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# A Survey on Deep Learning Techniques for COVID-19 Detection using Medical Imaging

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***Abstract*— Covid-19 has disrupted lives throughout the world. It has spread all over the world and detection of the virus is an imperative step in beating the virus. Methods such as the RTPCR and Rapid antigen tests are not only time consuming but also complex and expensive. Since the virus attacks the lungs, the Xray images of the chest can be used for the detection of coronavirus. This paper summarizes as well as gives a detailed study of the research and various techniques used for this subject. Methods used for COVID-19 detection using medical imaging using Chest X-Ray (CXR) and CT scan images as well as role and usage of GANs in tackling this problem have been summarized.**

***Keywords*— Deep Learning, GANs, COVID-19 detection, CNN, Medical Imaging***

## I. INTRODUCTION

The year 2020 saw the rise of COVID-19 cases around the world and deaths of millions of people all around the globe, ways to identify patients has become a problem gathering a lot of interest. Since machine learning and deep learning have been used to tackle problems in the area of healthcare in recent times, such methods have also been applied to the problem of detection of COVID-19. Most approaches focus on medical imaging to help detect COVID-19. These mainly include use of CXR or chest CT-scan images.

Since the problem of COVID-19 is fairly recent, the amount of patient data available is low which can become a restraint for deep learning models which usually require high amounts of data for getting stable results. Problems like this have been tackled by use of Generative Adversarial Networks (GANs) and deep learning techniques to help generate data to supplement existing datasets by generating synthetic data.

Convolutional neural networks (CNN) have been used extensively for the purpose of detection of COVID -19 using medical images as they operate fast and are able to capture features from images efficiently. Using deep convolutional neural networks, high accuracies have been achieved. As stated earlier, due to low availability of patient data, these accuracies may not be stable as the models might have overfit to smaller datasets.

## II. USE OF CNN FOR COVID-19 DETECTION

Convolutional neural networks (CNN) have been used for working with medical images since they make use of convolutional images which work with kernels to deduct spatial information from images. CNNs are faster than other types of models when working on images and also provide better results as the convolutional layers are designed to manipulate images. Deep learning models require a large amount of data to train, and since COVID-19 pandemic is recent, the amount of CXR and CT scan images are low in number. This affects both the training and reliability of deep learning models. In [1] the authors review the effect of occlusion in images and how they can affect classification and mention techniques to alleviate the effects of occlusions in these images. [2] sheds light toward the difficulty of prediction of COVID-19 from chest CT scans due to boundary blurring and proposes a data driven framework to counter the same thus making an unbiased learning model.

In [3] the authors use deep learning to tackle the problem of COVID-19 detection. They use the EfficientNet model on chest CT scan images. They used fixed, cyclic as well as learning rate reduced on plateau strategy to fine tune their model where the plateau strategy performed best on their testing model with an accuracy of 89.7% followed by the cyclic learning rate which achieved an accuracy of 86% while a constant learning rate yielded 83% accuracy on their test set.

In [4] the authors use chest CT scan images to detect COVID-19 by using the LeNet-5 CNN architecture. They used data augmentation techniques to improve on the size of the dataset as there is lower availability of CT scan images of COVID-19 positive patients. They Converted all images to grayscale before feeding them to the model. They achieved 86.06% accuracy with this technique. In [5] the authors use low-dose chest CT images to detect COVID. The low-dose CT scan reduces the radiation exposure to the patients which is a safer method. They use a deep CNN for the classification process and conclude that the dosage can be reduced up to 89% while still keeping most of the information intact. [6] has a CNN for multiclass classification in which they combine numerous datasets to accumulate 10,200 chest CT images which include normal,COVID-19 positive as well as lung cancer patients and perform conversion so that the data is standardized. They got an accuracy of 94% with this model.

In [7], the authors propose a newer approach for recognition of COVID-19 from CT-scans based on deep learning. The authors employ CNN architectures with multi-task strategy for classification of the CT-scans into Normal, COVID-19 or community acquired pneumonia (CAP) classes defined by the authors. For the patient-level classification stage, the authors divided the CT-scans based on their number of slices, and used the models they trained previously on the slices of each group. Using this approach, they achieved an overall accuracy of 87.75%.

In [8], a two-stage CNN based framework is proposed by the authors for the classification of chest CT - scans in order to detect COVID-19 or Community Acquired Pneumonia. The dataset used by the authors is the SPGC Dataset, containing chest CT-scans of healthy, COVID-19 and CAP classes. The first stage is concerned with the detection of an infection of either COVID-19 or CAP using the DenseNet architecture. For the second stage, the authors employ a fine-grained multiclass classification using an EfficientNet architecture. Using this two stage approach, the authors managed to achieve a 94% accuracy at the slice level classification into COVID-19 or CAP, while the three-way classification reached an accuracy of around 89.3% into the classes of COVID-19, CAP or healthy for their validation set.

