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DCNET-DCGAN: A Novel Deep Convolutional Neural Network for COVID-19 Classification

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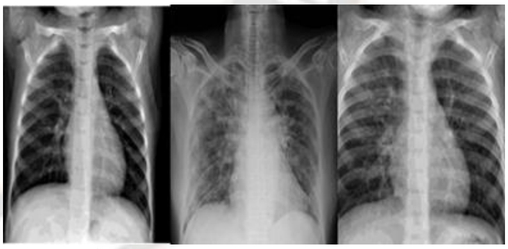
Abstract—Coronavirus referred to as COVID-19 affects innumerable lives, causing havoc on public health and global economy. The limitation of clinical expertise, medical tools, and testing kits increases the widespread of COVID -19 across the globe. An accurate identification process is necessary for early detection of COVID-19. Recent studies state that the images obtained from the chest X- Rays are highly consistent in diagnosing COVID-19 rather from RT-PCR (Reverse-Transcription-Polymerase-Chain Reaction). Developing an automated CXR image diagnosing method for the accurate prediction is the objective of the proposed model. This objective is achieved by developing a proposed model composed of Deep Convolutional Generative Adversarial Networks (DCGANs) and a Deep Convolutional Neural Network (DCNET) using four distinct datasets (COVID -19 X-ray, COVID-chest X-ray, COVID-19 Radiography, and Corona Hack-chest X-ray). The proposed model exploits the deep learning features of DCNET with four layers of convolution, three layers of max pooling and fully connected layers, thereby achieving a classification accuracy of 98.8% which is better than the pre-existing method. It classifies the result as Normal, COVID-19 and Pneumonia. This model will be an apt solution for facilitating faster screening process for affected patients.

Keywords- CXR, DCGAN, DCNET and RT-PCR

1. INTRODUCTION

The global spread of the COVID-19 pandemic had a sudden and profound impact on human health, resulting in prolonged and devastating consequences, thereby extending the duration of the pandemic. Due to this catastrophe, the national governments have introduced a lockdown that prevents the spread of COVID -19 among the human race. Till December 2020, there is no vaccination allocated for diagnosing COVID-19. The symptom may range from cold to fever which majorly affects the lungs; it is predominantly transmitted through droplets. RT-PCR is predominantly utilized as a screening technique for the diagnosis of COVID-19 cases. Although it is a high-standard screening process it suffers from high time consumption, laboriousness, and short supply. Due to its sensitivity, it doesn't provide a clear and consistent result. The insufficient testing capacity spurred the search for an alternative diagnosing method for COVID-19. The alternative diagnosing method has to support the radiologist to visualize the SARS-CoV-2 viral infection which is possible through Computed Tomography (CT) or CXR. The CXR and CT image support the radiologist to analyse the spreading rate of viral infection in the lungs through imaging. The main bottleneck for the COVID-19 diagnosis is a dataset, it is essential to use rich feature images in the classification. To obtain rich-featured images, we compared the CXR and CT images.



(a) (b) (c)

Figure 1. Three CXR images (a) Normal Condition (b) COVID-19, and (c) Pneumonia

In medical therapy, CXR visualization is less complex and simpler, providing a 2D image only. Due to its lower radiation exposure, the most cost-effective choice is to opt for CXR, which provides a two-dimensional image of the patient's condition. In contrast, CT scans, which offer a three-dimensional image, require extra space. CT is more time-consuming and more expensive, and it also produces more radiation. But CXR images have numerous advantages over CT images. It is preferable to utilize CXR images which provide detailed information about the COVID-19 cases. Figure 1 and Figure 2 illustrate the visual representation of

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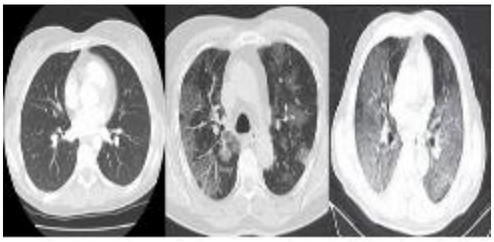
CXR and CT images portraying Normal, COVID-19, and Pneumonia conditions.



