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Creating High Resolution Chest X-ray Images using Incremental Deep Convolution Generative Adversarial Network (IDCGAN)

B. Sateesh[1], M. Swamy Das[2]

[1]Ph.D Scholor, Osmania University, Hyderabad
[2]Professor, Chaitanya Bharathi Institute of Technology, Hyderabad

Abstract
Deep Learning in the field of Medical Sciences is one of the most demanding areas nowadays. There are many types of medical images like x-rays, CT scans, MRI scans, ultra sound images etc. X-rays are very low cost, easy to produce and fast to diagnosis the abnormality [2]. Till today Radiologists are manually interpreting the X-rays. Many researchers contributed their work to increase the accuracy of classification of medical images like X-rays. But still there is high scope to improve accuracy of medical image classification. One of the biggest challenge is to get datasets to perform experiments. Because of law of privacy of patients, it's not an easy thing to get inputs from medical laboratories. Though there are datasets in public domains. Still there is scope to investigate new data augmentation techniques to produce high quality synthetic data. In this work Incremental Deep Convolution Generative Adversarial Network (IDCGAN) is implemented. It is based on Deep Convolution GAN [2]. The model learns to produce high quality images in an incremental manner. It starts to learn from 64 x 64 resolution. Later it is trained to produce high resolution images. The experimental results showed high resolution Chest X-ray images with resolution 2048 x 2048.

Keywords: Deep convolution GAN, Generator, Discriminator.

1. Introduction

One of the main challenges in Medical Image analysis to get input data sets. Because of Law of privacy, medical data is not available in public domains. Researchers get very limited data from authorized medical laboratories. Hence to produce synthetic data from original data, GAN's are used.

GAN also called as **Generative Adversarial Network** [1]. It is a type of machine learning model framework used in unsupervised learning tasks, particularly in generating new data instances that resemble the training data. GANs were introduced by Ian Goodfellow and his colleagues in 2014 and have since gained significant attention and application in various domains of artificial intelligence and machine learning.

1.1 Key Components of GAN:

1. Generator (G):

The generator takes random noise or a latent vector z as input and attempts to generate realistic data samples (e.g., images, audio, text) that resemble the training data. It learns to map the latent space z to the data space.

2. Discriminator (D):

The discriminator acts as a binary classifier that distinguishes between real data samples from the training dataset and fake data samples generated by the generator.

It learns to classify whether a given input data sample is real (from the training set) or fake (generated by the generator).

1.2 Working Principle:

- **Training Process**: GANs work in a competitive manner where the generator and the discriminator are trained simultaneously in a game-theoretic framework.
- **Adversarial Objective**: The generator aims to generate data samples that are indistinguishable from real data (fooling the discriminator), while the discriminator aims to correctly classify between real and generated data.
- **Loss Functions**:
- The generator is trained to minimize the probability that the discriminator correctly classifies generated samples as fake.
- The discriminator is trained to maximize its ability to correctly classify real and fake samples.

1.3 Advantages of GANs:

- **Generative Capabilities**: GANs can generate high-quality[4], diverse, and realistic data samples that resemble the original training data.
- **Versatility**: They can be applied to various types of data, including images, audio, video, and text.
- **Unsupervised Learning**: GANs do not require labeled data for training, making them suitable for unsupervised learning tasks.

