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A Novel COVID-19 Detection Model Based on DCGAN and Deep Transfer Learning

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Abstract

A continuing outbreak of pneumonia-related disease novel, Coronavirus has been recorded worldwide and has become a global health problem. This research aims to generate a constructive training data set for a neural network to detect COVID-19 from X-ray images. The creation of medical images is an issue in the field of deep learning. Medical image datasets are frequently unbalanced; using such datasets to train a deep neural network model to correctly classify medical conditions typically leads to over-fitting the data on majority class samples. Data augmentation is commonly used in training data to expand the dataset. Data augmentation may not be beneficial in medical domains with limited data. This paper proposed a data generation model using a Deep Convolutional Generative adversarial network (DCGAN), which generates fake instances with comparable properties to the original data. The model’s Fréchet Distance of Inception (FID) was 23.78, close to the original data. Deep transfer learning-based models VGG-16, Inceptionv3 and MobilNet, were chosen as the backbone for COVID-19 detection. The present study aims to increase the dataset using the DCGAN data augmentation technique to improve classifier performance.

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1. Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a novel strain of Coronavirus renamed COVID-19 by WHO on March 11, 2020. The virus is highly contagious and rapidly spread infection from humans to humans. The COVID-19 pandemic has reached more than ten million cases worldwide. Different countries followed various strategies to mitigate its effect and its spreading [1]. Infected patients were confirmed to have typical clinical symptoms, including fever, fatigue, unproductive cough, shortness of breath, normal or reduced leukocyte counts,

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and pneumonia. Deep learning (DL) is the state-of-the-art for many Medical Image Analysis and Computer Vision applications [2]. Its performance highly depends on the availability of vast amounts of labelled training data. The availability of sufficient labelled data is a critical issue in the medical field. This data scarcity is due to the high cost of acquiring medical images and the time required for processing and labelling. Many data sets in the medical sector possess substantial class imbalances because of the uncommonness of certain diseases [3]. GANs may overcome these two constraints by generating fake images from an implicit distribution that closely approximates the actual data distribution [4]. In this pandemic situation of COVID-19 worldwide, automated and fast screening of COVID-19 from the Chest X-ray (CXR) images has become an urgent requirement. The lack of COVID-19 datasets with CXR images is the primary motivation of this research.

Rahimzadeh and Attar [5] proposed concatenating the Resnet50v2 and Xception CNNs to classify CXR images into three classes COVID-19, normal, and pneumonia. Oh, et al. [6] proposed a patch-based deep convolutional neural network architecture with a relatively small dataset for COVID-19 diagnosis. A novel probabilistic Grad-CAM saliency map was used to visualize clinically interpretable adapted to the local patch-based approach. Ozturk et al. [7] proposed a fully automated DL based model, DarkCovidNet, to classify and detect COVID-19 from CXR images with an accuracy of 98.02 percent. The authors Waheed et al. [8] proposed CovidGAN to generate artificial training data based on the concept of the Auxiliary Classifier Generative Adversarial Network (ACGAN) model. The classification reports an improvement in efficiency from 85 per cent to 95 per cent accuracy when VGG-16 was trained on real data and synthetic CXR images. Loey et al. [9] proposed a GAN with three deep transfer learning models (Alexnet, Googlenet, and Resnet18) for COVID-19 detection in limited CXR images. The dataset has a collection of 307 CXR images of four classes normal, COVID, pneumonia virus, and pneumonia bacterial. In two class (COVID-19 and normal) classification problems, GoogleNet obtains 100 percent testing accuracy, and validation accuracy is 99.99 percent. Rajaraman and Antani [10] proposed weakly labelled data augmentation to recognize COVID-19 pneumonia opacities and improve COVID-19 detection performance in CXR images. In this paper, proposed the DCGAN can generate artificial COVID-19 X-ray images. High-quality fake X-ray images solve the imbalanced data problem. The fidelity of the fake image was assessed using FID.