(a) (b) (c)

Figure 2. CT images of three conditions (a) Normal (b) Pneumonia, and (c) COVID-19

Due to the rise of numerous positive COVID-19 cases, clinical experts need an integration of Artificial Intelligence (AI) with the researcher's opinions to ease the diagnosis process. Although there are several pre-existing convolution models which tried to diagnose the COVID-19 cases but suffer from limitations due to the smaller dataset, inaccurate, computational complexity, or less learning data. Although a certain degree of misclassification of the COVID-19 identification is acceptable it provides a misleading way to the clinicians to perform wrong treatment for a patient at an early stage. The proposed model addresses the mentioned constraint by building an automated CXR image classification module that successfully predicts COVID-19 cases using DCGAN data.

II RELATED WORKS

We analyse the various deep learning techniques that diagnosis the COVID-19 cases due to its advanced approach towards the medical field. Various researchers put forth their papers under this category with good results. Previous studies encountered limitations in terms of dataset capacity or inadequate outcomes, leading to certain drawbacks. These studies will be the building block for developing our proposed model.

A. Deep Learning Classification Models

Mukherjee et al. (2021) presented a paper on automatic COVID-19 identification utilizing CXR and CT scans, using the Deep Neural Network (DNN) model as a classifier for binary classification. It uses a limited number of CXR images due to dataset scarcity. Zhao et al. (2020) evaluated the relationship between the chest CT and clinical condition of pandemic thereby determining the severity of the disease. Through his investigation, he concluded that CT supports the medical expertise to detect COVID-19 cases by its score. Yadav et al. (2019) presented a paper in medical image classification to overcome the limitation of the dataset by combining the transfer learning and data augmentation method. The author alleviates the training data by transfer learning, and augmentation supports fine network-tuning, which alleviates the overfitting problem. However, this approach suffers from a time-consuming problem due to the augmentation process. Some of the studies (Kang et al. 2021; Mohammad et al. 2021; Rahimzadeh & Attar 2020) utilized deep learning models; however, they faced challenges regarding computational speed.

B. GAN Approach

Some of the studies (Fangming et al. 2020; Nazki et al. 2020; Santosh, Ghosh & Bose 2021) focused on deep learning-based generative models for reducing the time and effort for data collection and provided an efficient performance in COVID-19 prediction. Dargan et al. (2019), survived nearly 308 deep learning papers and concluded that the deep learning approach can articulate itself in the medical field and provide numerous advantages. Afshar et al. (2020), presented a paper on COVID-CAPS which build on numerous capsules and convolution layers and provide an efficient result but the model is under testing. Waheed et al. (2020), developed a COVIDGAN which speeds up the COVID-19 detection with minimal dataset and thereby improves the CNN performance. Apart from the minimal dataset, there are still some limitations in this work such as less trained GAN, and time constraints, and quality of the fake images. Wang et al. (2020) proposed a diagnosis algorithm for COVID-19 based on CXR data and also published an open dataset named COVIDNet which comprises thirteen thousand and nine hundred seventy five CXR images belonging to thirteen thousand eight hundred seventy subjects. When it comes to COVID-19 prediction, this technique has serious difficulty.

The aforementioned research papers deal with deep learning methods and suffer from an over-fitting problem and high computational time due to small datasets in the training process. Sometimes large datasets lead to low efficient outcomes. After analyzing numerous research papers, we found some innovative papers Afshar et al. (2020), Waheed et al. (2020), Wang et al. (2020), where they represent the new approach to the COVID-19 cases with some limitations. It will be highly supportive for robustly developing our DCNET-DCGAN model without limitations.

C. Contribution

The novelty of the proposed model is two-fold such as DCGAN and DCNET. The main contribution of the model is summarized below:

a. Proposed a Deep Convolutional Generative Adversarial Networks (DCGAN) for generating CXR images.

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b. Proposed a DCNET method for COVID-19 classification (Normal, COVID-19, and Pneumonia).
c. Using four different datasets for training DCGAN and DCNET in the generation and diagnosis process.

