COVID-19 detection from Xray and CT scans using transfer learning

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***Abstract*—Since the novel coronavirus SARS-CoV-2 outbreak, intensive research has been conducted to find suitable tools for diagnosis and identifying infected people in order to take appropriate action. Chest imaging plays a significant role in this phase where CT and Xrays scans have proven to be effective in detecting COVID-19 within the lungs. In this research, we propose deep learning models using Transfer learning to detect COVID-19. Both X-ray and CT scans were considered to evaluate the proposed methods.**

***Keywords*—COVID-19, medical imaging,Transfer Learning, Deep Learning, Chest XRay Images, CT Scans**

I. Introduction

COVID-19 is an illness caused by a novel type of coronavirus SARS-CoV-2. The risk of developing severe symptoms appears to be more higher with older people and patients with chronic medical conditions. By March 2021, more than 2.6M deaths and more than 118M people infected with SARS-COV-2 have been reported by World Health Organization (WHO) [1]. The increase in the number of infected people has posed a great responsibility to researchers to find effective ways for early detection.

RT-PCR has been considered as the key for diagnosing SARS-CoV-2 [1]. However, this could delay the diagnosis of patients, which is needed immediately to isolate them and stop the spread, due to the limited supply of the testing kits. By combining clinical symptoms and signs, chest computed tomography (CT) is a faster and an easier way to examine suspected patients. This has also being used in many hospitals to diagnose patients with SARS-CoV-2 [2], [3]. According to a research at Tongji Hospital in Wuhan, China, that compared the performance of CT and lab testing on 1000 patients with COVID-19, reveals that that chest CT gives more reliable results than PCR [4]. The researchers also mentioned that Compared to RT-PCR, chest CT imaging might be a more reliable, practical and a rapid method to diagnose and assess COVID-19, especially in the epidemic area.

Although many centers recommend the use of CT scans on Xrays, research [5] has revealed that Xrays can effectively predict which patients are more likely to develop their symptoms, especially for people aged 21-50, therefore early detection of COVID-19 using Xrays scans is very critic, and can help quickly isolating the infected people, as presented in "Fig. III-B", where the virus damages occurs differs day by day in the patient's lungs. It is also noted that SARS-CoV-2 Pneumonia should be initially distinguished from other pneumonia diseases since they present quite similar scans in some cases.

Therefore, it is important to establish an automated tool that helps doctors in detecting COVID-19 on chest scans.

Deep learning, in particular convolutional networks, has demonstrated state-of-art achievements in medical imaging analysis in many application areas, such as neurological disorders, retinal diseases analysis [6], pulmonary infections, digital pathology, breast anatomy imaging, cardiology, abdominal treatment, and musculoskeletal disorders [7].

Typically, convolutional networks perform better on large scale datasets; therefore, in case of small scale dataset, one way to overcome this deficiency is to use transfer learning. In the latter, a model is trained on one task (where a large scale dataset is available) is fine-tuned on the second task (where only a small sale dataset is available). Most traditional learning methods build and train new baselines and classifiers from scratch for each classification task [8]. On the other hand, Transfer learning re-use and transfer knowledge learnt from a source classifier that have been trained on large scale databases to simplify the construction of a classifier for a new target task. The use of pre-trained models in image classification tasks has increased lately, due to both the diversity of instances employed in very large scale pre-trained models that enable them to accommodate new unforeseen scenarios raised by new classification tasks and the continuous increase in memory and computational resources available in nowadays computer systems. In this study, we aim to develop new deep learning based strategy for Covid-19 detection from Xrays and CT-scans images. The proposal makes three pillar-structures. First a data augmentation strategy is employed for the purpose of increasing the size of original dataset. Second, a first pre-trained model DenseNet convolution network is applied to the augmented dataset. Third, a second pre-trained model using Inception V3 is employed on the augmented dataset as well. Both models make use of the very large scale ImageNet [1] data to construct their pre-trained models. The newly developed architectures are therefore employed for both three class classification problem (Healthy, Pneumonia and Covid-19) and two-class problem (Health, Covid-19). The rest of this paper is structured as follows. Section II summarizes previous works related to the detection of COVID-19 using Xrays and CT scans. Section III describes both of the datasets used in our study, along with the data collecting and processing phase. Section IV presents the tuning our pre-trained models on both datasets illustration, and analysis are also mentioned. Finally, section V summarizes the significant findings of our research, Furthermore, concluding the use of deep learning in detecting COVID-19.