2. Material and Method

A literature review shows many Artificial Intelligence efforts to detect COVID-19. In this paper, the DCGAN network was used to increase the COVID-19 dataset. FID was used to evaluate the quality of a fake image. The generated fake images and the original images gave the input to the pre-trained CNN for COVID-19 detection. Deep transfer learning-based models VGG-16, Inceptionv3, and MobilNet, were chosen for COVID-19 detection from CXR images.

2.1. GAN

Goodfellow et al. [11] introduced generative adversarial networks (GANs) that were game-theory-based learning generative models. GAN can be capable of capturing the data pattern of images and generating spurious samples automatically. Recent advancements in medical imaging and computer vision may enable the use of GAN to address a range of critical challenges, including data annotation, data scarcity, data access, imbalance dataset, dataset modifications, and data privacy, among others [12]. Over the last several years, numerous architectures have been proposed to improve the quality of images produced by GAN [13]. By combining GAN and CNN, Radford, Metz, and Chintala [14] developed a new GAN structure called deep convolutional generative adversarial networks (DCGAN). Numerous additional architectures, such as conditional GAN [15] and Wasserstein GAN [16], have been developed based on the DCGAN.

The GAN structure is composed of a pair of neural networks, as shown in figure 1. One Generator $G$ with parameters $\theta_g$ and one Discriminator $D$ with weights $\theta_d$, which compete with each other over the training data $X$ to enhance their performance. In mathematical terms, $D$ and $G$ play a two-player minimax game with the following cost function $V(G, D))$ [17].

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim P_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim P_z(z)}[\log(1 - D(G(z)))]$$ (1)
The above equation shows how the Generator and Discriminator play the min-max game.

1. The generator $G$ tries to minimize the loss function. It follows up with two cases:
   
   (a) When the data is from the data distribution: $G$ has the task of forcing the discriminator to predict the data as a fake image.
   
   (b) When data is from the Generator: $G$ can force the discriminator to predict the data as an actual image.

2. The discriminator $D$ tries to maximize the loss function. It follows up with two cases:

   (a) When the data is from the data distribution: $D$ tries to predict it as an actual image.
   
   (b) When the data is from the Generator: $D$ tries to predict the data as a fake image.

2.2. Deep Convolutional Generative Adversarial Network (DCGAN)

GANs were unreliable in training. After some epochs, the network may collapse where the Generator generated nonsensical outputs. Original GAN was modified with five necessary modifications as DCGAN for systematic improvement of performance [14]. DCGANs used for Traffic Sign Recognition, drug design, X-ray image augmentation Tomato Leaf Disease Identification.

The first modification was to use convolutional layers only instead of conventional alternating convolution and max-pooling layers. In the Generator $G$, the max-pooling layers were replaced with fractional-strided convolutions (Transposed Convolution) to learn its spatial up-sampling. The pooling layers were substituted with strided convolutions in the discriminator $D$ that allow the $D$ to learn its spatial down-sampling. The second one is the elimination of fully connected layers in the $G$ and $D$ networks. Generator $G$ takes the distribution of noise $z$ as input that can be considered as a complete connection. For the $D$ network the last convolutional layer is flattened to be fed into the sigmoid. The third one was to apply batch normalization in $G$ and $D$ networks. Batch normalization means normalizes data to zero mean and unit variance. The fourth change is using the activation function ReLU for the $G$ network and leaky ReLU for the $D$ network to speed up the training process. The fifth one is activation functions used at the output layer, $Tanh$ activation function for the $G$ network, and the $D$ network’s Sigmoid activation function.

2.2.1. Generator

The generator network $G$ takes a uniform noise distribution vector of random numbers drawn as input and outputs a CXR image of size $64 \times 64 \times 3$. The latent vector was reshaped to a size of $4 \times 4 \times 512$, and transposed convolutional
layers were used to up-sample the image with a $4 \times 4$ kernel. Batch normalization and ReLu activation function apply to each transposed convolution layer, except the output layer. The generator network structure is shown in figure 2.