The manuscript is outlined as follows. The details pertaining to the dataset is discussed in section III, as well as the DCGAN and DCNET architectures for COVID-19 diagnosis. Section IV provides detailed information about the proposed methodology, DCNET-DCGAN. The results obtained are discussed elaborately in section V. The concluding remarks and the scope for the future work is discussed in section VI.

III. COVID-19 DIAGNOSIS

This section details the characteristics of the dataset used and the proposed architecture of DCGAN and DCNET for COVID-19 classification.

A. Dataset

The proposed DCNET was trained and tested on four distinct datasets, utilizing the synthetic images generated by DCGAN. The dataset used for training the model comprises of COVID-19 Radiography, COVID-19 Chest X-rays, COVID-19 X-ray, and Corona Hack-chest X-ray, of COVID-19 affected subjects. The COVID-19 Radiography dataset, recognized as the Kaggle community winner for COVID-19 datasets, was created by researchers from Qatar University in collaboration with clinical experts, specifically focusing on chest X-ray images for COVID-19. A collection of patient's chest X-rays and CT images are made available to the public under COVID-chest X-ray dataset. The COVID-19 X-ray dataset, developed by a Chinese team, was intended to study anomalies in chest CT images. Lastly the CoronaHack -Chest X-Ray dataset comprises healthy, COVID-19 affected chest images as well as Severe Acute Respiratory Syndrome and Acute Respiratory Distress Syndrome to learn the discriminating features of COVID-19 from other respiratory illness.

B. DCGAN Architecture

DCGAN architecture is designed to overcome the COVID-19 dataset limitations which generate the CXR images thereby boosting COVID-19 classification. DCGAN consists of two models such as Generator as well as Discriminator. The main responsibility of the generator model is to generate new images whereas the role of the discriminator provided the image and label decides if the image is fake or real.

The generator network uses random noise to create visual images. It takes gaussian noise as an input, representing an arbitrary location in the embedding space. The role of the discriminator is to differentiate the given image and identify if the image belongs to the real distribution or fake. The discriminator takes the input image and outputs $D_{dis}(x)$. The output vector indicates the probability of the input image x belonging to the real/true distribution. The output represents the probability that x belongs to the real distribution. If the discriminator's output is 1, it indicates that the given image belongs to the real distribution whilst the output of 0 indicates the fake distribution.

The adversarial network function on the basis of min-max game playing algorithm which is represented in equation 1,

$$\underset{G_{gen}}{\mathrm{Min}}\,\underset{D_{dis}}{\mathrm{Max}}\, V(D_{dis}, G_{gen}) = Enc_{x\sim p_{data}(x)}[\log D_{dis}(x)] + Enc_{z\sim p_z(z)}\left[\log\left(1 - D_{dis}\left(G_{gen}(z)\right)\right)\right] \quad (1)$$

G_{gen}	=	Generator
D_{dis}	=	Discriminator
$p_{data}(x)$	=	Real data distribution
X	=	Sample from $p_{data}(x)$
z	=	Sample from $p_z(z)$
$D_{dis}(x)$	=	Discriminator Network
$G_{gen}(z)$	=	Generator Network
p_z	=	Generator distribution
Enc	=	Encoder of Generator

The calculation of D_{dis} involves a logarithmic function, where $D_{dis}(x)$ equals 1 when the input is considered real. Following the principles of min-max game theory, the discriminator D_{dis} is optimized by maximizing or minimizing the data generated by the generator $G_{gen}(z)$. Initially, during the early stages of training, the generator produces noisy images, but after 500 epochs, it begins to resemble the original image.

C. DCNET Architecture

Deep learning architectures offer robustness and valuable semantic features in various domains, making them widely utilized. In this context, we provide a concise understanding of the generic architecture of the proposed DCNET and introduce key concepts of deep convolutional neural networks. The DCNET architecture draws inspiration from the DCGAN-CNN architecture, as referenced in a study by Sharmila and Jemi Florinabel (2021).