In [9] the authors have used a hybrid method of using a CNN and the Histogram of Oriented Gradients to introduce a model to help classify the CXR images as covid positive or negative. Image augmentation techniques were also used in order to expand the dataset. The results indicated that the most efficient results were obtained when all the features of the CNN and HOG were combined together, resulting in a 99.67% testing accuracy.

In [10], the authors propose an AI model which would classify an X-Ray image into four classes, namely COVID-19 , CAP or healthy CXR images. The system works in two stages. The first stage classifies the image as pneumonia or non-pneumonia. If stage 1 classifies the image as pneumonic, then stage 2 classifies it into COVID-19 positive or negative. The dataset used in this paper was acquired from SIRM and ESR. Stage 1 achieved a maximum accuracy of 96.5% and stage 2 classification had an accuracy of 98.31%.

In [11] the authors use transfer learning for COVID-19 detection using 3D Resnet50. Instead of training on just 2D images, this technique uses volumetric analysis for a multiclass classification for normal, pneumonial and COVID positive classes. The data was full volumetric chest CT scans for the patients rather than just a single slice from it. They use a novel preprocessing technique for this data which includes resampling, pulmonary segmentation as well as volume range selection to extract salient features from the slices. They achieved an accuracy of 85.56%.

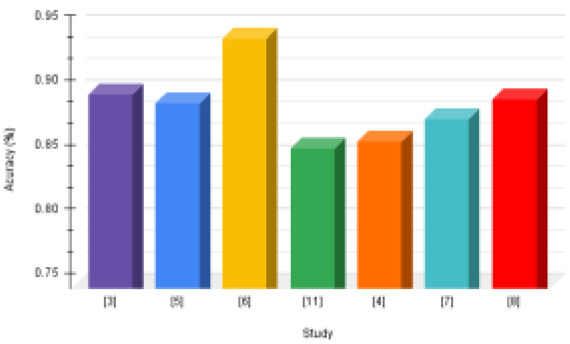


Fig. 1. Accuracy comparison of CNN on chest CT scan

Figure 1 shows the comparison of the accuracies of the CNNs developed in various research articles. In [12] the authors present a model to predict COVID-19 using a deep convolutional neural network called CheXNet from chest x-ray images. CheXNet consists of 121 layers, and helps in detection of COVID-19 by producing a heatmap which helps in the localization of the area which indicates high chances of symptoms for diseases with another metric of prediction probability. For the model proposed, the authors built a CheXNet model by using a pre-trained model of DenseNet121. The authors used the chestXray14 dataset for training their model, and achieved an accuracy of 99.9% in classifying images in binary classes (normal and COVID-19). They discuss implementing the model for real-time scenarios with further developments and working with a bigger dataset for better results. [13] introduces COVID-MobileXpert, which is a lightweight deep neural network based mobile application. This app can scan CXR images for Covid-19 Screening. The deep neural network was a fine-tuned Resident Fellow network for classification of the image into COVID-19 positive or negative, pneumonia or no pneumonia followed by a lightweight medical student network. They concluded from the experiments and results that the MobileNetV2 based COVID-19 app was resource hungry and had higher accuracy as compared to the SqueezeNet based mobile app which was not as resource hungry but also compromised on the accuracy of the app. This means that the MobileNetV2 based app could be used in high performance devices whereas the SqueezeNet is more suited for low end mobile devices. In [14] the authors propose a method based on deep learning. The purpose of the model is detection and localisation of pneumonia in CXR scans. "Pneumonia Ratio" is the metric calculated from the localization maps which is then used to calculate the severity of pneumonia. The backbone of this deep learning model was ResNet50. A localization head fused the intermediate layers of ResNet to form a localization prediction. A detection head was integrated for detecting pneumonia. The RSNA Pneumonia Detection challenge dataset, the Covid19 Image data collection dataset as well as the COVID19 Chest Xray Dataset were used in different combinations for model training. The model achieved accuracies ranging from 0.86 to 0.95, the minimum when just the RSNA Pneumonia Detection challenge dataset was used and the maximum when all the datasets were leveraged.

[15] explains the use of an ensemble model for detection of COVID and uses ensemble and deep learning techniques to mitigate the using snapshots of the models proposed in [16] and a weighted average type ensembling technique taking care of the different sensitivities of the models. [17] uses the VGG-16 based model for COVID-19 detection. [18] proposes a novel CNN architecture which has accuracy of 99.02%. It made use of X-Ray images for the detection of COVID.

