Received: 2 March 2022 | *Revised: 31 March 2022* | *Accepted: 31 March 2022*
DOI: 10.37917/ijeee.18.1.12 *Vol. 18| Issue 1| June 2022*

Open Access

Iraqi Journal for Electrical and Electronic Engineering
Original Article

Expanding New Covid-19 Data with Conditional Generative Adversarial Networks

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Abstract

COVID-19 is an infectious viral disease that mostly affects the lungs. That quickly spreads across the world. Early detection of the virus boosts the chances of patients recovering quickly worldwide. Many radiographic techniques are used to diagnose an infected person such as X-rays, deep learning technology based on a large amount of chest x-ray images is used to diagnose COVID-19 disease. Because of the scarcity of available COVID-19 X-rays image, the limited COVID-19 Datasets are insufficient for efficient deep learning detection models. Another problem with a limited dataset is that training models suffer from over-fitting, and the predictions are not generalizable to address these problems. In this paper, we developed Conditional Generative Adversarial Networks (CGAN) to produce synthetic images close to real images for the COVID-19 case and traditional augmentation that was used to expand the limited dataset then used to train by Customized deep detection model. The Customized Deep learning model was able to obtain excellent detection accuracy of 97% accurate with only ten epochs. The proposed augmentation outperforms other augmentation techniques. The augmented dataset includes 6988 high-quality and resolution COVID-19 X-rays images. At the same time, the original COVID-19 X-rays images are only 587.

KEYWORDS: deep learning, COVID-19, Augmentation, Generative Adversarial Network, Conditional Generative Adversarial Network, image synthetic.

I. INTRODUCTION

The people of China's regions were contaminated in 2003 by (severe acute respiratory syndrome) a particular type of severe disease of the lungs (SARS) later renamed (SARS-COV1) [1]. In December of 2019, COVID-19 was detected for the first time in Wuhan. It soon spread throughout the world, killing millions of people. The pandemic was announced in late March of 2020 by the Organization of the Health World, and on 21 July, across 188 nations worldwide, there have been nearly 14 million verified infections and 609,198 fatalities [2]. Coronavirus illness is a respiratory infection caused by (SARS-CoV2). The coronavirus family includes alpha (α) followed by beta (β), gamma (γ), and delta (δ) coronaviruses, as well as omicron, until now. In 2003, a SARS coronavirus epidemic afflicted 26 nations, resulting in over 8000 cases. SARS-CoV-2 (COVID-19) has infected about 1.5 million people in 150 countries, with a fatality rate of 6% as of this writing. SARS-CoV-2 has a higher transmission rate than SARS coronavirus [3][4]. The most common symptoms of Covid-19 are a dry cough, a loss of appetite, liver damage, and weariness [5][6].

COVID-19 may be identified in different ways, like PCR [6], Chest computed tomography (CT) imaging, and chest radiography (X-rays). These methods are more sensitive to COVID-19 uses fewer resources than classic RRT-PCR [6], [7]. PCR has limited sensitivity for COVID-19 detection.

Because COVID-19 virus's widespread change in approaches, medical practitioners may lack the necessary knowledge to execute proper diagnoses based on medical field images; chest radiography (X-rays) with computed tomography (CT) are two examples. Consequently, practitioners may use artificial intelligence (AI) and deep learning technologies to help automate COVID-19 diagnostic processes. Deep learning techniques play an essential role in medical image Developing based on diagnostic tools for COVID-19. The diagnostics of medical images can deliver accurate and concise analytical findings using deep learning techniques. The lack of COVID-19-related medical imaging data, like X-rays and CT images, is one of the most critical issues; the dataset that is accessible is often limited in size. So, we need to extend these data safely to get excellent and accurate detection results. Deep learning models may be used to detect COVID-19[8]. Deep learning algorithms for detecting COVID-19 show promising results; such models should be viewed cautiously since they are based on a small sample of data. When the deep learning models are trained on a limited dataset, the critical problem is that they are prone to overfitting. To overcome this problem, proposed professional Generative Adversarial Networks [8],[9]. Especially the conditional-Augmentation GAN (CGAN) model [10]. In this research, to create x-rays synthetic COVID-19 images to augmentation dataset and then utilized in deep detection model, prepared proposed work-based CGAN model to produce synthetic X-ray including Normal and COVID-19 images. As a result, unsupervised data augmentation was a possible instance when labels were available for a sample of the images in the dataset.

