Iraqi Journal of Science, 2023, Vol. 64, No. 7, pp: 3642- 3656
DOI: 10.24996/ijs.2023.64.7.40

ISSN: 0067-2904

Automatic Diagnosis of Coronavirus Using Conditional Generative Adversarial Network (CGAN)

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Received: 29/5/2022 Accepted: 3/10/2022 Published: 30/7/2023

Abstract
A global pandemic has emerged as a result of the widespread coronavirus disease (COVID-19). Deep learning (DL) techniques are used to diagnose COVID-19 based on many chest X-ray. Due to the scarcity of available X-ray images, the performance of DL for COVID-19 detection is lagging, underdeveloped, and suffering from overfitting. Overfitting happens when a network trains a function with an incredibly high variance to represent the training data perfectly. Consequently, medical images lack the availability of large labeled datasets, and the annotation of medical images is expensive and time-consuming for experts. As the COVID-19 virus is an infectious disease, these datasets are scarce, and it is difficult to get large datasets due to patient privacy. To address these issues by augmenting the COVID-19 dataset. In this paper, we adjusted conditional generation adversarial networks (CGAN) along with traditional augmentation (TA). The augmented dataset includes 6550 X-ray images that can be used to improve the diagnosis of COVID-19, and we have implemented five models of transfer learning procedures (DTL). The proposed procedures yielded high detection accuracy of 95%, 93%, 92%, and 92% in only ten epochs, for VGG-16, VGG-19, Xception, and Inception, respectively, and a custom convolutional neural network. Experimental results prove that our model achieves a high detection accuracy of up to 96% compared to other models. We hope it can be applied in other fields with rare data sets.

Keywords*:* Deep Transfer Learning, COVID-19, Augmentation, Generative Adversarial Network, Conditional Generative Adversarial Network, synthetic image.

التشخيص الآلي لفايروس كورونا باستعمال شبكات الخصومة التوليدية المشروطة

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الخلاصة
ظهر وباء عالمي نتيجة انتشار مرض فيروس كورونا .(COVID-19) تستعمل تقنيات التعلم العميق (DL)لتشخيص COVID-19 بناءً على عدد كبير من الأشعة السينية للصدر . نظرًا لندرة صور الأشعة السينية المتاحة، فإن أداء DL للكشف عن COVID-19 متخلف ويعاني من فرط التركيب. يحدث التجهيز الزائد عندما تقوم الشبكة بتدريب وظيفة ذات تباين كبير بشكل لا يصدق لتمثيل بيانات التدريب بشكل مثالي. وبالتالي، تفتقر الصور الطبية إلى توافر مجموعات بيانات كبيرة تحمل علامات، كما أن شرح الصور الطبية مكلف ويستغرق

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وقتًا طويلاً بالنسبة للخبراء، نظرًا لأن فيروس COVID-19 مرض معدي، فإن مجموعات البيانات هذه نادرة ومن الصعب الحصول على مجموعات بيانات كبيرة بسبب خصوصية المريض .في هذه الورقة، قمنا بتعديل شبكات الجيل المشروط العدائية (CGAN) جنبًا إلى جنب مع التعزيز التقليدي .(TA) تتضمن مجموعة البيانات المعززة 6550 صورة بالأشعة السينية يمكن استعمالها لتحسين تشخيصCOVID-19 ، وقد نفذنا خمسة نماذج لإجراءات التعلم المنقولة .(DTL) أسفرت الإجراءات المقترحة عن دقة اكتشاف عالية بنسبة 95٪ و93٪ و92٪ و92٪ في عشر حقب فقط، VGG-16 وVGG-19 وXception وInception، على التوالي، والشبكة العصبية التلافيفية المخصصة. تثبت النتائج التجريبية أن نموذجنا يحقق دقة اكتشاف عالية تصل إلى 96٪ من بين النماذج الأخرى.

I. Introduction

Coronavirus is a viral disease associated with Corona Virus 2 (SARS-CoV-2), which attacks the respiratory system and leads to the severe acute respiratory syndrome. In 2019, the disease appeared in China, spatially in the city of Wuhan; then the infection quickly spread around the world [1]. The World Health Organization has publicly declared the viral epidemic to be a public health emergency. This virus is highly infectious; the patient must be detected and isolated as early as possible. Several techniques have emerged to detect the disease, such as polymerase chain reaction (PCR) testing, antibody testing, chest x-ray, and computed tomography [2].

One of the most important clinical procedures that can be used to determine the degree of lung disease is a chest X-ray. This is due to the limited cost as an advantage that makes it available in all medical centers, even in non-developing countries [3]. The dilemma arose from the lack of diagnostic experts who make accurate diagnoses of the disease compared to the increasing number of infected people. Thus, technical support should be used as an aid to relieve pressure on the health system. Recently, the DL approach has played an important role in the fields of classification and diagnosis of medical images based on X-ray, CT scanning, MRI, etc. DL requires a large number and variety of patient data sets to achieve high detection rates. The drawback of medical images is that they are scarce and therefore not easy to get or share due to the privacy of patients. COVID-19 data is likely to be scarce.

The results are not accep for training DL models on a limited data set. The critical problems that these models suffer from are overfitting, lack of generalization, and low detection performance [4]. Therefore, we need to increase the datasets to have sufficient DL on the one hand and, on the other hand, to protect medical staff from potential infection when caring for COVID-19 patients and relieve their suffering. To solve this daunting task, they proposed Generative Adversarial Networks (GANs) to artificially augment the dataset [5], especially Conditional Generative Adversarial Networks (CGANs) [6].

