# Covid-19 Detection with X-ray Images and Transfer Learning Techniques

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***Abstract*** ***– The novel coronavirus (covid-19) with a starting point Wuhan, China has spread rapidly amongst countries all around the globe. There are approximately 22 Million confirmed cases as of August 2020. Compared to the daily rises in cases, there are few covid-19 testing kits available. There is a need for testing kits and some countries and regions are in much more need than others. Due to the lack of testing kits available to the public, it is necessary to implement a detection system as an alternative diagnosis method for covid-19. With rapid advancements in medical image processing techniques, the development of intelligent prediction and diagnosis tools have also increased at a rapid rate. Machine learning techniques are widely accepted as a prominent tool to improve the prediction and diagnosis of many illnesses such as cancer. In this study, a dataset of X-ray images from patients with common bacterial pneumonia, confirmed Cd-19 disease, and normal incidents is utilized for the automatic detection of the Coronavirus disease. The procedure of transfer learning was adopted using three different computer vision models that were pre-trained on thousands of images from ImageNet. The models used for this specific purpose are VGG16, VGG19 and ResNet101. The dataset was generated by gathering different classes of images and combining them to form a dataset of size 1GB for better accuracy.***

***Keywords – Deep Learning, Transfer Learning, Image Recognition, ImageNet, Covid-19, X-ray images***

## I. Introduction

Deep learning techniques have made major breakthroughs in the past decade. Image Recognition using Deep Learning techniques, specifically Convolutional Neural Networks (CNN) have facilitated robust image recognition in computer vision tasks.

Applications of computer vision tasks are many. The task of image classification finds its way in our day to day lives with X-ray images to label illnesses such as cancer, classifying hand-written digits and face recognition. Computer vision has many other applications including Object Detection, Object Segmentation, Imagine Reconstruction and Image Synthesis, to name a few. In our paper, we will be focusing on the Image Classification aspect of Computer Vision.

Covid-19 has put a lot of physical and mental strain on society. We realized the need to expand and maximize our efforts to conduct accurate virus testing which led us to use CNN and Image Recognition techniques to label chest X-ray images. This paper discusses predicting images and labeling images as Covid-19 positive, Pneumonia positive or Normal, being negative for both cases. The images cannot overlap and should only fit into one class each. Labeling chest X-ray images for Covid-19 and Pneumonia will allow us to differentiate between the two and obtain a more accurate diagnosis for Covid-19.

*Transfer Learning Techniques*

In this section, we will provide a prequel to our approach and implementation methods which were carried out using Transfer Learning techniques. Transfer Learning in Machine Learning involves storing knowledge gained while solving one problem and applying it to a different but related problem. An example of transfer learning is knowledge gained to recognize cars could also be applied to recognizing trucks [1]. According to Apostolopoulos et. al, with Transfer Learning, the detection of various abNormalities in small medical image datasets is an achievable target, often yielding remarkable results [2].

Similar to Apostolopoulos et. al, in our case, Transfer Learning was used in the form of CNN and Computer Vision models. The authors, however, used a different amount and different versions of these models which will be discussed in more detail in the implementation section. The models used for our study are VGG16, VGG19 and ResNet101.

The final dataset was generated by combining various images from different datasets. Images were collected for Covid-19 Positive, Pneumonia Positive and Normal classes.