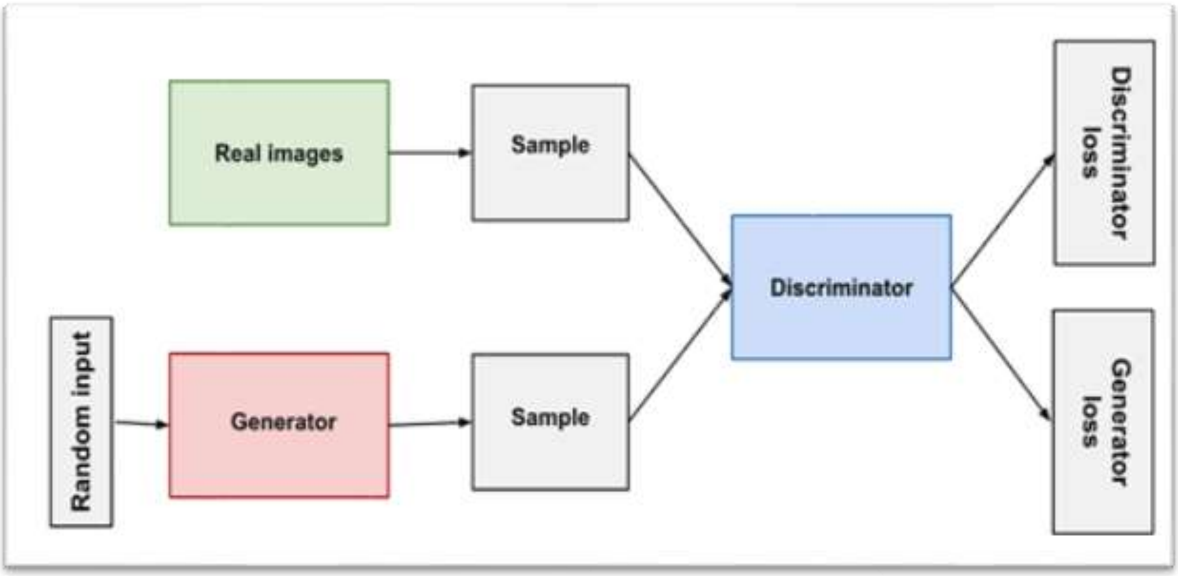

Fig 1: GAN architecture

2. Related Work

Several approaches were proposed and published by the researchers in improving accuracy of identifying

diseases using X-Ray images. The following section illustrates details of work carried out particularly in Noise Reduction, Augmentation and Classification of X-Ray images.
In 2019, Vedant Bhagat, Swapnil Bhaumik proposed a method to improve Pneumonia classification in Chest X-Ray images [1]. For Data Augmentation they proposed Progressive Generative Adversarial Networks(ProGAN). Using ProGAN, they generated the datasets. Rather than using the conventional GANs which produces the images of 64 x 64 and 120 x 120, the ProGAN [2] grow steadily by adding one layer at a time to handle high resolution images generated during training process. The proposed approach stabilize training, training time is reduced and produced state of art results. The sample data is generated with high resolution 1024 x 1024 which is highly important to get desired results. The authors used Pneumonia public data set from Kaggle and a variant of AlexNet model[2] as the deep convolutional neural network (DCNN) for feature extraction and classification. The produced samples are later used for training purpose. A set of 128 images with 64 original images and 64 synthetic images were given to Radiologist to examine the difference. According to him, real and synthetic images possessed similar characteristics and features.
The experimentation was carried out on the classification on two data sets D1 and D2. In D1 consisting of 4273 x-ray images of patients who suffered with pneumonia and 4000 images without pneumonia. D2 data set is generated using data augmentation. D2 consists of 11154 normal chest x-ray images and 11122 x-ray images with pneumonia. Classification accuracy on D1 is 79.5% where as it is 91% on D2. Authors concluded that performance of their proposed work was good when compared to conventional approach. They also concluded that there is still a room to improve performance of this approach.
In 2019, S. Prabhu, V. Balamurugan, K. Vengatesan proposed a Histogram Equalized (HE) based Cognitive and intelligent image filter for suppression of noise level in medical images[1]. For low contrast images, improving contrast is very much needed. The primary objective of authors was to improve contrast of low quality X-Ray images i.e to keep intensity at maximum variation. Out of all related works carried out in improving contrast, Histogram Equalization is highly preferred to improve the low contrast X-Ray images[5]. These filter functions by using the principles of adaptive selection theorem. A fuzzy based model is used to select filters.

3. Proposed work

In this work, DCGAN is trained with low resolution images. Gradually, resolutions of images are increased. To generate high quality chest X- Ray images, Initially the model starts from 256 x 256 resolution. Gradually resolution is increased to 2048 x 2048.