It is a special type of standard GAN that can generate synthetic invisible COVID-19 X-ray images by learning the distribution of data from the actual dataset based on the given class label. CGAN was adjusted along with traditional X-ray image-based augmentation methods to augment the COVID-10 dataset and then used to improve COVID-19 detection performance. Several researchers have created detection systems for COVID-19, but they are mostly based on limited data sets [7-9]. Other researchers have used CGAN to generate COVID-19 x-ray or CT scans [10]. Unfortunately, these trials did not produce detection models for COVID-19. In this paper, we augment the COVID-19 dataset first and then use it to improve an automatic COVID-19 detection model based on five deep transport models and a custom CNN.

The transport models are VGG-16, VGG-19, Xception, and InceptionV3 [11,12]. These models can accurately distinguish between positive and normal COVID-19 cases on chest X-ray images, achieving high accuracy. Several assessment procedures were used, including accuracy, recall, precision, confusion matrix, and F1 score [13]. The values of each of these scales were determined with the help of the ratios of the different training and test samples. The contributions of this paper are a safe method of collecting COVID-19 X-ray data relies on the synthetic images applied to data augmentation, showing that (CGAN) and classical augmentation are effective techniques for increasing the X-ray COVID-19 dataset, a safe and efficient method of collecting the COVID-19 dataset in a short time, and demonstrating a customized CNN model to detect COVID-19 that aids in solving the lack of experts annotating medical images.

The remainder of the paper is arranged in the following: Section 2 presents a review of the related work; Section 3 describes the research materials. Section 4 depicts the proposed architectural scheme and result. Section 5 contains a description of the performance outcomes and results in the analyses. Finally, section 7 indicates the conclusion of the article and future work.

II. Related Works

DL has recently impacted several scientific domains [14]. It is spatially used in the medical field to categorize diseases. Because of the scarcity of data in medical images, researchers have investigated techniques to increase datasets. Since [15] published the first paper on GANs, which generate new synthetic images, medical imaging has benefited from its usage in generating previously unknown data. [16] applied DL on COVID-19 X-ray images. They performed three DTL (ResNet50, VGG-16, and EfficientNetB0), and a lightweight CNN model with. They obtained detection performances of 94.3%, 90%, and 96.8%, respectively.

The limitations are the GAN structure and the training phase must be performed. [17] developed (ACGAN) called CovidGan to generate images that improve the performance of COVID-19 diagnosis. The limitation is that the quality of synthetic images is low. Cross-center validation on data has not been performed [18]. [19] presents traditional augmentations and conditional GAN mixed with five transfer learning models based on CT images. This method's limitations are that it cannot generate unique data, and the newest DTL is ResNet-18, where many recent state-of-the-art methods are not compared [20]. The authors [21] proposed a semi-supervised detection based on IAGAN and DCGAN for the identification of COVID-19 and pneumonia in X-ray images. The limitation is that there is no significant change in performance even after adding the augmentation methods. [22] The authors propose the COVID-Net model to classify the X-ray dataset into three categories: COVID-19, Normal, and Pneumonia. They achieve 92.4% accuracy. The limitation is that no augmentation technique was applied.

[23] suggested a multiclass categorization deep model which employs the VGG-16 model for categorizing X-ray images into COVID-19, healthy, or pneumonia, categories. [24] The authors present (CVAE-GAN) were able to create synthetic COVID19 X-ray images with different deep models; ResNet; and InceptionV3; were evaluated. The ResNet model demonstrated high accuracy when training and testing. [25] analyzed how different data augmentation methods of the VGG-16 model used progressive (PG-GAN) worked based on how well X-ray images. The augmentation is used to balance datasets, solve the problem of training images, or prevent models from generalizing.

Previous works discussed suffered from some problems, including poor quality of generated images and a lack of diversity, as well as low achievement in diagnosis. Amal A. Al-Shargabi et al. [26] exploited the Covid-19 dataset and used a conditional GAN to build a synthetic image (COVID-CGAN). The original dataset included COVID-19, normal, and pneumonia for CGAN model training. The limitations are: slowness because its training time roughly takes **16 hours** to complete the movement; the proposed model is complex and takes a long time to prepare and generate images. Tirth Mehta et al. [27] introduce a conditional GAN (CGAN) synthesis strategy based on a chest X-ray image. Experiments classified the X-ray dataset into six classes: Normal, COVID-19Mild, COVID-19Medium, COVID-19Severe, Tuberculosis, and Pneumonia. The suggested method can create realistic synthetic chest X-ray images.

Furthermore, to detect chest disease, they apply five DTL; ResNet-50, ResNet-101, Xception, DenseNet-201, and DenseNet-169, which achieve test accuracy of 0.93, 0.91, 0.92, 0.92, and 0.90, respectively. The limitations are the poor quality of generated images and the lack of diversity. This work only focuses on the evaluation results of classification accuracy and does not claim the quality of the synthetic chest X-ray images. [26,27].

This work is the closest to our work; our proposed models exceed them due to the optimal use of hyperparameters. Additionally, the diversity of the dataset has resulted in the diversity of images generated in our work. These issues were solved by an adjusted CGAN algorithm and combined with traditional augmentation.

I.Research Materials

A. Dataset's Collection

Chest X-rays are critical in diagnosing viral diseases. We adopted the X-ray technique in the data collection process. It is available in most medical clinics and has a low cost. In this study, we utilized an available online chest X-ray collection with three different categories: normal (10192) images for healthy people, COVID-19 (3616) images for a positive case, and pneumonia images (1345) [28,29]. These images had pixel values ranging from [0, 255] and varied in format. The dataset was last updated in 2021. Figure 1 depicts several samples of the X-ray images.