The DCNET comprises an input layer, four Convolutional Layers, four Max Pooling Layers, four Batch Normalization Layers, four Rectified Linear Unit (ReLU) Layers, a Fully Connected Layer, and an Output Layer, as depicted in Figure 3. Among the four 2D convolutional layers, the first layer employs 16 filters with a window size of 77x77. Throughout

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the training process, the same padding is applied during the kernel operations. Batch normalization and ReLU activation take place thereafter. Subsequently, a max-pooling 2D layer summarizes the image features into patches using strides of size 2, effectively downsampling the feature map. The second Convolution 2D layer reduces the filter size to 39x39 and utilizes 16 filters. This is followed by another set of batch normalization, ReLU, and max-pooling 2D layers. The third Convolution 2D layer reduces the filter size to 19x19, employing 32 filters, while the final Convolution 2D layer comprises 64 filters with a size of 9x9. The number of filters increases for each set of Convolution 2D layers. The DCNET performs feature extraction through the combined operations of convolution and pooling layers.

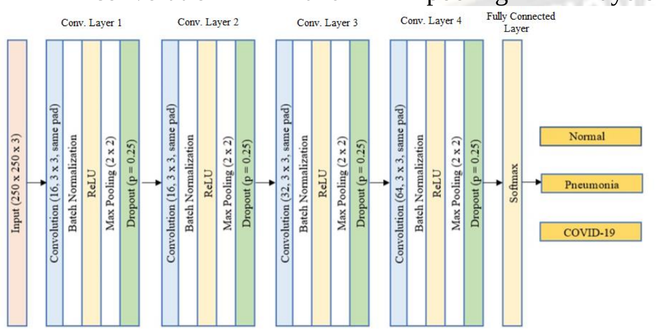

Figure 3. Architecture of DCNET

The convolutional layer plays a crucial role in detecting image features like edges and shapes. Batch normalization is employed to accelerate the training process. Neurons in the convolutional layer are connected to previous layers via local patches, each with its set of weights. The sum of these weighted inputs is then passed through an activation function. The convolutional layer aims to identify combinations of features from the preceding layer, while the pooling layer combines similar features through downsampling, reducing the weights based on the window size. To minimize computational costs, three pooling layers are utilized in the proposed model. Additionally, pooling layers help balance variations between input and output layers linearly, reducing the loss function. Max-pooling, which selects the maximum value within a given window, is utilized for its ability to process image data quickly. Activation functions, such as ReLU and Softmax, are employed. ReLU effectively eliminates negative values and facilitates fast image data processing. The fully connected layers calculate the likelihood of each class using the output features. Finally, the Softmax activation layer assigns a probability distribution to each node in the output layer, allowing for the prediction of multinomial probabilities for the given input data.

IV PROPOSED DCGAN-DCNET METHODOLOGY

As aforementioned, the proposed model is divided into two-fold for accurately accomplishing the COVID-19 classification. The proposed model's (DCNET-DCGAN) architecture is illustrated in the Figure 4. Initially, we split the datasets into training and testing where 70% of data is used for training the DCNET for understanding the salient features of images then it will be tested by 30% of testing data. The input image is resized into 250*250 shaped images.

Then the dataset is converted into grayscale images for reducing the math complexity. The DCGAN is built using many neural network layers that extract training image features and random noise to construct a fake image. It extracts the local features in the first few levels before extracting global characteristics. The encoders will down-sample the data until it reaches the bottleneck, and then the decoder will up-sample it. The input is down-sampled and features are learned in the first four layers of G, but after the fifth layer, up-sampling occurs, which reconstructs the image. The discriminator will determine whether the produced image is real or fake.