3.1. DCGAN formulation

One well-liked and effective GAN network design is DCGAN. It is mostly made up of completely connected or convolution layers without max pooling. For the down sampling and up sampling, it employs transposed convolution and convolutional stride. The generator network design is shown in the diagram below. The following are few important steps in DCGAN

1. Use transposed convolution for up sampling.
2. Eliminate fully connected layers.
3. Use Batch normalization except the output layer for the generator and the input layer of the discriminator.
4. Use ReLU in the generator except for the output layer, which uses Tanh

5. Use LeakyReLU in the discriminator.

Notations

G- Generator

D- Discriminator

X- be the image generated by Generator G.

D(X) - is the probability to tell whether image is real or fake, where X is an image generated by G. Which means if D(X) is 0 then image is considered to be real, else if D(X) is 1 then image is considered as fake.

The goal of Discriminator D is to maximize the probability value of D(G(Z))

The goal of Generator G is to minimize the probability value of D(GZ)

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[log D(x)] + \mathbb{E}_{z\sim p_z(z)}[log(1 - D(G(z)))]$$

The above shown is GAN equation [1]. To train the models, both networks Generator and Discriminator uses Binary Cross Entropy loss. Generator tries to minimizes it and in other hand Discriminator tries to Maximize it.

The DCGAN is implemented using incremental approach where model initially tries to produce image with very low resolution. Later stages, model is trained incrementally to produce high resolution images. The algorithm is as follows

Algorithm IDCGAN

Input : *Dataset images with different resolutions ranging from 64 x 64 to 2048.*

Output : *Producing augmented data with resolution images.*

Procedure *:*

Initialize the following parameters

Number of worker threads to load data from datasets

Batch size

Number of channels

Number of epochs and Learning rate

Load the datasets using worker threads

Create object instances for Generator and Discriminator

Set the activation functions for Generator. Other than output layer, action function should be ReLu. For output layer, activation function should be Tanh

Set the activation function Leak ReLu for Discriminator

Start training Generator and Discriminator

Incrementally change the resolution of images in training dataset

Check Generator and Discriminator loss

Continue above training for all epochs , still high-resolution images are generated.

End

4. Experiment Results

Hardware and S/W used to perform experiments

Hardware used :-

13th generation Intel i5 processor with 6 cores, 16 GB RAM DDR4.

Software, frameworks and libraries used :-

Kernel 5.4 Ubuntu server OS, Pytorch framework and libraries used are numpy, matplotlib

Datasets used :-

The original data with 214 images in which 138 are normal Chest X-rays and 76 are abnormal chest X-ray images. To produce quality images, incrementally resolution should be increased. Hence the original dataset is replicated as three different sets with different resolutions D1,D2,D3,D4 Where D1 has resolution with resolution 64 X 64, D2 has images 128 X 128 and D3 has 512 X 512 , D4 has images 1024 x 1024. D5 has 2048 X 2048. All sets D1 to D5 has similar images with different resolutions.

The training is performed to initially generate images with 64 x 64 resolution. Incrementally the samples are modified by replaceing 64 x 64 with few 128 x 128 images. After few iterations, DCGAN learnt to generate 128 x 128. In the same way, model generated 512 X 512, 1028 X 1028 and 2048 X 2048 images. The training is performed separately on normal X-ray images and abnormal X-ray images to generate samples.

The following Table shows the input parameters for training DCGAN on Normal Chest X-ray images

Table 1: Input parameters for training DCGAN on Normal Chest X-ray images-I

Number of samples	138
Batch Size	8
Learning Rate	0.0001
Number of Channles	1
Size of feature maps in Generator	8
Size of feature maps in Discriminator	8
Number of Epochs	15

The following graph shown below is the Discriminator loss and Generator loss when model is trained with normal chest X-ray images. Number of epochs are 15.