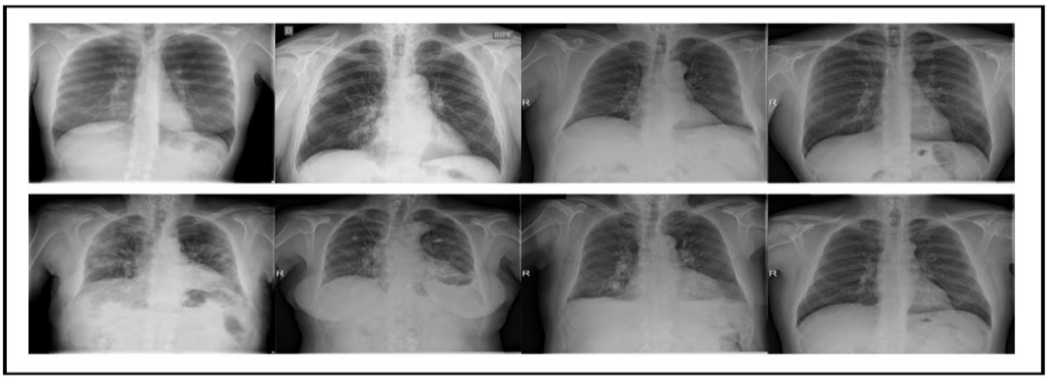

Figure 1: X-ray images sample of COVID-19 and Normal case from the considered dataset.

B. Conditional Generative Adversarial Networks (CGAN)

Efficiency in training is achieved if the dataset is large. The generation of more realistic images that provide augmented datasets is possible because the GAN models can generate new random, plausible examples for a given dataset. There is no way to manage the types of images generated. The CGAN is a version of the traditional GAN. It can be described as a training framework for generative artificial neural networks that can generate synthetic data. CGAN consists of two networks: generators and discriminator networks. These two networks have opposite learning goals. The generator network (G) takes noise distribution (z) from the original image as input and class label (y). If a class label is given, image generation can be conditional on it, enabling the targeted synthesis of images of a specific type [30].

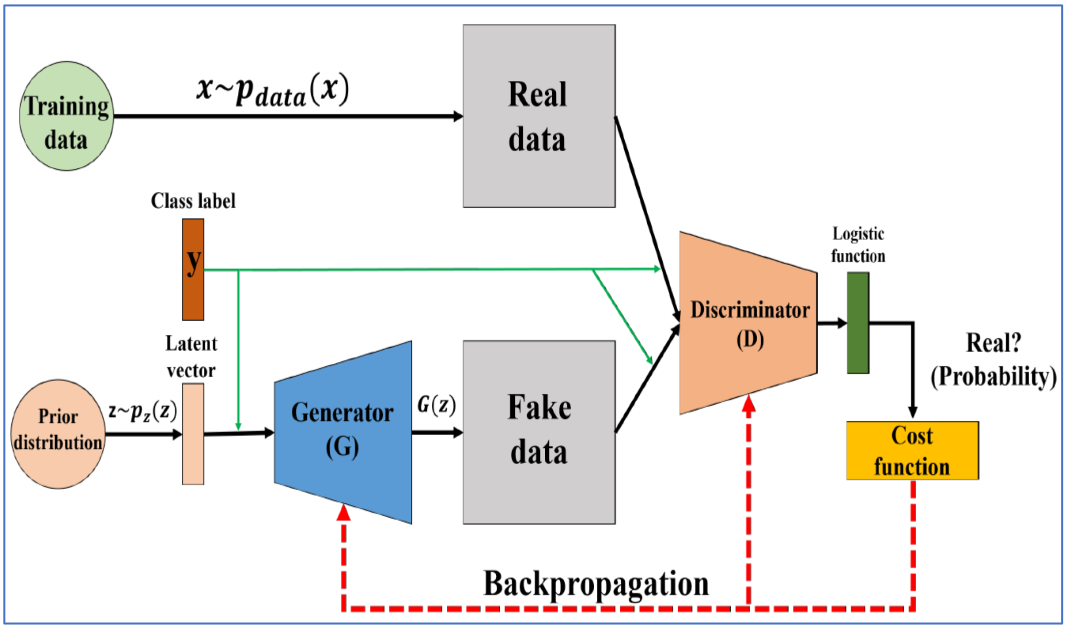

Figure 2: The basic structure of the CGAN [31]

The generator tries to generate a fake image G(z) that is similar to an original image. The generated image is passed to the discriminator (D) with the conditional information. The discriminator tries to distinguish between the fake image and the real image based on the real probability determined by the cost function. Figure 2 shows the basic architecture of CGAN. CGAN has been trained in the manner of a min-max algorithm. The loss function is similar to a min-max game with two players, as shown by Equation (1).

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

Where…

- D(x|y): denotes to the discriminator estimated the probability for the sample of real data.
- (x): is actuator reality for class (y).
- D(G(z|y): denotes the discriminator estimated the probability for the sample of fake data.

C. Traditional Augmentation

Traditional augmentation is useful in improving the performance of DL. The data augmentation tools make the data rich and sufficient and thus make the model perform better and more accurately, which helps in visual transformations. The transformation is mainly focused on image classification of basic alterations to add affinities like color modifications and transformation images such as scaling, converting, flipping, brightness, or boosting contrast, blurring, white balance, and sharpening [32].