The following are the most significant contributions made by this article:

• A modified CGAN was built to produce a significant number of X-ray images to detect COVID-19. This comprises the Generator and Discriminator network designs also the parameter settings.

• It was possible to generate Augmented COVID-19 images that included 5589 images that could be utilized to develop the detection models of COVID-19.

• detection model of COVID-19 using the high-quality generated X-rays images was created by the CGAN modified.

• good detection accuracy was achieved.

The remainder of our research is organized in the following manner: Section-1 this review provides an introduction, in section-2 related work review, Methodology principle, and some of its modifications in Section-3. Section-4 Explains the dataset utilized in our research; in section-5, there is an overview of the proposed models; in Section-6, we'll look into how GAN can be used to synthesize medical images. Section-6 and 7 summarize the overall review and the result.

II. Related Works

Receive continued to develop in medical research, especially those interested in Synthetic data generation that realistic-looking medical images have been proposed in the field of healthcare to increase the diversity and quantity of current training data. Ghorbani et al. [11] propose a synthetic data generator based on (GAN) to increase the diversity and quantity of skin lesion images. Kohlberger et al. [12] synthesize pathology images for cancer with natural out-of-focus characteristics to assess general pathology images for focus quality issues. Han et al. [13] propose that high-resolution artificial radiographs be created through synthetic generation. In the space of COVID-19, the authors of the article Xin Yi et al. [8] show GANs in medical imaging that goes beyond image synthesis. And Abdul Waheed et al. [14] employed the Odena et al. developed (ACGAN) to produce synthetic data to solve the constraints of traditional information augmentation. The limitation is Blurry results in poor image quality. Loey et al. [15] Conditional GAN (augmentation was utilized to improve multiclass classification accuracy to distinguish COVID-19 from ordinary. The limitation: limited data was used using only 345 images. Amal A. Al-Shargabi et al. [16] To exploit the Covid 19 dataset, used a (CGAN) to build a synthetic image (COVID-CGAN). The original dataset included COVID-19, Normal, and pneumonia to CGAN model training. The limitation: slow it trained timed roughly 16 hours to complete the training; the proposed model is complex and a long time to prepare and generate images. Mohd Asyraf et al. [17] creates synthetic data using (DC-GAN). The limitation: is that it does not do hyper-parameter tuning. Yifan Jiang et al. [18] presents a COVID-19 CT image synthesis approach based on CGAN. A disadvantage is that CT scans were used.

III. Methodology

A. *Overview Generative Adversarial Network (GAN)*

GAN stands for convolution neural network; it is an approach for learning deep representations without extensive training data. It was developed by a team of academics headed by Ian Good fellow (2014). There are two neural network models: generator (G) and discriminator (D). It competed against another in GAN. The noise (Gaussian or standardized distribution) generates samples from the required distribution [19]. (This is called the generator model). The discriminator model, which gets samples from the generator and training data, is in the second model.

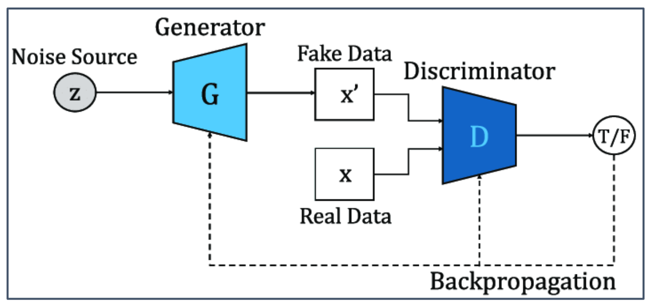

Fig.1: the Generative Adversarial Network's structure

Gan has been trained in the manner of a min-max algorithm. The loss function is similar to a min-max game with two players, shown by Equation (1).

$$\underset{C}{\text{Min}}\ \underset{D}{\max} V\,(\text{D},\text{G}) = E_{X\sim P_{data}(X)}\left[\log\left(d(X)\right)\right] + E_{z\sim P_{g}(Z)}\left[\log\left(1 - D\left(G(Z)\right)\right)\right] \quad (1)$$

• The possibility of instance x being real is predicted by d(x) by a discriminator.

• Ex The average of all actual data.

• G(z) the output in the presence of (z) gaussian noise.