## II. Literature survey

From the beginning stages of the discovery of Covid-19, researchers quickly divided their efforts in combating the illness by focusing on developing a vaccine on one hand and developing testing methods on the other. Detecting covid-19 using Machine Learning and discussing the clinical importance of this approach may make it easier to distinguish Covid-19 cases from Normal chest X-rays. In Apostolopoulos et. al's study [2], a dataset of X-Ray images from patients with common pneumonia, Covid-19, and Normal incidents were collected for the automatic detection of the Coronavirus. The aim of the study was to evaluate the performance of state-of-the-art Convolutional Neural Network architectures that have been proposed over the recent years for medical image classification. The dataset utilized for the author's study was a collection of 1427 X-Ray images. 224 images were confirmed and labeled with Covid-19, 700 images with confirmed common pneumonia, and 504 images of normal conditions were included. With Transfer Learning, an overall accuracy of

97.82% in the detection of Covid-19 was achieved utilizing CNN and Computer Vision models. The models used in this study are VGG19, Mobile Net, Inception, Xception and Inception ResNet v2. VGG19 and MobileNet achieved the best classification accuracy over the other models. The work provided the possibility of a low-cost, quick, and automatic diagnosis of the disease and may be clinically used for an accurate diagnosis.

To detect changes in two vascular trees, physicians manually analyze the chest computed tomography (CT) image of the patients in search of abnormalities. The proposed algorithm followed three main steps. First, a scale-space particles segmentation to isolate vessels; then a 3-D convolutional neural network (CNN) to obtain a first classification of vessels; finally, graph-cuts' optimization to refine the results. To justify the usage of the proposed CNN architecture, the authors compared different 2-D and 3-D CNNs that may use local information from bronchus and vessel-enhanced images provided to the network with different strategies. They also compared the proposed CNN approach with a random forests (RFs) classifier. The methodology was trained and evaluated on the superior and inferior lobes of the right lung of 18 clinical cases with non-contrast chest CT scans, in comparison with manual classification. The proposed algorithm achieved an overall accuracy of 94%, which was higher than the accuracy obtained using other CNN architectures and RF [3].

In the domain of pathological brain image classification starting from classical to the deep learning approaches like convolutional neural networks (CNN) there has been a lot research conducted [3]. The classical machine learning methods need hand-crafted features to perform classification. CNN's, on the other hand, perform classification by extracting image features directly from raw images. The features extracted by CNN strongly depend on the training data set size. If the size is small, CNN tends to overfit. So, deep CNN's (DCNN) with Transfer Learning has evolved. The aim of the presented paper was to explore the capability of a pre-trained DCNN VGG-16 model with transfer learning for pathological brain image categorization. Only the last few layers of the VGG-16 model were replaced to accommodate new image categories in the present application. The pre-trained model with transfer learning has been validated on the dataset taken from the Harvard Medical School repository, comprising normal as well as abnormal MR images with different neurological diseases. The data set was then partitioned using a 10-fold cross-validation mechanism. The validation on the test set using sensitivity (Se), specificity (Sp), and accuracy (Acc) reveal that the pre-trained VGG-16 model with transfer learning exhibited the best performance in contrast to the other existing state-of-the-art works [4].

## III. Approach and Implementation

In this section we will cover our own approach for detecting Covid-19 with X-ray images. The implementation, models and methods beginning with the dataset generation will be discussed.

### *Dataset*

The first part of this study was to collect the dataset. The final dataset comprises of three different classes of images. It was developed using various X-ray image datasets and combined to generate a sizeable dataset of 1GB. The classes in this dataset are confirmed Covid-19, confirmed Pneumonia and Normal chest X-ray images.

The images in the dataset were mapped to a CSV file with the correct labels and metadata (for example: marked 0 if the patient was Covid-19 positive, 1 if Pneumonia Positive and 2 if Normal). Using labels, a program in Python was created to map and move all images of each class into a separate folder.

Creating a separate folder for each class allowed us to differentiate between the classes and input. Combining, labeling and separating the images was a crucial step in the process which allowed us to gather a large number of images.

### *The programming language: Python*

The programming language Python played a vital role in the completion of this study. Python was utilized for creating a program for data generation, data pre-processing, data processing and all the way through the end of the study to create models.

With its powerful libraries and frameworks for Machine Learning, we felt that Python was a great fit and would allow us to not only generate our final dataset but also every step needed to implement Computer Vision models to predict Covid-19.