D. Deep Learning Model

A convolutional neural network (CNN) has been proposed to build a deep learning model which can precisely diagnose and classify X-ray images. CNN is a type of neural network which has multiple layers [33]. Each layer is connected to the other. The input image represents the first layer of the CNN. The output of one layer is the input for the next layer. Each CNN layer has a filter. Generally, a filter is a 3x3 matric that is put on top of the image and slides as it makes matric calculations on the image. After these calculations are done, feature extraction takes place with the help of pooling. The most commonly used pooling method is the max pooling method, which extracts the highest value from each sliding calculation of the filter.

II.The Proposed COVID-19 Detection Model

The COVID-19 detection model is based on six phases: the setup, image collection, image preprocessing, image augmentation, splitting, and classification phase. Figure 3 shows the flow chart of the proposed model.

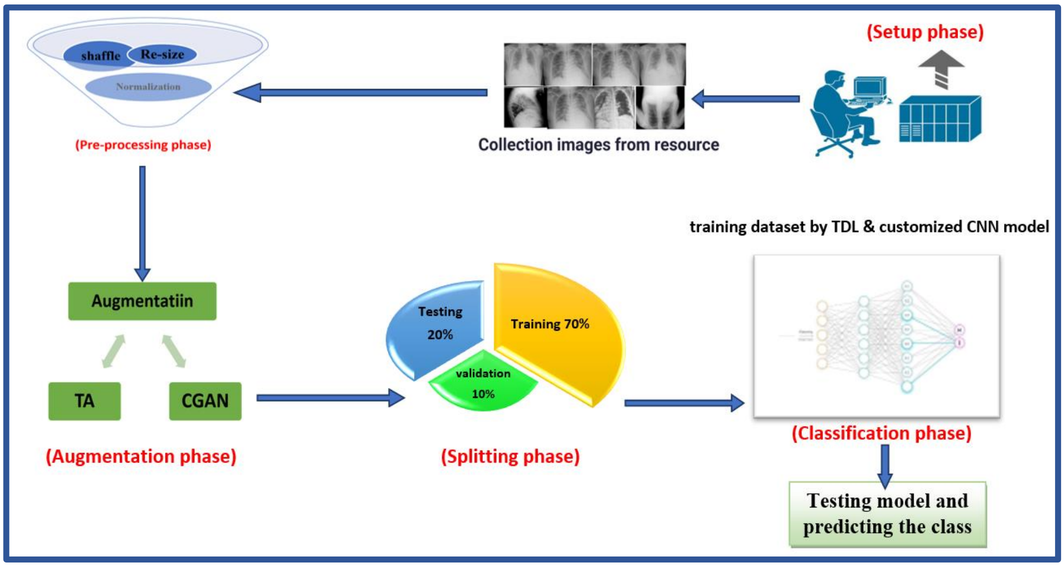

Figure 3: The six stages for the proposed detection model.

1. *Setup Phase:*

X-ray images were obtained from the available public online resource on GitHub. It has been shown that an unbalanced image collection due to COVID-19 is a novel virus, so only a limited number of images may be obtained.

2. *Preprocessing Phase*

In the preprocessing phase, X-ray images taken from the public dataset were pre-scaled to 224 x 224 pixels, using the same color scheme and style. In addition, some images were cropped to remove any features that were not part of the X-ray image, such as annotations and arrows. Several images were deleted, such as those scanned from side view and low-quality images. We preprocessed all the images in the collection so they are normalized to have a range between [-1, 1]. After the preprocessing stage, we used just 587 images for COVID-19 images and 6969 (normal case) images from the original datasets in our experiment.

3. *CGAN Augmentation phase*

CGAN augmentation was performed for the purpose of introducing new synthetic images.

A CGAN trained to generate a synthetic image for COVID is produced as a consequence of this procedure. We adjusted CGAN by changing the value of hyperparameters and the number of dense layers in the generator and discriminator. In this case, we experimented with the provided and custom combinations of dense layers to improve the quality of the generated images. The steps will be updated when the training network's learning rate is optimized. An optimal learning rate depends on the structure of the loss landscape, the model's architecture, and the available dataset. A larger learning rate will result in faster learning but will not give good results. A too-small learning rate will cost more computing power and result in overfitting. In our experiment, using an Adam optimizer, the learning rate is denoted by alpha and beta. Adam was selected to be part of our optimization algorithm for both the generator and discriminator [34]. Through compiling the discriminator by Binary Cross-Entropy, the loss function is Sigmoid activation plus a cross-entropy loss. Additionally, we used the Leaky ReLU activation function instead of ReLU. It consists of a small amount of slope when it comes to negative values. It is possible to reduce the capacity of the network while training and avoid overfitting by adding dropout layers to discriminator networks. Table 1 displays the hyperparameters in CGAN that are used.

Table 1: The hyperparameters are being used in the CGAN model

Hyperparameters	values
Batch Size	64
Learning Rate (LR)	0.0002
The Adam optimizer (Beta)	0.8
number of epochs	20000
Sample interval	5000

The number of iterations in the whole dataset that has been trained and the size of the training examples to be used in a single iteration is called batch size. The number of epochs was chosen based on the experiment so that reasonable image quality could be obtained when trained for a few epochs. The generated images were blurry and had a lot of noise. Therefore, the epochs and batch size have been increased and the learning rate has been decreased. Figure 4 shows CGAN trained for many epochs. The good-resolution synthetic image is generated after 500 epochs.