II. Related works

Recently, deep learning has become a preferred technique for analyzing Xrays [9], [10], and CT scans [11], [12] and is being applied for both classification and segmentation tasks.
Makris [13] used transfer learning technique to make a comparative study between different convolutional neural network pre-trained models: VGG16 [14] , VGG19 [14], MobileNetV2 [15], InceptionV3 [16], Xception [17], InceptionResNetV2 [18], DenseNet201 [19] , ResNet152V2 [20], NASNetLarge [21]. A combination of two publicly available datasets was used in [10], [11]; the first one contains 112 Posterior-Anterior XRay scans for COVID-19 confirmed cases, the second consists of 112 healthy scans (normal cases) and 112 scans for common bacterial Pneumonia. The authors fine-tuned VGG16 architecture by replacing the three last fully connected layers (FCL) by randomly initialized layers to train them on the learned features, and a softmax output layer. The best result was obtained using VGG16 with an overall accuracy of 95.88%. The other performance metrics show that VGG16 can detect COVID-19 cases with a precision of 96%. Although VGG16 yielded better results, the VGG19 structure with a total accuracy of 95.03% was more accurate in detecting COVID-19 cases with 100% accuracy.
Yildirim [22] proposed a deep convolutional neural network architecture called DarkCovidNet for detecting both COVID-19 vs. healthy and COVID-19 vs. healthy vs. pneumonia. His proposed architecture stimulate the DarkNet architecture which forms the basis of the YOLO (a real-time object detection model stands for You Only Look Once) model, [23] with some model's parameters tuning: in the number of layers, size of filters, and activation functions. A set of 127 COVID-19 confirmed cases from Dr. Cohen's github repository [2], 500 healthy scans and 500 pneumonia scans randomly choosed from ChestX-ray8 database [24] have been used to train the CNN. As a result, using a 5-fold cross validation method, they achieved 87.02% average accuracy for 3-class problem with precision of 97.9% in detecting COVID-19 cases where the binary classification (COVID-19 vs. healthy) problem obtained 98.08% as average accuracy with precision of 98.0% in detecting COVID-19 positive cases.
Most previous works related to COVID-19 detection have worked on either Xrays or CT chest images, contrastingly, in our study, we focus on both types of imaging.

III. Methodology

A. Datasets

As explained in section I, CT imaging and Xrays are both effective in detecting COVID-19, hence, we used both types of image scans to evaluate our proposed architectures. The size of the currently available dataset for COVID-19 for CT and x-ray is relatively small compared to the common public dataset for deep learning.

XRay dataset Contains 1130 X-Ray scans which were obtained from three different open source repositories: D1 containing 140 COVID-19 scans [3]; D2 containing 220 COVID-19 scans [4] and; D3 with 70 scans [5]
As already pointed out, we aim to distinguish COVID-19 Xrays from other pneumonia scans. Furthermore, to avoid the cases of unbalanced dataset, we took 374 scan samples, labelled with Pneumonia and regular Xrays scans from [25], resulting in a dataset with 1130 Xrays images, split as in "TABLE I". See also instances of dataset in "Fig. 1" and "Fig. 2".
CT scans dataset We used a publicly available SARS-CoV-2 CT scan dataset with 2482 CT scans in total, where 1252 CT scans that are positive for COVID-19 while the rest of the samples are non-infected COVID-19 scans, see "TABLE II". Instances of dataset are provided in "Fig. 3" and "Fig. 4".