2.2.2. Discriminator

The $D$ has the standard structure of CNN architecture that requires an X-ray image of $64 \times 64 \times 3$ and outputs the real or fake X-ray image classification. For minimizing spatial dimensionality, strided convolutions are applied to each convolution layer. Batch normalization and Leaky ReLu activation function apply to each convolution layer, except the output layer. Figure 2 show the discriminator network structure.

2.3. GAN evaluation

When training deep learning models, loss function was typically used to ensure that the neural network achieves convergence. GANs were trained using two neural networks concurrently to achieve Nash Equilibrium, and there is no objective loss function for the training progress and performance comparisons between the GAN models [18]. The goal of generative learning is for the model to generate similar data to the actual data. Generally, Quantitative Measures and Qualitative Measures are two approaches developed to evaluate the quality of the generated images by the GAN models [19]. Quantitative Measures such as Inception Score (IS) [20], Average Log-likelihood [11], coverage metric, Fréchet Inception Distance (FID) [21], Wasserstein critic [16] etc. and Qualitative measures such as Nearest Neighbors, Rapid Scene Categorization [11], Mode Drop and Collapse etc. The IS and FID are two generally accepted GAN evaluation metrics.

The Fréchet distance [22] was used to determine the difference between two Gaussian distributions. The Fréchet distance $d(\mu, \Sigma)$ between the Gaussian with mean and covariance $(\mu_r, \Sigma_r)$ obtained from $p_r(\cdot)$ and the Gaussian with mean and covariance $(\mu_f, \Sigma_f)$ produced from $p_f(\cdot)$ is referred to as the “Fréchet Inception Distance” (FID) and is defined as follows:

$$FID(r, f) = \left\| \mu_r - \mu_f \right\|^2_2 + Tr \left( \Sigma_r + \Sigma_f - 2 \left( \Sigma_r \Sigma_f \right)^{1/2} \right)$$  \hspace{1cm} (2)

3. Analysis of the chest X-Ray image dataset

Many radiological organizations put more effort into collecting the COVID-19 CXR images and making them available on the internet to promote radiologists’ knowledge sharing. For this study, the following key data were extracted from different public open-source datasets [23] [24]. First, the entire dataset comprises 234 COVID CXR images and 700 normal CXR images. In this experiment, 30 percent of original COVID-19 CXR images and normal CXR images were combined and used as a test dataset. To solve the issue of imbalanced datasets, the GAN and DCGAN model is used to generate fake CXR images. In the first Dataset-I, it was created with GAN generated fake CXR images and original CXR images. In the second Dataset-II comprises DCGAN generated fake CXR images and original CXR images of COVID-19 and normal CXR images.
4. Result

4.1. Training procedure

The goal of training the discriminator is to maximize $\log(D(x)) + \log(1 - D(G(z)))$ the probability of correctly classifying a given input as real or fake. The goal of generator training is to train the Generator by minimizing $\log(1 - D(G(z)))$ in an effort to generate better fake images. The training process for generator $G$ and discriminator $D$ has been done iteratively. DCGAN’s learning process is carried out by repeating these steps: i) The $x$ dataset images are used to train the $D$ network; ii) Insight images $G(z)$ produced by generative network $G$ from latent vector $Z$. The job of the Generator network is to learn the distribution of the data in $x$, so that it can produce real looking fake images. Finally, from the generated fake image, the discriminatory network $D$ weights are modified. This method aims to produce progressively more fake images from the dataset through repeated iterations of the $G$ training.