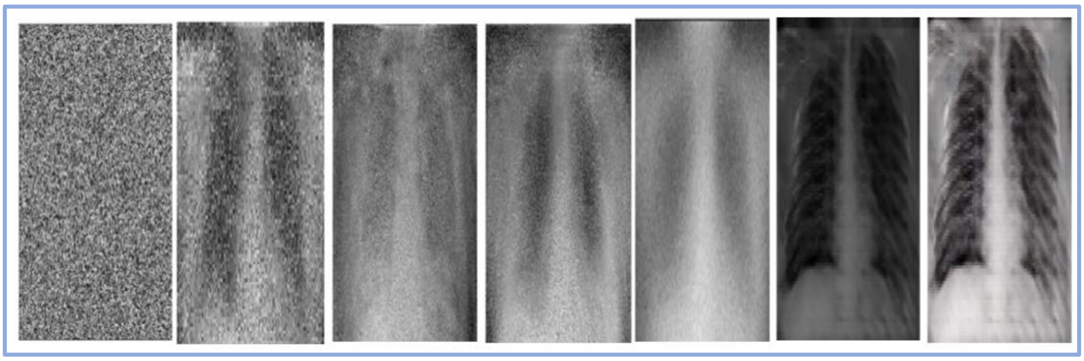

Figure 4: CGAN training to generate synthetic images over many epochs.

In this paper, CGAN requires approximately two hours and forty-seven minutes to train and generate images. After applying CGAN, the dataset number of images reached 1550 images for the COVID-19 class. These images have good resolution and variety. This will help in achieving better testing accuracy and performance matrices. The achieved performance measurement will be discussed in section (5). Figure 9 shows a sample of the generated images.

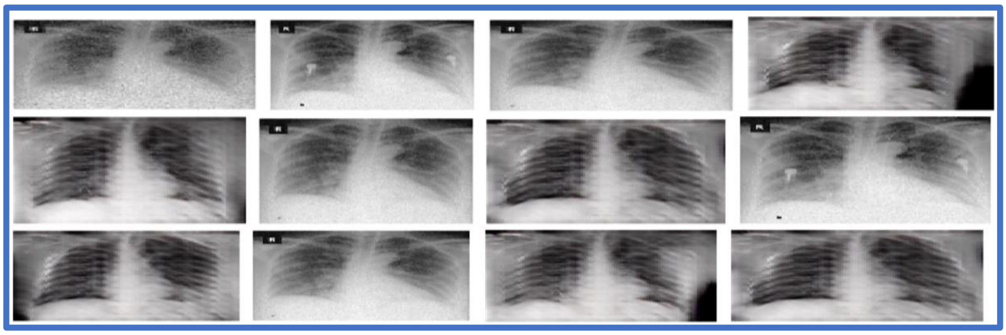

Figure 5: Sample of synthetic COVID-19 X-ray images.

4. *Traditional Augmentation phase*

The classical augmentation method includes shift, horizontal flip, vertical flip, rotating the image, and scaling using the ImageDataGenerator capability of the TensorFlow Keras framework [35]. The dataset after the traditional augmentation phase has 5587 images for the COVID-19 class. The traditional augmentation method is fast, dependable, and accessible, but it cannot generate unseen images. Therefore, we combined these images with images generated by CGAN. Figure 6 shows a sample of COVID-19 X-ray's traditional augmented images.

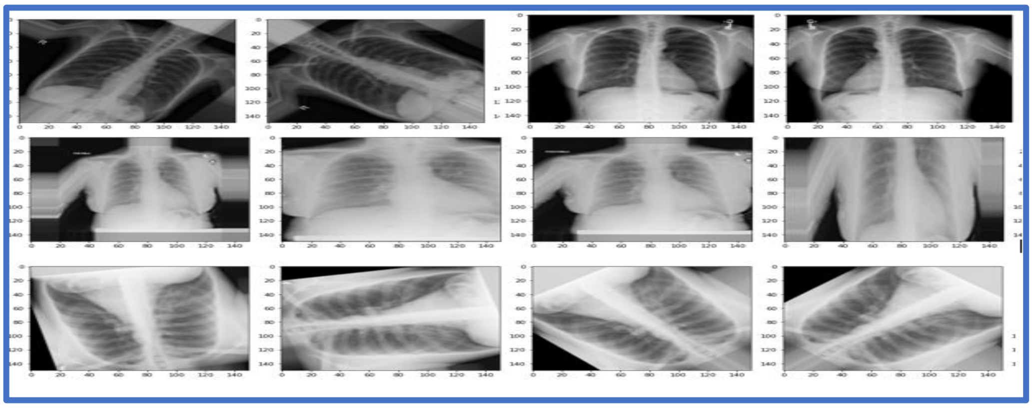

Figure 6: Sample of traditional augmentation dataset.

5. Splitting phase

In the splitting phase, we split the dataset into two parts. The first part of the dataset is dedicated to training. It contains 70% of the dataset, while the second part is devoted to testing and validation. It contains approximately 30% of the dataset. Table 2 lists the number of split images with traditional augmentation, and Table 3 lists the number of split images with CGAN augmentation.