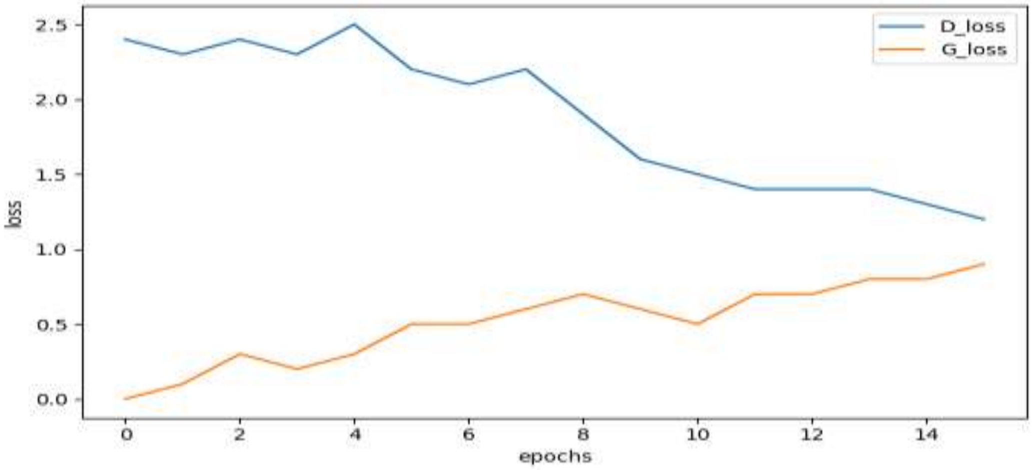

Figure 2 : Discriminator and Generator loss for Normal chest X-ray images-I

The following Table shows the input parameters for training DCGAN on Normal Chest X-ray images

Table 2: Input parameters for training DCGAN on Normal Chest X-ray images-II

Number of samples	138
Batch Size	8
Learning Rate	0.0001
Number of Channles	1
Size of feature maps in Generator	8
Size of feature maps in Discriminator	8
Number of Epochs	20

The following graph shown below is the Discriminator loss and Generator loss when model is trained with normal chest X-ray images. Number of epochs are 20.

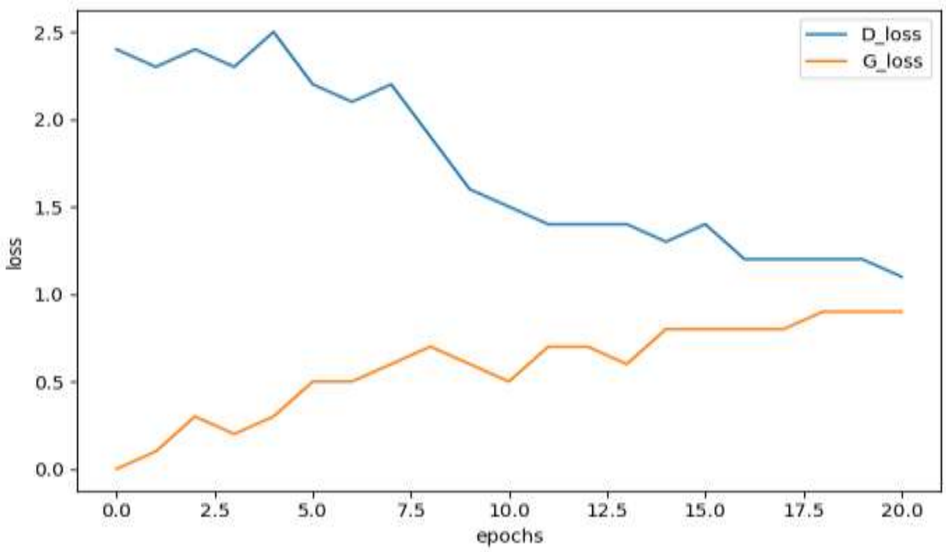

Figure 3 : Discriminator and Generator loss for Normal chest X-ray images-II

The following Table shows the input parameters for training DCGAN on Normal Chest X-ray images

Table 3: Input parameters for training DCGAN on Abnormal Chest X-ray images

Number of samples	138
Batch Size	8
Learning Rate	0.0001
Number of Channles	1
Size of feature maps in Generator	8
Size of feature maps in Discriminator	8
Number of Epochs	20

The following graph shown below is the Discriminator loss and Generator loss when model is trained with normal chest X-ray images. Number of epochs are 20.