### *Transfer Learning*

We introduced Transfer Learning briefly in the introduction. In this section we will go over it in more detail.

Transfer learning allows us to use knowledge gained in one task in completing another related task. For the purpose of this project, our transfer learning comes in the form of computer vision models tested on ImageNet datasets. ImageNet is a large image database used to train highly efficient models including the Computer Vision models used in this study.

Transfer Learning in Computer Vision allows us to take the last layers away from a predefined model integrating both the pre-trained model (trained on thousands on images) and our own image data as the last layers.

### *Computer Vision Models*

The three computer vision models and frameworks used for this study are VGG16, VGG19 and ResNet 101.

### A. *VGG16*

VGG-16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the university of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition” [5]. With a percent of 92.7% this model achieves the top 5 test accuracy in ImageNet.

The 16 in Vgg-16 refers to the 16 layers that have some weights. With 138 million parameters this is a large network. This network can be very simplistic, using only 3X3 convolutional layers stacked on top of each other, increasing in depth while also reducing the size that is handled by max pooling.

The main intuition behind VGG architecture, whether it’s 16 or 19 layers is that the multiple small filters in a sequence can imitate the effect of large filters. Due to its simplicity in a design and generalization power, VGG Architecture are widely used. Multiple different experiments and scenarios were tested within the Vgg-16 model. In the first scenario Normal X-rays vs Covid-19 X-rays where CNN architectures trained on 1341 Normal X-rays with 111 covid-19 cases while 234 cases of Normal with 73 cases of COVid-19 are used for testing. Sensitivity and Specificity are the measures used by CNN’s; Sensitivity is a measure of the proportion of diseased cases correctly detected while Specificity measures the proportion of healthy cases correctly.

The results for VGG-16 in scenario 1 showed that VGG-16 should not be used to detect Covid-19 in X-rays due to the percentage of sensitivity equaling 84.93%. A 90% threshold of sensitivity would be a successful detection of Covid-19 in X-ray images. Thus, leaving VGG-16 short a few percentages. In a second and third scenario where X-ray images are classified into different classes (Normal, covid-19, Bacteria, Viral) Sensitivity in VGG-16 still was very low with exception towards the bacteria results. Whether it was a normal sample size or reduced sample size as it was in the third scenario. With this information we were able to see that VGG-16 architecture may not help in differentiating X-rays between those 4 classes.

### B. *VGG19*

VGG-19 is also a convolutional neural network model, its architecture is essentially the same as VGG-19, difference being that VGG-19 contains 19 convolutional layers instead of 16 making it a larger system.

Due to VGG-16 and VGG-19 similarities resulted in some of the same results with a sensitivity of 0% for VGG-19 in its sensitivity in scenario 1. For Scenarios two and three across all 4 classes VGG-19 model again does not do a great job differentiating between the classes. With percentages going from 43-92 percent in scenario 1 and 12-90 percent in scenario 2 for class sensitivities. The range between numbers is too vast to get an accurate result from the images using this model.

### C. *ResNet101*

The makers of ResNet101 emphasized that deeper neural networks are more difficult to train and presented a residual learning framework to ease the training of networks that are substantially deeper than those used previously. [6]

ResNet offers reformulated layers as learning residual functions with reference to layer inputs, instead of learning unreferenced functions [6]. According to the authors research, ResNet frameworks are easier to optimize and gain accuracy from considerably increased depth.

The ImageNet dataset evaluated nets with a depth of up to 152 layers which is 8 times deeper than VGG frameworks while also having a lower complexity. An ensemble ResNet achieves only a 3.57% error rate on the ImageNet test set [6].

ResNet won 1st place in the ILSVRC 2015 classification task. With depth being of central importance in many visual recognition tasks, ResNet provides a refined way of object recognition.

### *Model Generation*

To create the models, the data was split in the following way. 80% for training, 10% for validation and 10% for testing.