Table 2: The number of images in the Covid-19 X-ray collection traditional technique

Main Dataset	Training Set	Validation Set	Testing Set
Original dataset	411	117	59
Original dataset + CGAN	1044	447	59

Table 3: Image numbers of Covid-19 X-ray collection with the CGAN technique

Main Dataset	Training Set Set	Validation Set	Testing
Original Dataset	**59**	**411**	**117**
Original dataset + TA	**59**	**3870**	**1658**
Original dataset + TA+ Proposed CGAN	**59**	**4544**	**1947**

6. Classification phase (diagnosis)

In this phase, we perform several deep transfer models and the proposed model that have coilability for the classification.

a. Deep Transfer Learning Models

In this section, several CNN architectures have been applied that were utilized to improve detection efficiency. The DTL models used are VGG-16, VGG-19, Inception, and XCeption. Each of the five deep transfer models was pre-trained on the augmented dataset, which includes both actual images from the original dataset and synthetic images from the augmented dataset. This model has different sizes, layers, storage space, and training time. A detailed description of each deep transfer model is covered in Table 4. All the models were pre-trained using identical parameter combinations to allow for fair comparisons between all of them.

Table 4: Configuration of DTL models

Models	Batch size	Momentum	Epoch	Learning Rate	Optimization
VGG-16 **VGG-19** **inception** **XCeption**	32	0.9	10	0.001	SGD

b. Proposed CNN

The proposed CNN model consists of four main layers employed: input layers, convolutional layers, fully connected layers, and output layers. The first input layer is an image with a size 224×224, which is followed by four convolution layers. The first one is a 2D convolutional layer with a kernel 3×3 and is employed after the ReLU activation function, which extracts the image features and passes them to the next layers, The next three 2D convolutional layers also use the ReLU activation function and 2×2 Max pooling layer. It decreases the computational cost by reducing the number of parameters, which helps to prevent overfitting to make the model computationally efficient. The output of the convolutional layers is converted to a long 1D feature vector by a flattened layer.

This output from the flattened layer is fed to the fully connected layer with dropout. In a fully connected layer, every input neuron is connected to every activation unit of the next layer. All the input features are passed through the ReLU activation function, and this layer categorizes the images according to the assigned labels. The sigmoid function is applied to predict the test image in COVID-19 and normal. During the training step, the Adam optimizer is utilized with a learning rate of 0.001 and momentum (Beta) = 0.5. The loss function is binary cross-entropy and the batch size is 64 with only ten epochs. The total parameters are 6,552,898. The model takes just 15 minutes, with an accuracy of 96%. Figure 7 depicts a proposed CNN utilized to detect COVID-19 X-ray images.

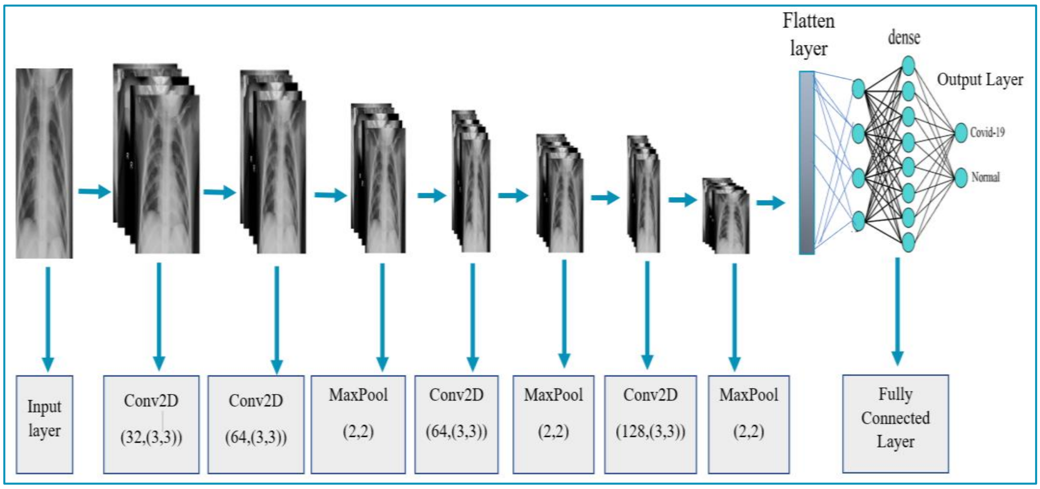

Figure 7: A proposed CNN model for COVID-19 detection.

c. COVID-19 Diagnosis

The primary aim of this paper is to develop an automated method for diagnosing COVID-19 and normal patients using chest X-ray images. Finally, the DL model can achieve an accuracy that exceeds that of human performance. Several CNN models help in the diagnosis of diseases, as well as the speeding up of initial medical treatment and determining the probability of diagnosis. Figure 8 shows the prediction of the proposed model for the diagnosis of COVID-19.

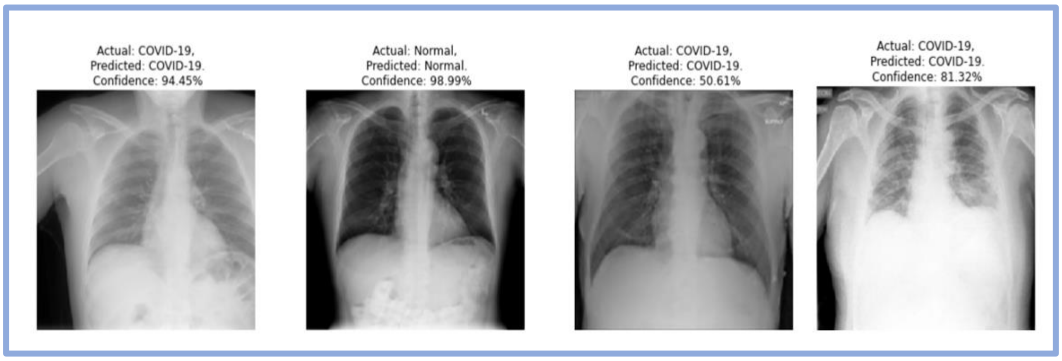

Figure 8: The results for the proposed CNN model and DTL models.