• The discriminator D(G(z)) estimate the likelihood of a fake sample being actual.

• The predicted value to random input data is given by the generator Ez.

In Gan, Generator (G) is trained to make an image look like an original image, while the discriminator discriminates between generated and actual data. G produces fake samples as training samples derived from the latent noise variable (z). In contrast, fake examples taken from Generator (G) are given to the Discriminator (D) to determine the difference between original and fake data. The error is backpropagated to the generator when the discriminator finds the fake data [20][21].

B. Conditional Generative Adversarial Network (CGAN)

Conditional GAN (CGAN) [22], a version of the traditional GAN that employs class labels to condition the class of the generated image from among all the classes in the training set, allowing for a more realistic image. Suppose both the G and D are conditioned with additional information, like class labels. In that case, GAN can be expanded to a conditional model. Conditioning can be done by adding the class label y to the Discriminator and Generator as an extra input layer. The last input, y, and noise pz(z), are combined with the joint hidden layer in the generator. The framework for adversarial training networks provides a lot of freedom in building this private representation [23].

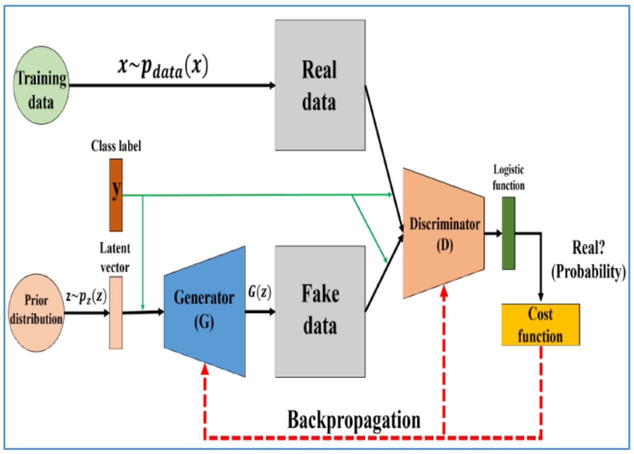

Fig.2: the CGAN general structure.

The discriminator takes inputs x and y then applies the discriminative.

Equation (2) is the objective function of a two players minimax game.

$$\min_{C}\max_{D} V(\mathrm{D},\mathrm{G}) = E_{X\sim P_{data}(X)}\left[\log\left(d(X|Y)\right)\right] + E_{Z\sim P_{g}(Z)}\left[\log\left(1 - D\left(G(Z|Y)\right)\right)\right] \quad (2)$$

- D(x|y) is a discriminator's estimation of the likelihood of actual data example
- (x) is a reality for a given class (y)
- The discriminator D(G(z|y)) estimation of the likelihood of a fake sample is to be fundamental for class (y) that is given.

IV. Dataset's Characteristics

Used a publicly accessible chest X-ray dataset with three categories: Normal (10,192) images for healthy persons, COVID-19 (3.616) for patients with a positive case, and Pneumonia for people with Pneumonia (1,345 images). The images were varied in size and type [24-29].

V. Proposed Model

The suggested architecture comprises two main stages: the first stage is standard data augmentation and the second with CGAN. Later, combined the two techniques and improve the evaluation. Figure 3 shows the flow chart of the proposed model.

