.real image b.fake image

Fig (5) the images created by the generator are on the right; those from the original dataset are on the left.

The proposed model possesses the capability to extract the inherent characteristics of the given images and afterwards consolidate them into a single composite image. Continuous training has the capability to generate a multitude of synthetic images. The suggested generative adversarial network has the capability to produce novel features that have not been previously observed. The phenomenon under discussion is commonly referred to as variety in image information. In this context, the preference for GAN over traditional methods is seen. The utilization of methods for producing previously viewed visuals is akin to the creation of artwork. Therefore, our model has demonstrated superior performance. The conventional techniques of augmentation, in contrast, are limited to modifying existing images rather than generating novel ones. Various alterations were applied to the identical image. The figure (6) depicts a range of the images that were created at various epochs and the loss function diagram for discriminator and generator during training step as shown in figure (7).

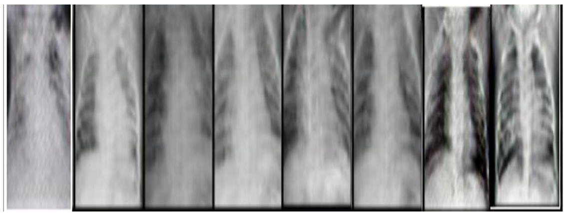


Fig (6) the generated results of GAN at various epochs

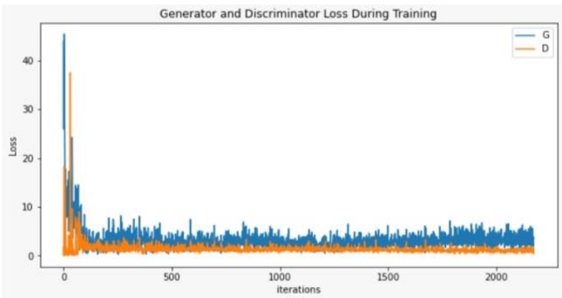


Fig (7) the loss function for discriminator and generator during training

8. CONCLUSION

Generative adversarial networks have made notable progress in the field of medical imaging, particularly in case when there is a scarcity of available data and the costs associated with gathering labeled data are prohibitive. This models based on a GAN are more used as data augmentation methods to increase the quantity and variety of medical images, we used convolutional generative adversarial networks (GAN) to simulate data from an underrepresented class in a dataset, in this case, a chest x-ray image. We've shown that it's possible to sort x-ray images of pneumonia into positive and negative categories. In contrast to approaches that depend primarily on transfer learning, we construct our model from scratch. Our primary emphasis is on image creation. GANs are most commonly utilized generative models and they possess significant capabilities for generating authentic synthetic data samples.

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