VI. Result Evaluation and Discussion

The effect of the multi-augmented dataset used for improving the detection of COVID-19 has been discussed. The implementation of CGAN and CNN models' architecture is done by TensorFlow and the Keras DL library. The training of the models was done online on an

Intel(R) Core (TM) i5-4302Y CPU, 64-bit, using the Python language, and Google Colab pro, which is available for free from Google Cloud Platform.

1. Performance Matrices

To evaluate the Deep Learning models, it is necessary to establish several criteria. One of these criteria is testing accuracy. In our experiment, the best deep learning model that we examined is the proposed model, which has the highest testing accuracy of 0.96% when employed with the COVID-19 X-ray dataset. The deep learning detection model was evaluated on various performance metrics, including precision, recall, accuracy, and F-Score. Table 5 describes the testing accuracy for all scenarios applied in this paper.

Table 5: Testing accuracy for the different scenarios

Dataset	VGG-16	VGG-19	Xception	Inception	Proposed model
COVID-19	85.31%	87.88%	82.43%	82.67%	90.12%
COVID-19 with TA	90.52%	89.38%	88.57%	89.41%	95.11%
OVID-19 with CGAN	89.34%	86.89%	89.23%	88.73%	94.57%
COVID-19 with TA and CGAN	95.64%	93.71%	92.35%	92.85%	96.55%

Table 5 shows the COVID-19 detection performance for different models. Note that when the models are trained using the multi-augmentation technique, high accuracy is achieved. The proposed model outperformed the other models with a better rate of performance. The pre-trained models are trained using a huge dataset such as the ImageNet dataset, which consists of more than 14 million images. Therefore, it has a complex architecture as the network depth increases, takes longer to extract features, and becomes slow to train and test. This causes weight dispersion and difficulty generalizing. While the proposed model is efficient for the augmented data set, it is less complex, and the convolution layers are sufficient to extract the required features, so it outperforms the rest of the models. Detailed performance measurement metrics for the proposed model and its benchmarked methods are shown in Table 6.

Table 6: Performance metrics for the considered DTL models as well as the proposed model

model	precision	recall	f-score
VGG-16	0.94	0.88	0.93
VGG-19	0.96	0.88	0.93
inception	0.90	0.96	0.93
XCeption	0.97	0.87	0.92
Proposed model	0.96	0.96	0.96

Precision, recall, and F1 score have been used to analyze the performance of CNN models with multiple multiplexed data sets. Precision refers to the classifier's ability to accurately classify all people with the disease, while recall refers to the classifier's ability not to designate a negative sample as positive (the true positive rate). The weighted average of precision and recall is used to obtain the F1 score. The proposed model achieved the best results compared to the pre-trained models because it does not contain extra layers that cause weightlessness during training. Learning curves are commonly used in DL to diagnose typical generalization and learning activities. Figure 9. Presentation of the accuracy and loss curves that occur between training and validation of the proposed model

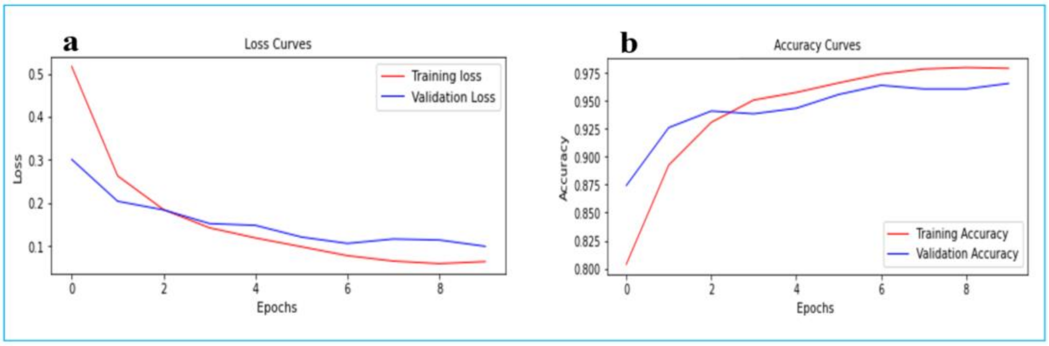

Figure 9: (a): Training and validation Loss. (b) Training and validation Accuracy of customized CNN.

Figure 9 shows the evaluation of training accuracy and cross-entropy during the training phases. Training accuracy is the proportion of images in the given dataset that were correctly classified. Cross entropy is a loss function that provides insight into how effectively the learning process is proceeding. accuracy. Where the horizontal axis represents epochs, the vertical axis (left) represents loss, and the second vertical axis (right) represents accuracy. The validation loss graph drops from the lowest to a fixed point after ten epochs, with a small gap between it and the training loss, indicating that our model has achieved good agreement.

2. Confusion Matrix Metric

The confusion matrix is a performance measure that gives more insight into achieved test accuracy. The confusion matrix displays the model rating and the model's categorization result for the test set. There are 0.95% true positive data points, 0.5% false-positive data points, 0.98% true negative data points, and 0.2% false negative data points in this data categorization. Hence, COVID-19 represents the positive case, and normal represents the negative case. This indicates that the model has correctly identified all of the normal X-rays. Figure 10 shows the confusion matrix for the test data.