B. Preprocessing

The resulting dataset contains XRay images with different shapes and resolutions. In order to normalize the input dataset and ensure consistency across all dataset, we reshaped all images with a fixed size of 224×224 pixels.

[1] http://www.image-net.org/

[2] https://github.com/ieee8023
[3] https://github.com/ieee8023/covid-chestxray-dataset
[4] https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
[5] https://www.kaggle.com/nabeelsajid917/covid-19-x-ray-10000-images

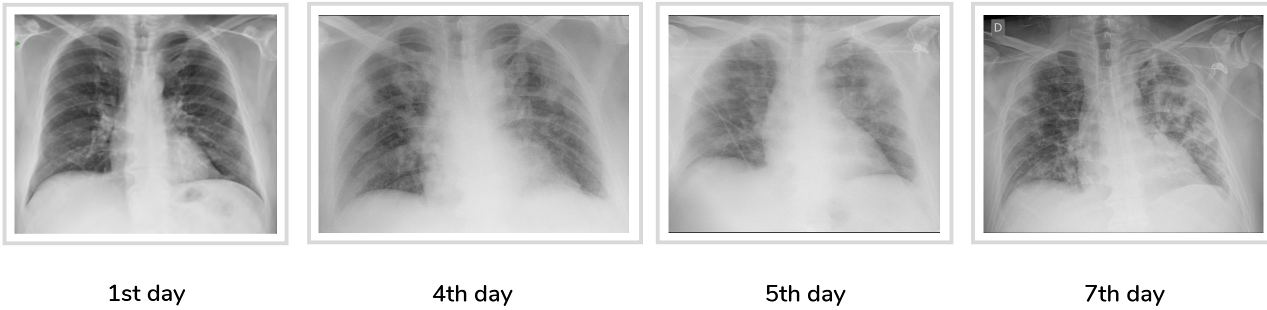

Fig. 1. Chest XRays of a COVID-19 patient over a week [5]

TABLE I
NUMBER OF XRAY CHEST IMAGES AND STATISTICS OF THE USED IMAGES RESOLUTION FOR EACH CLASS.

	COVID-19	Pneumonia	Normal
Number of XRay chest images	430	326	374
Min. image resolution (in pixel)	63232	104648	802100
Max. image resolution (in pixel)	15065600	3049728	6828621
Mean image resolution (in pixel)	1471336.81	1029847.16	1773917.23
Standard deviation	1744859.82	302354.24	1163297.96

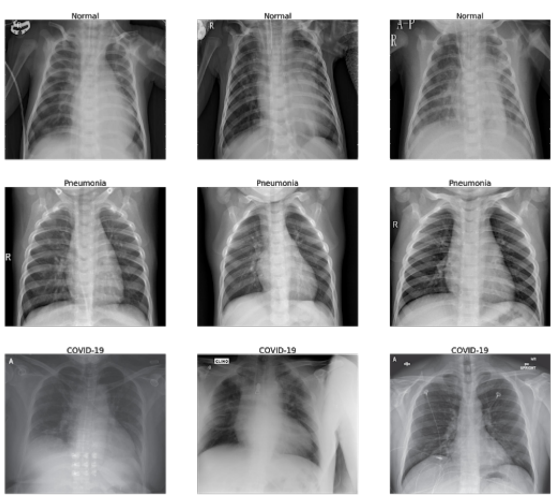

Fig. 2. Samples of XRay dataset

TABLE II
NUMBER OF CT SCANS AND STATISTICS OF THE USED IMAGES RESOLUTION FOR EACH CLASS FOR EACH CLASS.