After generating the models, we used test data in the form of a chest X-ray image to make predictions. For this step, we created an application which upon running will prompt us to the screen in Figure 1 below and allow us to select an image to label.

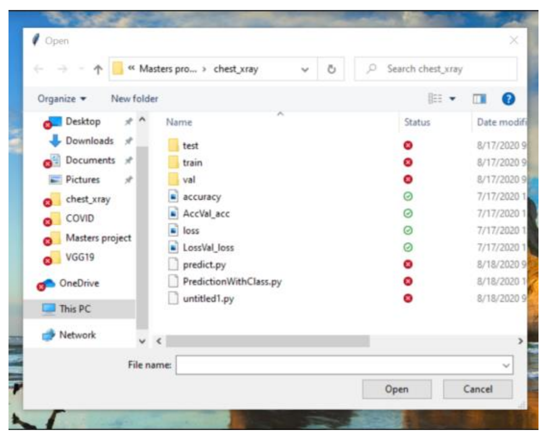


Figure 1.

Figure 2 and 3 below show an image of a chest X-ray that is Covid-19 positive and another image which is Pneumonia Positive, respectively. The label can be extracted from the classes above the image. The first class being Covid-19 positive, second Normal and third Pneumonia positive.

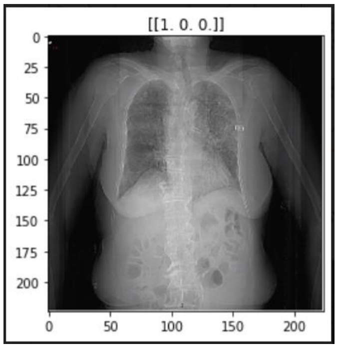


Figure 2.

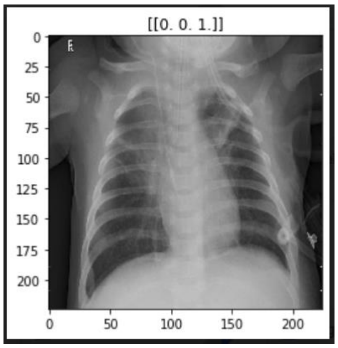


Figure 3.

## IV. RESULTS & DISCUSSION

The models VGG16 and VGG19 were developed and tested for accuracy for a maximum for 5 epochs. ResNet101 was tested with a total of 10 epochs.

The table in Figure 4 displays the results of each model over 1 to 5 epochs. All models performed well when all models were compared at 5 epochs, ResNet101 had the best accuracy rate at 0.9746%. This was followed by VGG16 at 0.9647% and then VGG19 at 0.9532%.

**Model Training Accuracy vs 1-5 epochs**

| **Model** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **VGG16** | 0.9155 | 0.9561 | 0.9530 | 0.9633 | 0.9647 |
| **VGG19** | 0.8999 | 0.9398 | 0.9541 | 0.9525 | 0.9532 |
| **ResNet101** | 0.9183 | 0.9539 | 0.9582 | 0.9661 | 0.9746 |

Figure 4

The figures in this section (Figures 5-10) depict training and value accuracy and training and value loss of all three models.