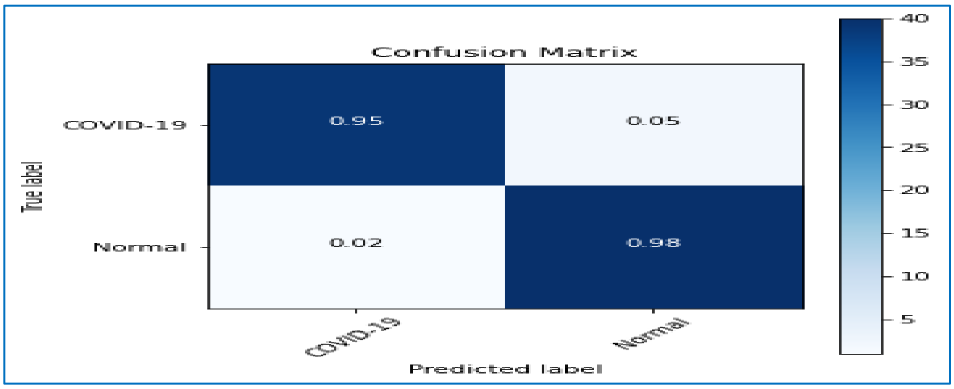

Figure10: Confusion matrix for test data of CNN model.

3. Comparative analysis

The experiments of the proposed model and other methodologies are presented in this section. Table 7 summarizes related studies and our work.

Table 7: A comparison between the proposed model and previously reviewed models

Other Study	Image Type	Method	Mean Accuracy
[16]	X-ray	CGAN+lightweight CNN model with three DTL (ResNet50, VGG-16, and EfficientNetB0)	0.94%, 0.90%, 0.96%

[17]	X-ray	ACGAN (CovidGan)+proposed that CNN	0.95
[19]	CT	CGAN with five transfer learning models (Alex Net, VGG-16, VGG-19,GoogleNet,ResNet)	0.76%,0.78%,0.73 %,0.77%, 0.81%
[21]	X-ray	IAGAN+DCGAN with CNN model	0.80% 0.80%
[22]	X-ray	No augmentation with the COVID-Net model	0.92%
[23]	X-ray	No augmentation with the VGG-16 model	0.86%
[24]	X-ray	GAN with two DTL (inception, ResNet)	0.85%,0.87%
[27]	X-ray	CGAN+ResNet-50 , ResNet-101, Xception , DenseNet-201 , DenseNet-169	0.93,0. 91, 0.92, 0.92, 0.90
proposed model	X-ray	CGAN with proposed CNN + five DTL (VGG-16, VGG-19, inception, Xception, ResNet50)	0.96

In Table 7, the classification accuracy obtained by the proposed model and the current models is shown. [24] The authors applied DL to COVID-19 X-ray images, used Cycle-Gan with conventional augmentation for data set augmentation, and performed three DTL for the detection task. They select 300 images for each category, and Cycle GAN produces only 100 images. The data set after the augmentation is still small. [25] introduced the ACGAN-based Covid-GAN model to generate X-ray images for COVID-19. They chose 403 for the COVID-19 images and 721 for the normal images. They use the VGG16 model trained on the original data set and the augmented data set. They apply fine-tuning to adjust the parameters of the pre-trained VGG-16 model, so that it can adapt to the new task at hand. The generated dataset is small and unbalanced.

[27] applied CGAN with traditional augmentation to generate 5,256 images and further distinguish between COVID-19 and non-COVID-19 CT images. They only used pre-trained models for task classification, and the pre-trained models were insufficient for the amount of augmented data set. [29] proposed semi-supervised detection based on IAGAN and DCGAN for identification (pneumonia and COVID-19). The augmented data set is unbalanced with only 589 images of COVID-19. [30] developed the COVID-Net that relies on a deep neural network for COVID-19 detection. They selected a dataset containing 183 COVID-19 cases, 5,538 cases with pneumonia, and 8,066 normal cases. They produced a test set of 100 images of pneumonia and normal lungs but only 31 cases of COVID-19. In their work, the no-augmentation method and the unbalanced data set were implemented.

[32] has evaluated the performance of several models based on deep learning that classify different respiratory diseases, and the dataset contains a total of 108,948 X-ray images. This dataset is categorized into 8 major categories of chest-related illnesses, with only 133 images, including COVID-19. In this paper, we analyzed a large dataset consisting of 6,550 images. Previous works discussed suffered from some problems, including poor quality of generated images, lack of diversity, and low achievement in diagnosis. In our work, these issues were solved by an optimized CGAN algorithm and customized combinations of dense layers to enhance the quality of the synthetic generated images. The augmented dataset is balanced as the data in each category converges. The CGAN model takes approximately two hours and forty-seven minutes to complete the run. It also proposed a classification model adapted to the training data.

V. Conclusions

The widespread scope of coronavirus (COVID-19) adversely affected healthcare systems. Medical images, such as X-ray images, are used to diagnose COVID-19 infection. The main problem with medical images is the limited dataset that is used to train the Deep Learning models. To address this problem, adjusting CGAN and traditional augmentation techniques generates more realistic images and combines the two methods. The dataset consists of 6550 COVID-19 X-ray images. The size of the augmented dataset became suitable for training and obtaining reliable results. The augmented dataset allows DTL such as VGG-16, VGG-19, Inception, Xception, and the proposed CNN model to diagnose COVID-19 efficiently. We also investigated the performance of models. The results illustrate that the proposed CNN model can consistently achieve over 96% accuracy over 10 epochs, which confirms the high performance when trained with an augmented dataset and also an increase in precision and recall. Future work includes the development of certain computer vision technologies that can aid in the fight against COVID-19, such as lung X-ray image semantic segmentation and quick lung X-ray image-based COVID-19 diagnosis.

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