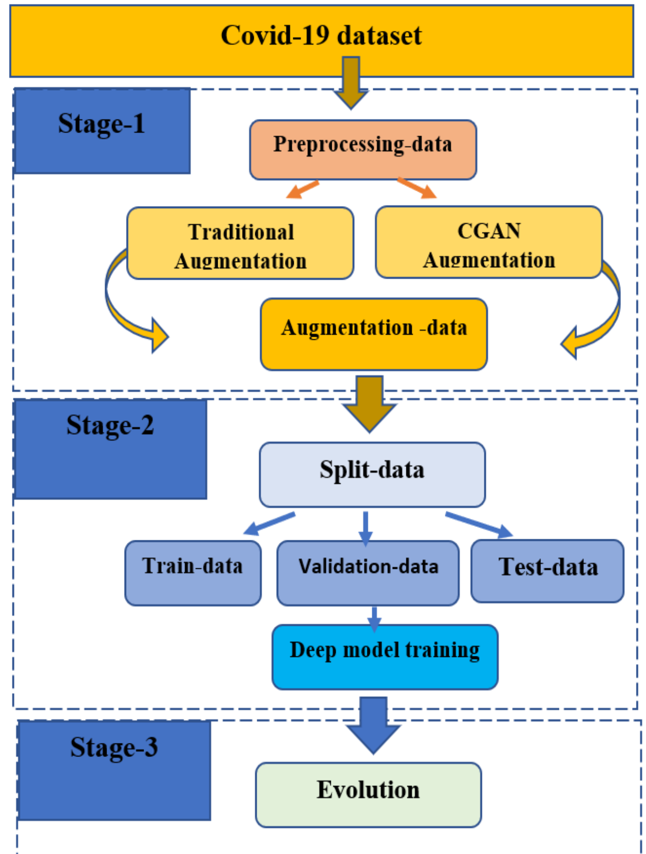

Fig.3: Proposed Model for data augmentation in three design stages

A. Image Preprocessing

The X-rays images were preprocessed using the same color system, style, and size images were resized to (128 x 128 pixels). Additionally, some of these images were cropped to delete any details not part of the primary X-rays images like the header and footer. X-ray-generated annotations and arrows were also deleted from the images. Non-linearity activation Tanh in the CGAN architecture, normalized images to the [-1, 1] range. All of the images in the dataset were treated to remove any scans that were of poor-quality Figure 3. COVID-19 patients' cleaned X-ray images. This was done to allow a fair comparison with other standard cases whose data had an Anteroposterior (AP) frontal view of the X-rays images removed from the dataset. To show the usefulness of the suggested model, we utilized just 589 images from the primary datasets in our experiment. It could only operate with a few images, roughly 10% of the total data. The dataset was updated in 2021[30].

B. Image Augmentation

Large volumes of data are required to create solid and generalized deep learning models. On the other hand, Data on medical imaging is limited and difficult to get because of the patient privacy issue; moreover, labeling this data is expensive.

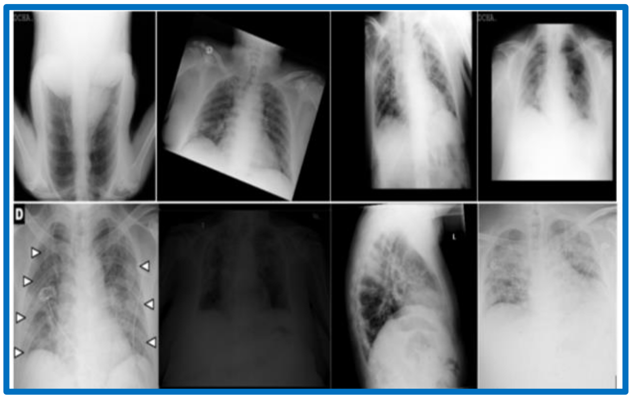

Fig.4: displays several X-ray images that were not utilized in the experiment.

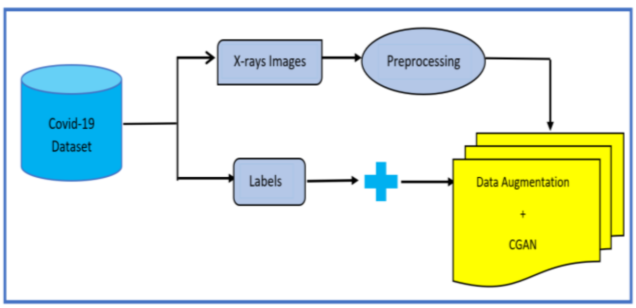

Fig.5: Proposed CGAN and traditional data augmentation are employed in the design stage

1) Traditional Image Augmentation

Traditional Image Augmentation used Random rotation, scaling, flipping, and shift operations [31][32]. To construct the Image Data Generator function of the TensorFlow from the Keras framework [33]. In the traditional augmentation methodology. COVID-19 X-ray augmented images are shown in Figure 6.