	COVID-19	Normal
Number of CT chest images	1252	1230
Min. image resolution (in pixel)	23478	29631
Max. image resolution (in pixel)	199104	201344
Mean image resolution (in pixel)	87267.70	98752.51
Standard deviation	25245.2	29146.79

C. Data Augmentation

After collecting the dataset from the difference sources, we found that the datasets' sizes are relativeley small and not adequate for training deep learning models such as CNNs. Consequently, we apply data augmentation in order to increase the number as well as the diversity of the chest scans. Training deep learning neural network models on a large scale dataset is a pre-requisite to ensure satisfactory results. The use of data augmentation techniques that create variations of initial images contribute to this goal. This can take several forms depending on the dataset [26]. For this purpose, the images on our datasets were **rotated, zoomed, horizontally flipped and shifted**, making the dataset larger and diverse. See "Fig. 5".

Fig. 3. Samples of CT scans (COVID-19)

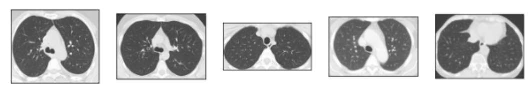

Fig. 4. Samples of CT scans (Normal)

D. Training

As part of transfer learning approach advocated in our study, we fine-tune two pre-trained models: DenseNet (as illustrate in "Fig. 7") and InceptionV3 (as illustrate in "Fig. 6") that have been trained on a very large dataset named ImageNet, the weight of both models were frozen after the training, then we downloaded their weights and fine tuned them on our image classification tasks.
We empirically demonstrate DenseNet's and InceptionV3 effectiveness on both Xray and CT chest scans.
We tuned both pre-trained models, by replacing the last fully-connected layers of the pre-trained model with a new fully-connected layer, and adding a softmax function to the output layer.
We used Tensorflow library [27] since it provides the weights of these models and makes it easy to build and train deep

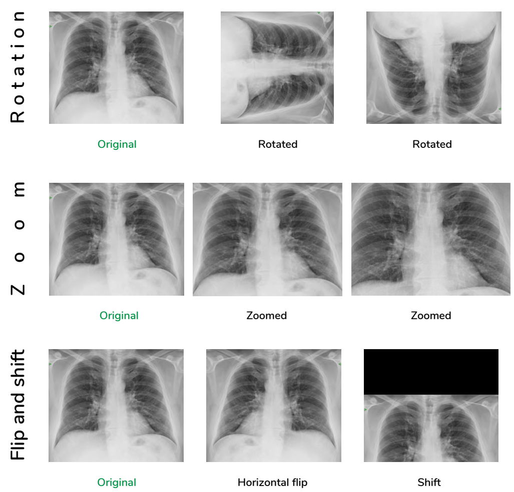

Fig. 5. Samples of augmented data

models.

E. DenseNet architecture

DenseNet, or Dense Convolutional Network def proposed in [28] lately in 2017, is a robust model that was trained on ImageNet, each layer of the model obtains additional inputs from all preceding layers and passes on its own feature-maps to all subsequent layers.

F. DenseNet tuning

We add at the top of the Densest model a convolutional layer that performs feature extraction, which typically consists of a combination of linear and nonlinear operations [29], and at the bottom a dense layer followed by regularization techniques for reducing overfitting, dropout layer [dropout] by preventing complex co-adaptations on training data, and BatchNormalization that allows each layer of a network to learn by itself independently of other layers. We chose these configurations after conducting several experiments.

G. InceptionV3 tuning

The Inception model was first introduced as GoogLeNet (or Inception V1) [16], the models then had multiple variation and distillations, first by the introduction of the batch normalization (in the Inception-v2 model). Then by additional factorization ideas in the third iteration which will be referred to as Inception-v3 in this report is a pre-trained model that contains 7 million parameters and a 42-layer deep learning network. For fair comparisons, we trained all models for 50 epochs on Tesla K8 GPU, we used Adam optimizer and learning rate at 0.0001.

IV. Experiments and Results

We split each data to 80% for training, and the rest 20% of images are used to test the model. For both Xray scan images and CT images, we report the accuracy of the classification results and compared the outcomes with that of DenseNet and InceptionV3 models, used as baseline. Empirical evaluations of DenseNet and InceptionV3 are highlighted in "TABLE III", while the result of the augmented-DenseNet architecture are summarized in "TABLE IV".