The training of DCGAN was mathematically expressed as:

$$\min_G \max_D L(D, G) = E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

(3)

Discriminator loss was defined as

$$D_{loss} = \text{real loss}(D(x)) + \text{fake loss}(D(G(z)))$$

(4)

Generator loss is defined as

$$G_{loss} = \text{real loss}(D(G(z)))$$

(5)

Where $z$ is Noise vector, $x$ image from the training dataset, $G(z)$ is generated image, $D(G(z))$ is discriminator output on the generated image, $D(x)$ is discriminator output of a training dataset. First, using the GAN network, we created fake CXR images. Dataset I is composed of images produced by the GAN network. In these fake X-ray images, it does not see the outline of the lungs correctly. The Fréchet Distance of Inception (FID) for the GAN was 48.77. Pre-trained models VGG-16, Inceptionv3, MobilNet models are trained with the first Dataset I. With the test dataset, the classification accuracy got for the VGG-16, Inceptionv3 and MobilNet models is 0.862, 0.853, and 0.831, respectively.

The Dataset II is composed of images produced by the DCGAN network. Figure 3 shows the images generated by DCGAN, the left side images are real CXR images, and the right-side images are fake images. Adam optimizer used in Generator and discriminator. Progression of fake X-ray images generation by DCGAN for different
Fig. 4. The fake images generate by DCGAN Progression

| Iteration | Images |
|-----------|--------|
| 0         | ![Iteration 0 images](image0)
| 500       | ![Iteration 500 images](image500)
| 1000      | ![Iteration 1000 images](image1000)
| 1500      | ![Iteration 1500 images](image1500)
| 2000      | ![Iteration 2000 images](image2000)
| 2500      | ![Iteration 2500 images](image2500)
| 3000      | ![Iteration 3000 images](image3000)

Fig. 5. Generator and discriminator loss for \( G = 0.0001 \) and \( D = 0.0001 \) iterations is shown in figure 4 for the LR of Generator \( G = 0.001 \) and discriminator \( D = 0.0002 \). The Fréchet Distance of Inception (FID) for the DCGAN was 23.78, close to the original data. In the DCGAN, the generator and discriminator loss is examined to generate quality fake CXR images with different learning rates (LR). The Generator’s LR from 0.01 to 0.0001 and the LR of discriminator 0.002 to 0.0002 is modified to generate fake X-ray images. Fake CXR images are fine at learning rate \( G = 0.001 \) and \( D = 0.0002 \). Figure 5 is the plot of the Generator and Discriminator training losses reported after each epoch for learning rates of \( G = 0.001 \) and \( D = 0.0002 \).

Pre-trained models VGG-16, [25] Inception-V3,[26] and MobilNet [27] models are trained with Dataset II. With the test data set, the classification accuracy obtained for the VGG-16, InceptionV3 and MobilNet models is 0.931, 0.959 and 0.914, respectively. The testing accuracy of InceptionV3 model is the highest. It is 0.959. Classification results on test data sets of VGG-16, InceptionV3 and MobilNet pre-trained models trained on Dataset-I (GAN) and Dataset-II (DCGAN) are illustrated in figure 7.
5. Discussion and conclusion

The primary significance of this research is the development of a DCGAN model to generate synthetic X-ray images. The DCGAN network was used to increase the COVID-19 dataset. Besides, pre-trained CNN model classification accuracy was investigated when the training dataset was enhanced by including synthetic X-ray images. A comparison of fake X-ray images generated by different models was shown in figure 6. Waheed et al.[8] proposed an ACGAN based model called CovidGAN to create synthetic chest X-ray (CXR) images as shown in figure 6 (a). Loey et al. [9] used the GAN network to generate synthetic COVID-19 X-ray images. The generated synthetic X-ray image was shown in figure 6(b). The testing accuracy was 0.86 obtained from the VGG-16 model trained with the first Dataset I of images generated with the GAN model. In the second Dataset II of images generated with DCGAN, the testing accuracy achieved with the Inception V3 model was 0.959. The FID for the DCGAN was 23.78, which was close to the Real data. Fake X-ray images generated with a DCGAN network is much better than a synthetic image generated with different models.

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