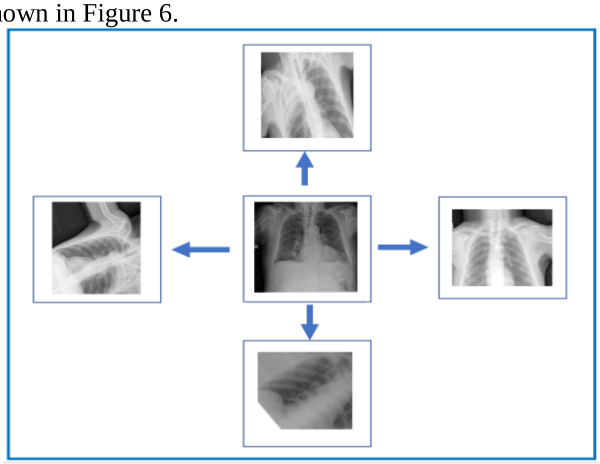

Fig.6: Classical Augmentation Techniques, which augment the limited COVID-19 chest X-rays images.

Data splitting with a ratio of 70:30, where training data is 70%, testing data is 20%, and validation data is 10%.

TABLE I
The number of images in the Covid-19 X-rays collection traditional technique.

Main Dataset	*Training set*	*Validation set*	*Testing set*
Original dataset	370	176	41
Original dataset + traditional augmentation	2511	717	359

2) CGAN Image Augmentation

In this research, the total layers employed in the initial phase of network generation were four transposed convolutional layers, followed by three ReLU activation function layers. For normalizing the values, batch normalization with three layers and used Tanh activation Layer for the output. There are four convolutional layers in the discriminator phase, followed by three leaky ReLU activation layers. To normalize the values applied two batch normalization layers and three drops out. Finally, for the output, used the sigmoid activation Layer. Each transposed convolutional and convolutional layer seems to have a 5x5 filter size.

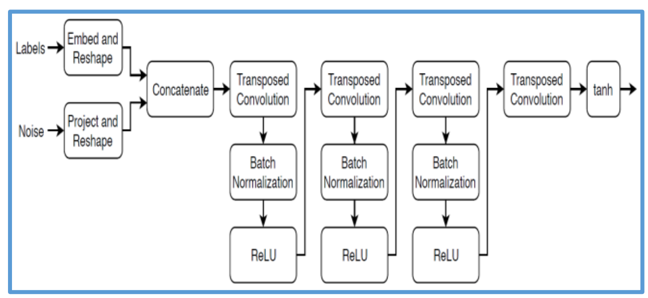

Fig.7: layered proposed CGAN generator

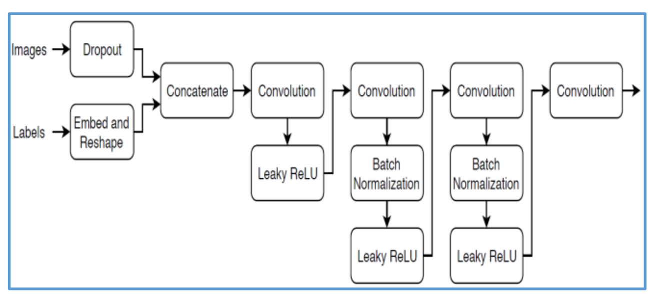

Fig.8: layered of proposed CGAN discriminator

CGAN generated sample is assigned the appropriate label of class (C) and distribution noise (Z). The (G) generator creates fake images $X = G(c,z)$. Discriminator (D) produces a probability distribution to class labels and inputs.

$$P(S \mid X),\ P(C \mid X) = D(X)$$

Discriminator layers are initially configured to be non-trainable. As a result, the discriminator updates the generator. This results in a CGAN composite model trained to generate fake images for COVID and Non-Covid classes. Resized generated images to (128 × 128 × 1) and normalized with the range [0, 255] to [1, 1] during the image preparation stage. (The technique of Normalization for changing the capacity of image pixels.) Its solution is to transform an input image into a set of pixels that are more recognizable or natural to the human eye. The optimizer function Adam is employed [34]. Adam is simple, works with sparse gradients, takes up minimal memory. As a result, Adam was chosen as the optimizer. For CGAN training, the hyperparameters are being used in Table II.

TABLE II
The hyperparameters are being used in the CGAN model.

Hyperparameters	values
Batch Size	256
Learning Rate (LR)	0.0002
The Adam optimizer's momentum (Beta)	0.5
number of epochs	20000
Sample interval	5000

The model takes around two hours, forty-seven minutes, and six-second to train and generate images. Loss functions optimize the GAN is Binary Cross-Entropy (BCE). in the design of Table III, all training, validation, and testing data results are achieved.

TABLE III
Image numbers of Covid-19 X-rays collection with the CGAN technique.