TABLE III
Accuracy of recognizing COVID-19, Normal, Pneumonia from XRay chest images

InceptionV3	**92.35%**
DenseNet	63.56%
New-DenseNet	85%

TABLE IV
Accuracy of recognizing COVID-19, Normal from CT images

InceptionV3	84.51%
DenseNet	60%
New-DenseNet	**95.98%**

The DenseNet model performance was enhanced when we added the Convolution layer at the top and the regularization terms in the bottom of the model, making the learning much better.

V. Conclusion

In this paper, novel deep learning architectures have been put forward for the purpose of identification of COVID-19 cases from Xray and CT chest scan images. The proposal makes use of a data augmentation step and, next, integrating an extra convolution layer to DenseNet model. In short, the approach tunes the pre-trained models on two datasets related to Xray and CT scan dataset to classify COVID-19, Pneumonia, and typical cases. The developed approach outperformed the baseline models, constituted of DenseNet and InceptionV3 models by at least 12 percent, which demonstrates the feasibility and effectiveness of the proposal.

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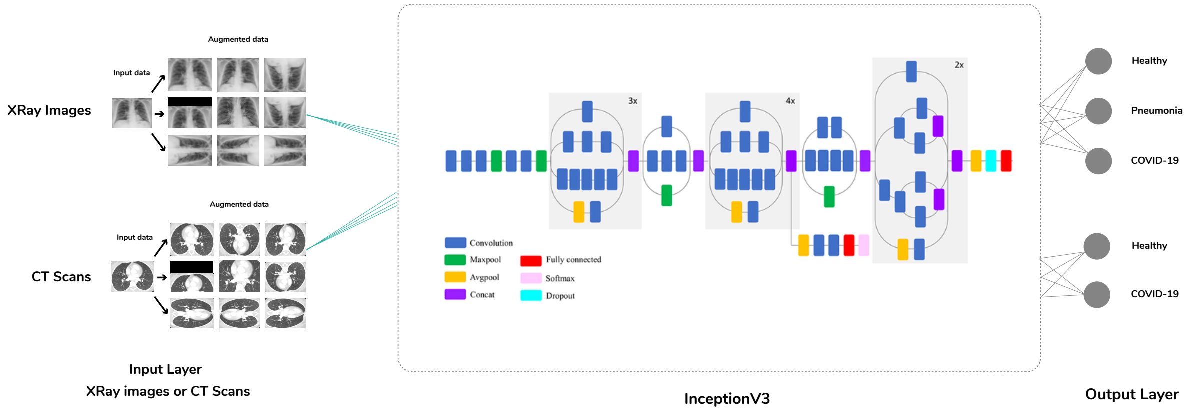