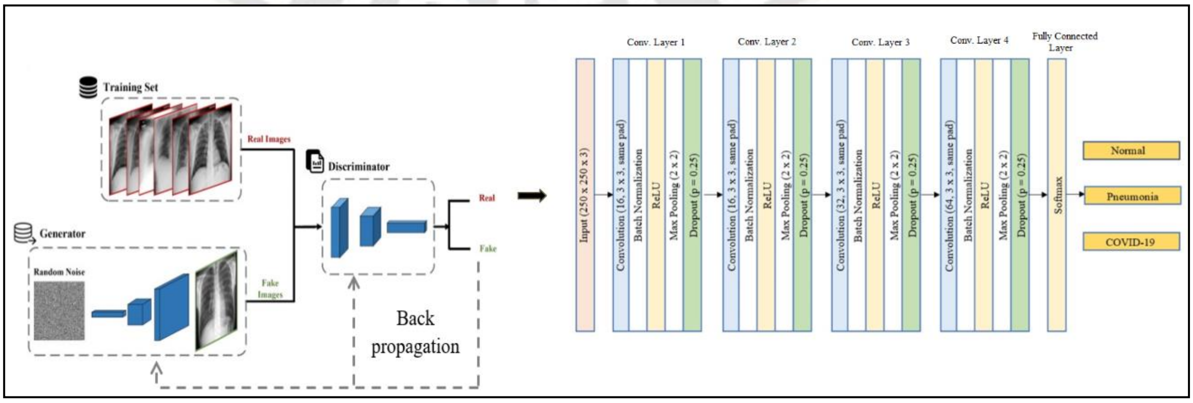

Figure 4. Architecture of DCNET-DCGAN Model

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The generated dataset is fed into the DCNET Classification procedure as an input. The proposed DCNET model depends upon the function of the Convolution Neural network. CNN composes of convolutional, max-pooling, and activation layers among that convolution layers, are the main layer that applies the kernel to all input layers. The convolution layer generates a feature map as an output which contains rich data about input images. The proposed model consists of four convolution 2D layers and then batch normalization followed by the activation layer with ReLU as the activation function and a maximizing pooling 2D layer. To the end a fully-connected layer combined with softmax layer is employed to diagnose COVID-19 cases. The first Convolution2D layer uses 16 filters with a size of 77*77 which convolve the input training images.

The batch Normalization layer normalizes the input layer and increases the learning process among the hidden layers. Then the image non-linearity is maintained by the ReLU activation layer. After that max-pooling or subsampling layer samples each feature map independently. To mitigate overfitting issues in the network layers, the feature map's spatial size is reduced. This reduction helps to select sharper and more effective features from the images compared to other pooling layers. After that remaining three convolution 2D layers are processed and extract the deep feature map of training images. The size and the total number of filters of each convolution layer are explained in section 3. At last, a deep feature map is available from the model which is passed through the fully connected layer. The fully connected layers utilize the feature probability values to classify images into three categories: Normal, COVID-19, and Pneumonia. For the final evaluation, the proposed DCNET-DCGAN is subjected to testing and its performance is represented under three metrics like accuracy, precision, and recall.

V EXPERIMENTAL RESULTS

To assess the effectiveness of the DCNET-DCGAN model in COVID-19 classification, we employed MATLAB 2020a version and executed the proposed model on an Intel i7 processor with GPU support. The evaluations involved utilizing four distinct datasets to measure accuracy, precision, and recall metrics.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad \textbf{(2)}$$

$$Precision = \frac{TN}{TN+FP} \quad \textbf{(3)}$$

$$Recall = \frac{TP}{TP+FN} \quad \textbf{(4)}$$

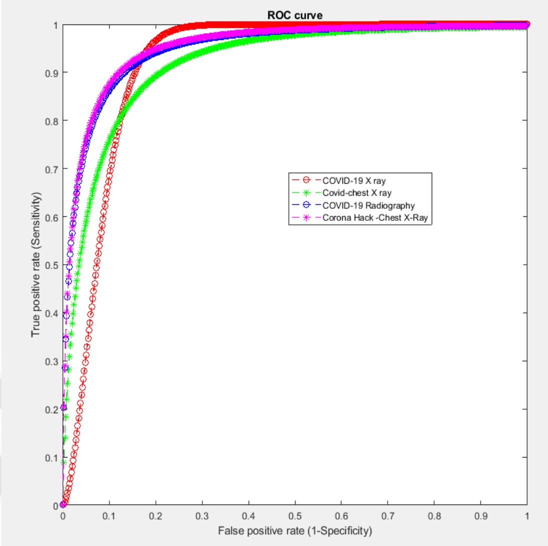

Figure 5: ROC Curve of the proposed model with four different datasets

Table 1: Area under Curve (AUC) of the DCNET-DCGAN model

Dataset	AUC
COVID-19 X-ray	0.94
COVID-chest X-ray	0.96
COVID-19 Radiography	0.95
Corona Hack-chest X-ray	0.98