Main Dataset	Training set	Validation set	Testing set
Original dataset	370	176	41
Original dataset + traditional augmentation	2511	717	359
Original dataset+ proposed CGAN	1970	563	281
Original dataset + traditional Augmentation+ proposed CGAN	4892	1398	698

3) Deep Learning Model

With the aid of medical image classification and detection, Deep Learning models have achieved substantial advancements in various digital image applications, including quicker and earlier identification of any diseases. Through sounds, texts or images, the Deep Learning model learns the classification tasks directly. The DL model can achieve an accuracy that exceeds the level of human performance. The proposed deep learning model detection is a CNN model. In the customized CNN model conation of X-rays image as the input layer convolution layers, Relu activation functions employed after the convolutional layer to activate the layers, Max pooling layers, fully connected layers, and for output layer, sigmoid activation functions are applied to predict the test image into COVID-19 and Normal, which was trained using the optimizer an Adam just ten epochs, the learning rate is 0.001. The loss function was categorical cross-entropy, all models were trained until convergence. the network was trained with batch size 32 to input images with only 6,552,898 parameters, Comparatively, the proposed model utilizes less memory than ResNet-50, a commonly used deep learning model that employs 23,567,299 parameters for comparison.
However, the DropOut is 0.5, which is essential in avoiding overfitting issues of the proposed method.

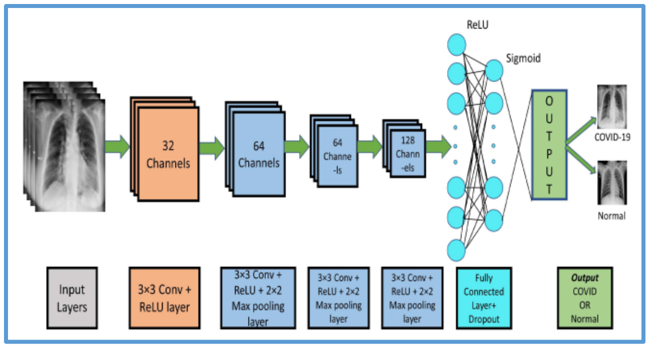

Fig.9: Model for COVID-19 detection using a proposed CNN.

TABLE IV
The hyperparameters are being used in the Customized model

Hyperparameters	values
optimizer	Adam
Learning Rate (LR)	0.001
momentum (Beta)	0.5
number of epochs	10
Batch Size	32

VI. Experimental Results and Discussion

The recommended model was trained on python Google colab storage than Pro with an increased graphics processing unit (GPU) and supported GPU learning using the package and library of TensorFlow machine learning. Colab pro Gradient provides paid-tier instances of the NVIDIA M4000 and NVIDIA P5000 and instances up to V100. The proposed model has been evaluated in three distinct scenarios: the first utilizes the original chest X-rays dataset to augment traditional augmentation techniques, the second uses the CGAN model, and the third scenario combines the two approaches. The (COVID-19/Normal) groups were included throughout all experimental trials. The generated image to data augmentation shows in figure 10.

The approach of the deep detection model was evaluated on various performance metrics, including accuracy (ACC), total parameters, and numbers of image generation. Also, discussed many current deep learning approaches current deep learning approaches that have been developed mainly for COVID-19 classification and compared their performance. Detailed performance metrics for the proposed model and its benchmarked methods are shown in Table V.

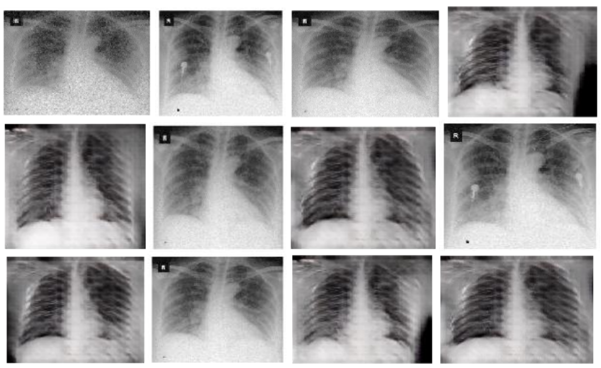

Fig.10: Sample the generated high-quality resolution covid19 images by the proposed CGAN.