Fig. 6. Tuned InceptionV3 for problems of 2-class and 3-class

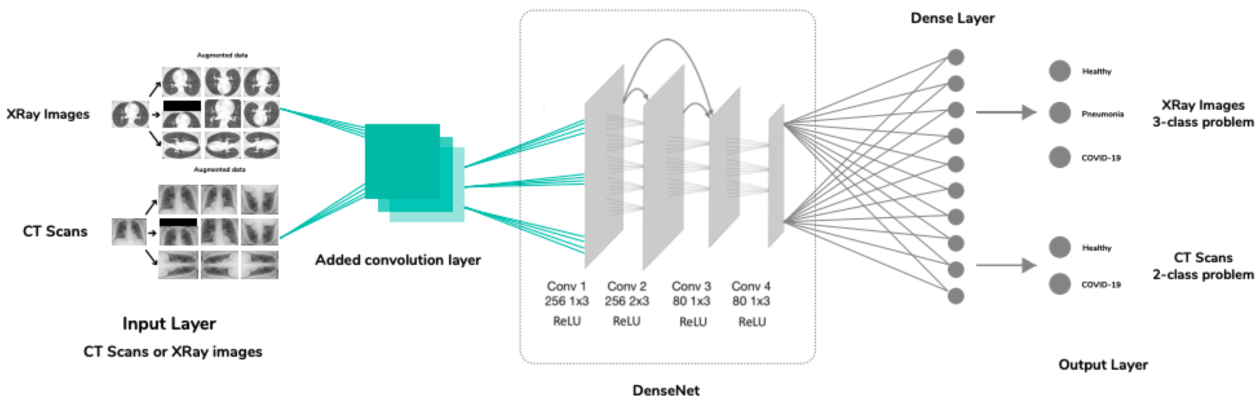

Fig. 7. Tuned DenseNet for problems of 2-class and 3-class

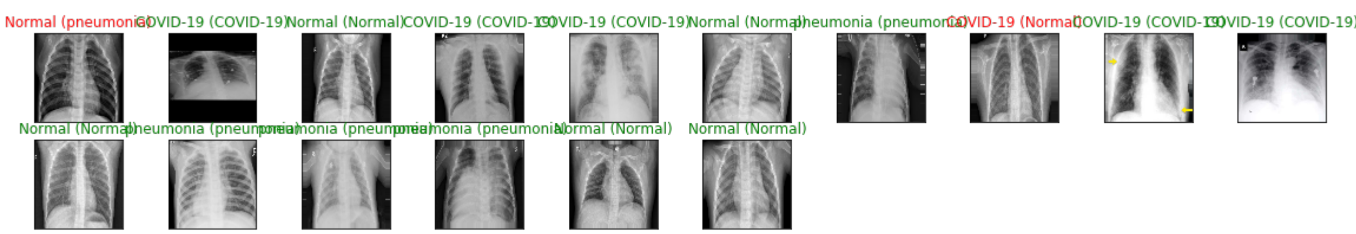

Fig. 8. The Fine-tuned denseNet model tested on 16 Xray scans.

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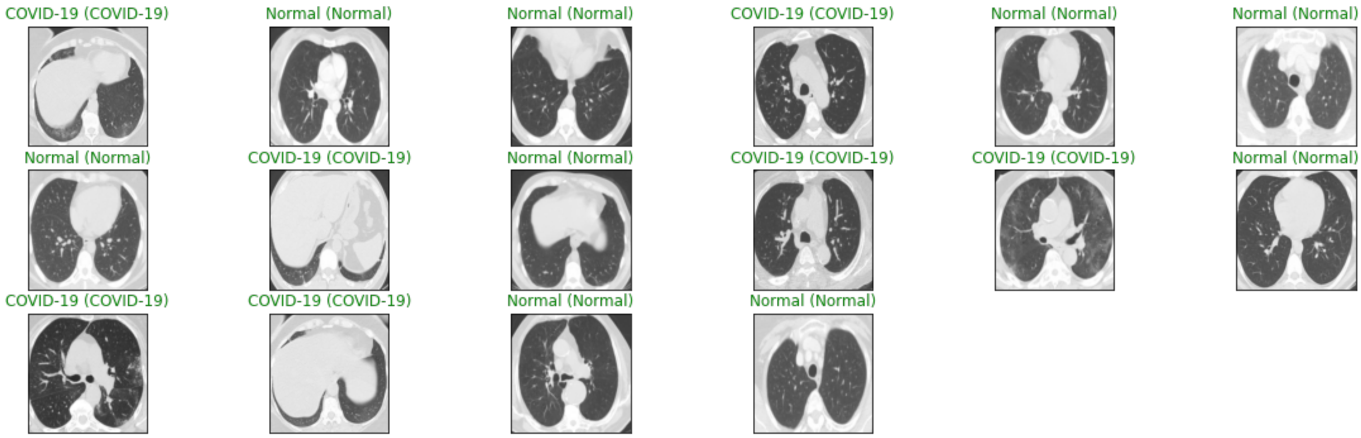

Fig. 9. Fine-tuned denseNet model tested on 16 CT scans.

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