**VGG16 Accuracy and Loss**

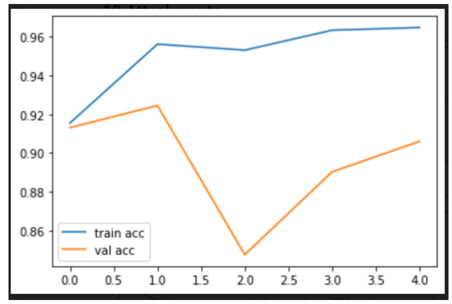


Figure 5

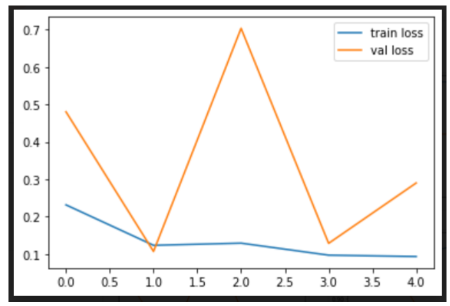


Figure 6

**VGG19 Accuracy and Loss**

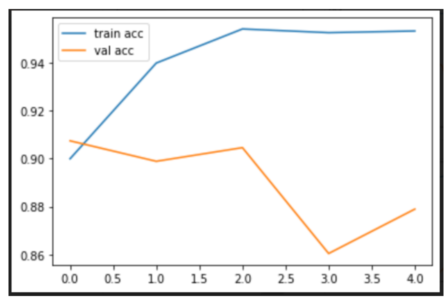


Figure 7

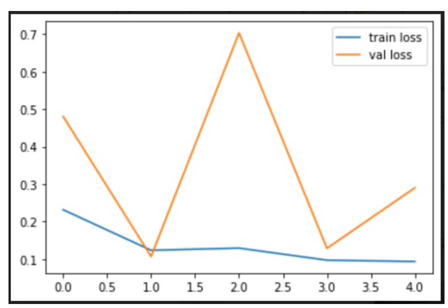


Figure 8

**ResNet101 Accuracy and Loss**

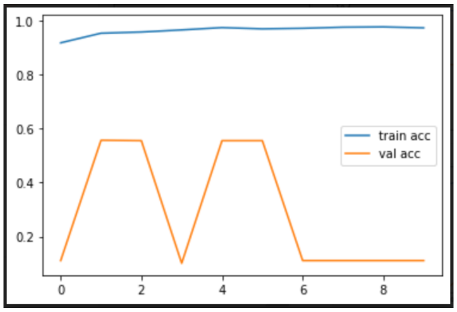


Figure 9

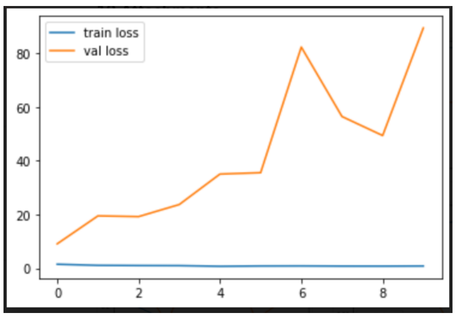


Figure 10

Although the studies mentioned in the VGG16 and VGG19 model sections indicate that these models may not accurately diagnose Covid-19, Apostolopoulos et al. and our study led to the conclusion that the VGG framework gives a good accuracy rating for labeling chest X-ray images. Using ResNet101 proved to be beneficial as it outperformed both VGG models.

## V. CONCLUSIONS

Based on the achieved results, we exhibited that deep learning with CNNs have considerable effects in the automatic detection of extraction of essential features from X-ray images that are related to diagnosis. Utilizing Transfer Learning and Computer Vision models generated high accuracy rates in Covid-19, Pneumonia and Normal case detection.

The study contributes to the possibility of a low-cost, rapid and automatic diagnosis of the disease. This proposed framework may be employed as a supplementary tool in screening covid-19 patients in emergency medical support services.

Despite the fact that the apt treatment is not determined solely from an X-ray image, an initial screening of the cases would be beneficial, not as a treatment, but in the appropriate application of quarantine measures in the positive samples, until a more comprehensive examination and a specific treatment or follow-up procedure is followed.

Few limitations of the study can be overcome in future work. As a higher quality corpus of covid-19 X-ray image data

becomes available, it may be possible to produce models for faster diagnosis of covid-19. Such a tool would be helpful in the areas where testing kits are unavailable. The data size used was already very large but having even more data could add to a higher accuracy rate.

A more in-depth analysis requires much more patient data, those suffering from covid-19. For future approach, the focus could be on distinguishing patients indicating mild symptoms, rather than pneumonia symptoms.

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