TABLE V
The experiments of the suggested model and other methodologies are presented in this section.

study	Image type	GAN Type	Mean accuracy
Abdul Waheed et al[14]	X-rays	ACGAN	0.95
Loey et al[15]	CT	CGAN	0.82
Amal Al-Shargabi et al[16]	X-rays	CGAN	99.7
Mohd Asyraf et al[17]	X-rays	DCGAN	0.92
Saman Motamed et al[35]	X-rays	IAGAN + DCGAN	0.80 0.80
proposed model	X-rays	CGAN	0.97

Table V describes the evaluation of the present detection models, the suggested augmented deep model, on the other hand, was developed using X-ray images of the chest and a huge number of samples. Amal Al-Shargabi et al. [16], although the classification accuracy is high at 99%, the CGAN used takes a lot of time to train. It needs 16:05:55 to generate images; the number of images generated is only 2796 out of 500, while the proposed simple CGAN take less time and generates 5589 images in only three hours. Saman Motamed et al. [35], This work employed two forms of GAN, namely IAGAN and DCGAN, yet the classification accuracy was 80% campier than the proposed method is 97%. Loey et al. [15], Using a deep convolutional generative adversarial network to produce synthetic data] employed a CGAN with CT images rather than CXR images. It achieved a testing accuracy of 0.82%.

CGAN trained on the original dataset that involved two classes and then generate images for each category depending on (given label). Figure 8 depicts the CGAN training process regarding the generator and discriminator's loss scores; the generator tries to reduce the loss function as much as possible, which may fool a discriminator. CGAN generated 2814 COVID-19 images. The number of epochs was decided depending on the resolution of the generated images, the quality of the produced images increased over 500 epochs and increased gradually until could generate high-resolution images. CGAN was trained for many iterations.

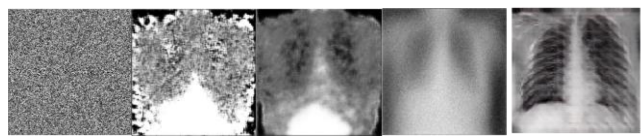

Fig.11: The output of the CGAN at different time intervals.

Accuracy is a measure of the total number of correct predictions produced by the model, and it is defined in the following ways.

$$\text{Accuracy} = \frac{(\text{TN} + \text{TP})}{(\text{TN} + \text{FP} + \text{TP} + \text{FN})} \tag{2}$$

When dealing with deep learning classification situations where the output may be divided into two or more classes, the Confusion Matrix is used as a performance evaluation.

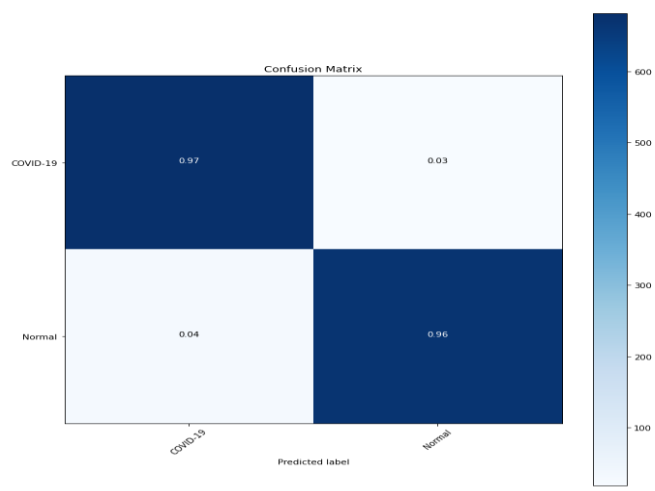

Fig.12: Confusion matrix with Covid-19 diagnosis using CNN, utilizing synthetic data and actual data as inputs.

VII. Conclusions

The world was attacked by a novel coronavirus in late 2019 that caused death and infected millions of people in just a few months, to prevent the spread of the virus we need early detection as a result we proposed a deep learning approach based on traditional augmentation and Conditional Generative Adversarial Networks (CGAN) to expending limited COVID-19 dataset, the CGAN Technique could generate realistic synthetic COVID-19 X-ray images that have never been seen previously by learning the distribution noise of images, our dataset expanding from 587 to 6988 with high-quality images and variety. The augmented dataset improves the performance of the customized detection model and resolves the overfitting issue. The experiment showed that the deep learning model can significantly improve the speed diagnosing of COVID-19 cases with high accuracy of 97%.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

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