In [19] the authors make use of Rmsprop and SGD optimizers for faster computational performance. The purpose was to make a real time COVID-19 detection system. They were able to speed up the time required for training and testing using these optimizers which results in faster classification thus more people can be classified early and the rate of spread of pandemic can be lowered. In [20] the authors use CLAHE to enhance the images to improve performance and also compare their CNN using CLAHE against a VGG-16 with transfer learning and show its superior performance where the CLAHE enhanced model receives 98% while using VGG16 with transfer learning gives only about 50% accuracy rate. In [21], the paper discusses how the current research for Pneumonia diagnosis focuses on only a single modality of

TABLE I. A BRIEF SUMMARY OF SOME OF THE ARTICLES AND THEIR METHODOLOGIES

| Study | Approach | Classification | Accuracy (%) |
|---|---|---|---|
| [12] | CheXNet | Binary Classification on CXR (Healthy or COVID-19) | 99.9% |
| [21] | Concatenation of ResNet50 and VGG16 | Binary Classification on CXR and CT scan (Healthy or COVID-19) | 98% For CT scans 98.93% for X ray Images |
| [7] | CNN Architectures | Multiclass classification on CXR (Healthy, COVID-19 and Cap Classes) | 87.75% |
| [8] | Two Stage CNN | Multiclass classification on CXR (Healthy, COVID-19 and Cap Classes) | 89.3% |
| [14] | ResNet50 | Multiclass classification on CXR (Healthy, COVID-19 and Pneumonia) | Ranging from 86% to 95%, depending on the combination of the datasets used. |
| [13] | COVID-MobileXpert | Multiclass classification on CXR (Healthy, COVID-19 and Pneumonia) | MobileNetV2 and SqueezeNet were used. Concluded that MobileNetV2 is more resource hungry than SqueezeNet along with higher accuracy. |
| [10] | 2 Stage AI Model, Stage 1: Pneumonia / no Pneumonia Stage 2: Covid / Non Covid | Multiclass classification on CXR (Healthy, COVID-19 and Pneumonia) | Stage 1: 96.5% Stage 2: 98.31% |
| [9] | Hybrid Model: CNN and Histogram of Oriented Gradients | Binary Classification on CXR (Healthy and COVID-19) | CNN + HOG: 99.67% |
| [4] | LeNet-5 CNN | Binary Classification on CXR (data aug: grayscale images) (Healthy and COVID-19) | 86.06 |

data such as CT Scans or X-rays or some other modality. The authors discuss how different biomarkers may be able to provide information for detection of COVID-19. Following this, the authors propose the concatenation of two transfer learning models for which they use an open-source dataset, divided into binary classes of COVID-19 Pneumonia and Normal. By concatenating different transfer learning models, the authors get great accuracy, achieving the highest accuracy of 99.87% by concatenating ResNet50 and VGG16 networks.

Table 1 summarises the Articles reviewed in this paper. The approach, type of classification and the accuracies achieved are tabulated as shown. [12] has the best accuracy for binary classification as opposed to [4] which does not have a very high accuracy.

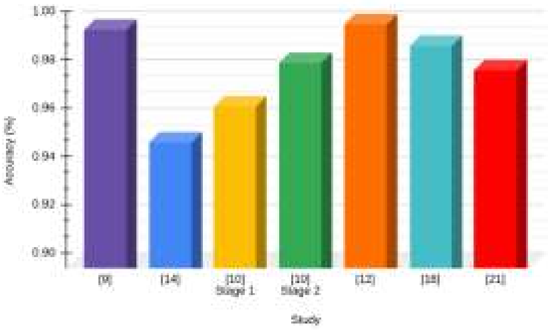


Fig. 2. Accuracy comparison of CNN on CXR images

They also managed to achieve a 98.00% accuracy for single modality CT-scan images with the ResNet50 network. An accuracy of 98.93% was achieved for X-Ray images with VGG16 networks.

Figure 2 visualises the comparison of the CNNs developed in some more research articles.

## III. Limitations of Existing Work

Most of the work done in COVID-19 up until now, has been done on datasets of relatively smaller size, which makes the results of these papers unreliable, and thus unfit for practical purposes in real life situations. Thus, the unavailability of bigger datasets for COVID-19 is the major limiting factor for most researches related to COVID-19.