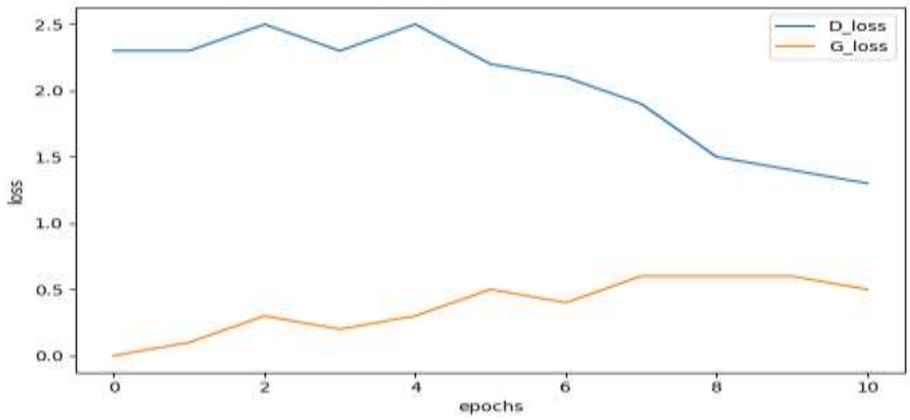

Figure 4: Discriminator and Generator loss for abnormal chest X-ray images

The following tables shows the time taken in hours to train the models using datasets normal and abnormal chest X-ray images for different epochs.

Table 4: Time taken by DCGAN

Epochs	Normal	Abnormal
10	NA	2 Hours 21 Mins
15	4 Hours 48 Mins	NA
20	6 Hours 13 Mins	NA

The below is the sample input of normal and abnormal Chest X-ray image samples from data set D1.