In equations (2), (3), and (4), TP (True Positives) and TN (True Negatives) represent correctly labeled classes, while FN (False Negatives) and FP (False Positives) represent misclassified labeled classes. As previously mentioned, four different datasets were utilized for training and testing the DCNET-DCGAN model. The model was trained separately on each dataset, and its performance was evaluated by plotting the corresponding ROC curves. The true positive rate of the proposed model for the different datasets is depicted in Figure 5 and tabulated in Table 1. The performance metrics for the four datasets are presented in Table 2. Among these datasets, Corona Hack-chest X-ray (0.98) demonstrated exceptional support for the proposed model in effectively distinguishing the output classes. This dataset significantly enhances the classification efficiency of the proposed model.

Table 2: Evaluating the performance metrics of the datasets.

Classes	Metrics	COVID -19 X-ray	COVID -Chest X-ray	COVID -19 Radiography	Corona Hack-Chest X-Ray
Normal	Accuracy	96.6	96.4	97.9	98.7
	Recall	0.92	0.93	0.96	0.97
	Precision	0.97	0.96	0.95	0.96
Pneumonia	Accuracy	95.9	96.4	98.2	97.6
	Recall	0.93	0.94	0.94	0.95
	Precision	0.95	0.93	0.95	0.96
COVID-19	Accuracy	97.3	97.3	96.8	98.6
	Recall	0.95	0.93	0.95	0.97
	Precision	0.92	0.94	0.96	0.98

The maximum iteration for training the proposed model is 180. The learning rate is about 0.01. For each epoch, there will be three iterations where the total epoch is 60. Nearly 313 mins is taken as elapsed time for completing the training process. There is a constant learning rate schedule. To optimize the accuracy of the DCNET-DCGAN epoch values are fine-tuned. The training progress of the proposed DCNET is depicted in Figure 6. In order to assess the performance of the DCNET-DCGAN model, a comparative analysis was

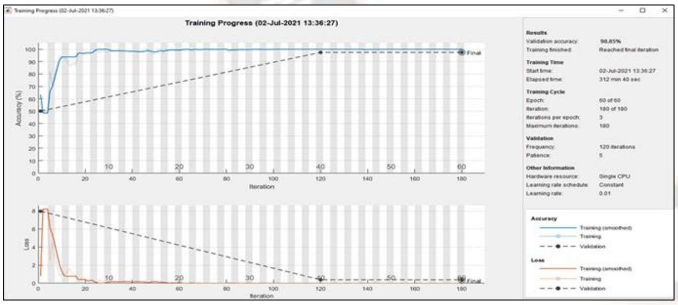

Figure 6. Proposed DCNET-DCGAN Model training progress

conducted with existing methods such as COVID-CAPS (Afshar et al., 2020), COVIDGAN (Waheed et al., 2020), and COVID Net (Wang et al., 2020). Although there were differences in the datasets used in these methods, they all focused on CXR images. The performance metrics were gathered and tabulated in Table 2. The results indicate that the proposed model achieved an accuracy of 98.8%, surpassing the performance of the existing methods.

6. Conclusion

In this research paper, proposed deep learning-based DCNET-DCGAN is developed for diagnosing and classifying COVID-19 cases from Normal, COVID-19, and Pneumonia. Analyzing the deep features from the input image play a vital role in classification accuracy, we develop the proposed DCNET for learning the high dimensional parameters. One of the major challenges faced by the pre-existing methods is the limited availability of datasets and computational complexity. The proposed model uses four different datasets as an input training dataset for the DCGAN model for generating fake images thereby overcoming the misclassification and poor learning capability. Among the four datasets, the best dataset is analyzed using ROC Curve which shows that the Corona Hack-chest X-ray provides better performance with the DCNET-DCGAN. In addition to training the DCNET-DCGAN model, we conducted a comparative analysis to evaluate its accuracy rate in COVID-19 classification against existing methods such as COVID-CAPS, COVIDGAN, and COVIDNet. The results demonstrated that the DCNET-DCGAN model achieved an impressive accuracy rate of 98.8% in this classification task. These findings highlight the robustness and reliability of the proposed system, suggesting its potential for initial testing in clinical settings.

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