## IV. Use of GANs For Covid-19 Detection

GANs or generative Adversarial networks utilize two models, a generator and a discriminator. For generating synthetic images, the generator tries to model fake images from noise while the discriminator tries to judge whether the image it received was generated by the generator or it came from a dataset with real images. This allows the generator to train as it tries to maximize the discriminator's loss. GANs have been used to generate images to supplement existing datasets as COVID-19 datasets generally do not have enough images themselves to be able to effectively train deep learning networks.

### *A. Background: GANs in Healthcare*

[22] employs deep adversarial learning for segmentation of mammograms, using a fully convolutional network. [23] uses GANs for converting an image to another, the authors introduce a GAN capable of translating a PET image into a CT-Scan, in addition to this it is also capable of reducing noise in MRI image as well as PET image denoising. [24] uses a GAN model implemented using a variational autoencoder to supplement MRI images generated using a new ASL technique. In [25] the authors propose a GAN implementation which treats low and high quality images differently and also constrains the structure and illumination of the images to enhance them. [26] uses two different GANs to generate and supplement a dataset to improve performance of a CNN used to detect liver lesion in images. [27] works on denoising CT scan images using GAN, the authors use Wasserstein distance for this implementation. In [28], the authors implement a combination of two GANs to improve the resolution of low quality images for better performance on deep learning networks and test it on medical ultrasound images. In [29] the authors use a DC- GAN to generate COVID-19 positive chest CT scan images to supplement available datasets.

### *B. GANs for COVID-19 Detection*

In [30] the authors use an auxiliary classifier GAN to help supplement datasets with synthetic CXR images and improve performance of a CNN by supplementing using these synthetic images. [31] uses Edge cloud computing with GANs in which they have local GANs which share data with each other over the cloud and this is combined to make a better performing global GAN. [32] undertakes training of a model that employs deep learning to classify COVID-19 cases using a GAN and generic data augmentation methods on CXR images, this helps make the model robust, they also compare this model to widely used CNN models such as ResNet and DenseNet. [33] uses a teacher student model as well as transfer learning GAN to generate realistic CXR images that improves the performance of not only a binary classifier but also multi class classifiers similar to [2] and [34] which also detect pneumonia.

GANs have also been used to generate and supplement chest CT-scan data such as in [35] where the authors display the risks of collecting CT scans from infected patients for medical staff and how the safer GAN route can thus outperform those images. In [36], the authors implement image to image translation by using a GAN to transform normal CXR images to COVID-19 positive CXR images to help generate more data and remove imbalances in the datasets. [37] proposes a GAN model for a reverse effect where they generate normal CT scans from COVID-19 CT scans and employ a novel method to make the realism of the GAN generated synthetic COVID-19 data more effective, by this they try to learn the localization mappings used for classification to assist classification systems.

## V. Proposed Methodology

Use of deep learning techniques for COVID-19 detection has shown promising results, also shown by other methods mentioned in [38]. They can be applied in the real world in conjunction with other techniques such as RT-PCR tests currently, and with stable models and enough data, we might be able to use such models independently. Since the amount of training data is low, the models may have overfit and the results may not be stable so using only these techniques would not be viable since it is a matter of health care. Thus, we propose that by supplementing datasets with GAN generated images and making models more stable, these problems may be alleviated a little.

We propose a system that might be able to produce more stable models with the help of GANs
The system also uses data from multiple sources to increase volume since deep learning models are more stable if they have a large quantity of data to train on and have less chance of overfitting.

The first step is to gather data from various sources such as available datasets as well as hospitals and medical institutions to create a combined dataset for training the models. Since these images are from different sources we can use preprocessing techniques like resizing, cropping as well as contrast equalization to make a more homogenous dataset.

Since the amount of COVID-19 positive medical images are low, we could use a GAN to synthesize fake COVID-19 positive images similar to the ones present in our dataset and use them to supplement our bigger dataset.

We could then train CNN models or other deep learning models on these supplemented datasets which should improve overall accuracy of detection

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} * 100\% \quad (1)$$

## VI. Conclusion And Future Scope

There is a lot of scope for deep learning for this task and with increase in the amount of available data as well as GAN usage we might see better and stable results with newer techniques. This will increase the accuracy of existing models not only on existing datasets but also larger amounts of newer data that the models have not seen before.

Data can be handpicked from the datasets which are available as of now and then a GAN model can be trained on this handpicked, high-quality data. Handpicking high quality data would ensure that the GAN model trained would give results which are as close to the real images as possible. An augmented dataset can hence be created with the help of using the GAN generated images. This dataset can then in turn be used to train various classifiers which can then be used, at scale, to detect and identify COVID-19 from Chest X Ray Scans.

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