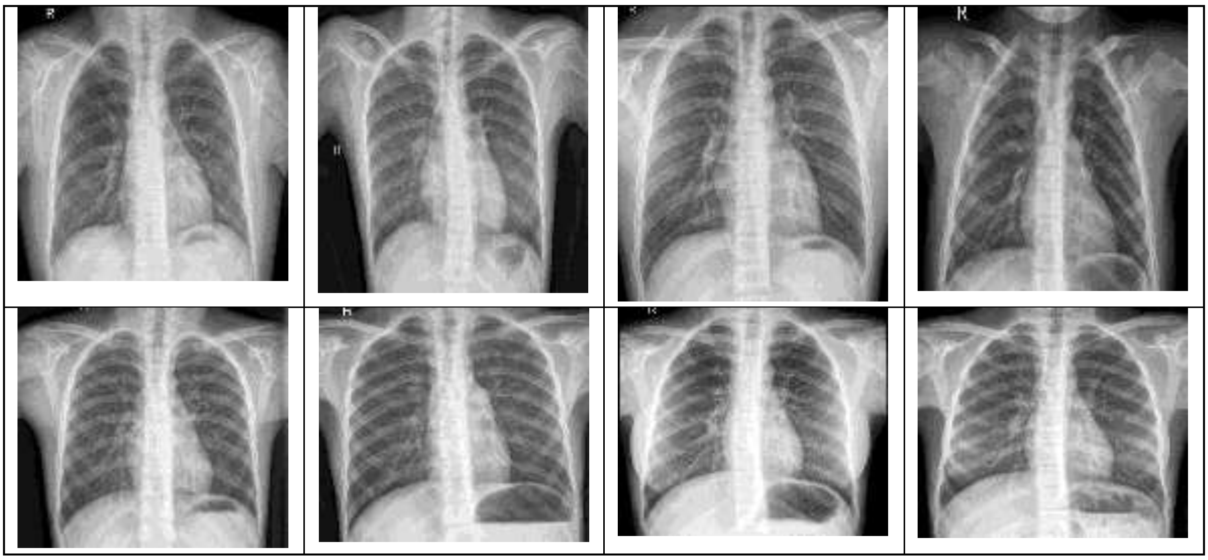

Figure 5 : Normal chest X-Ray images from Original Dataset

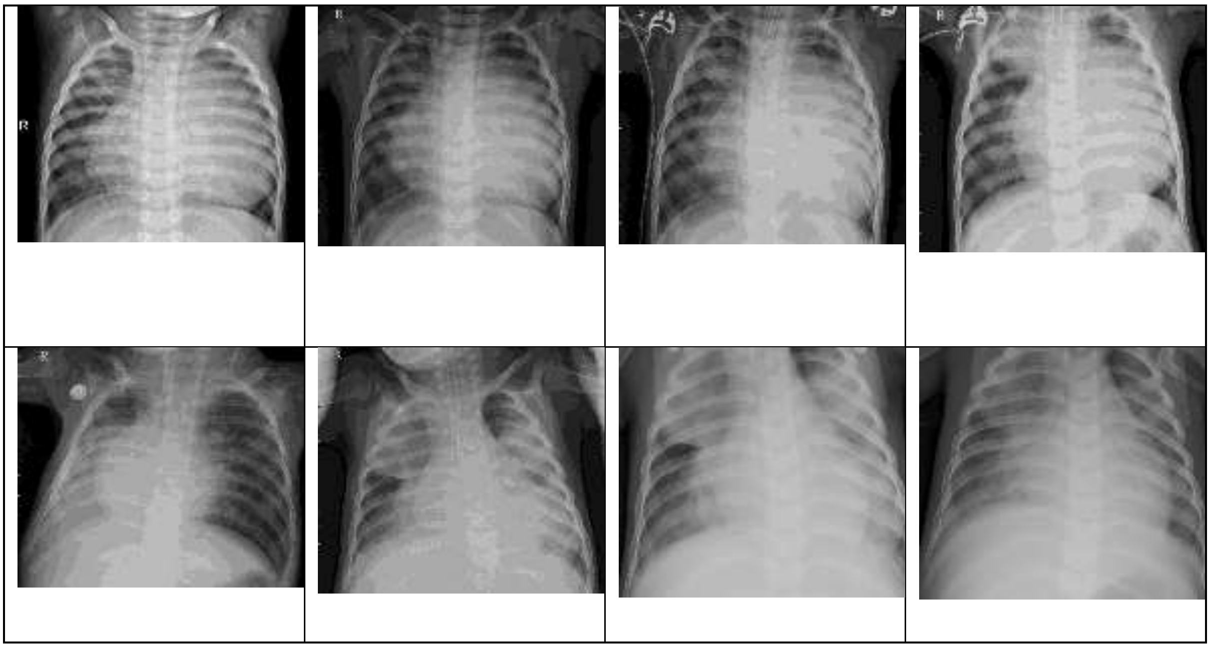

Figure 6 : Abnormal chest X-Ray images from original dataset

The following are the sample augmented output images generated by DCGAN

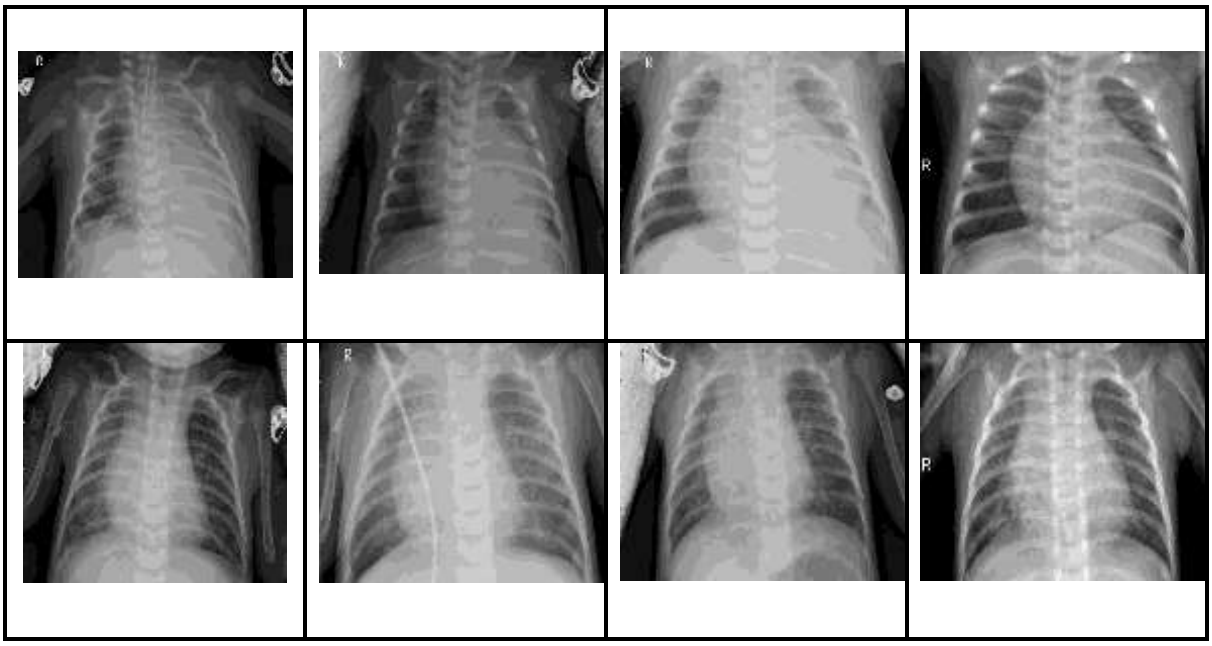

Figure 7 : Augmented Normal chest X-Ray images

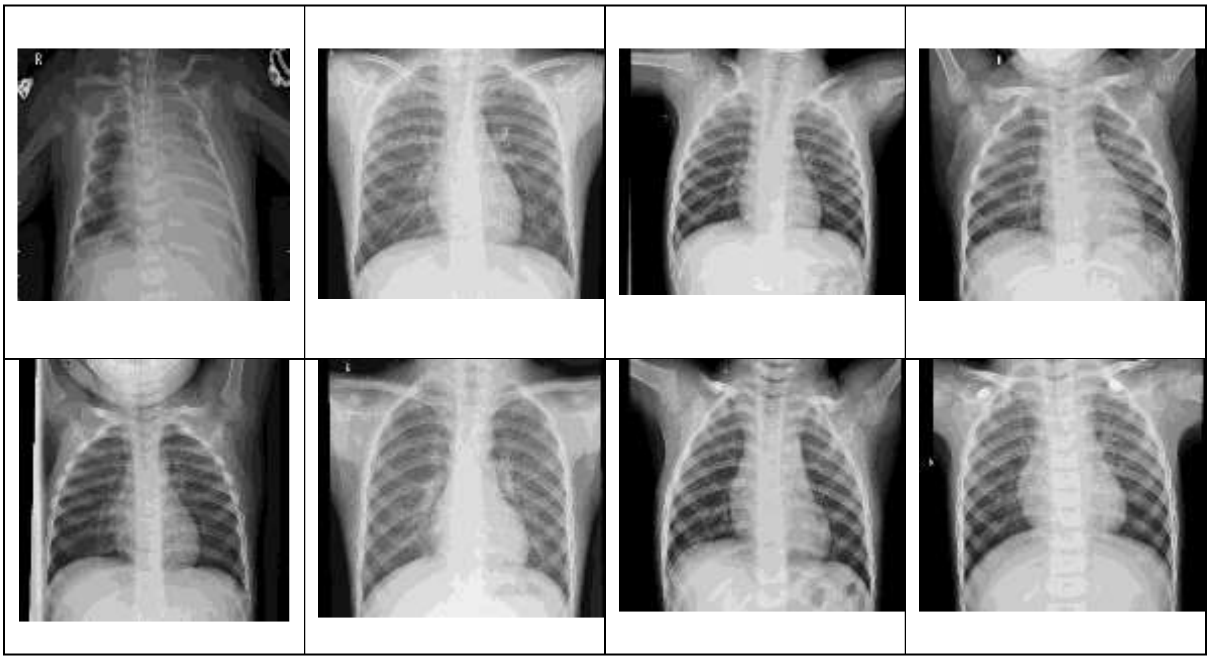

Figure 8 : Augmented abnormal chest X-Ray images

The total number of augmented chest X-ray images generated using incremental DCGAN are 846 with resolution 2048 x 2048. Out of which, 628 are normal X-ray images and 218 are abnormal X-ray images.

Conclusion:

In order to produce high resolution synthetic images, Incremental DCGAN is used in this work. Experiments are conducted with different number of epochs to produce optimal results. The Chest X-ray images are used in the data set with different resolutions starting from 64 x 64 to 2048 x 2048 to produce 848 Chest X-ray images with 2048 x 2048 resolution. Out of 848 Chest X-ray images, 628 are normal and 218 are abnormal Chest X-ray images.

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