COVID-19 X-ray Classification Progress Report

Muhammad Hassan, Omar Mohammadi, Jaeyong Kim
Georgia Institute of Technology, Atlanta, Georgia, USA

Video presentation:
https://www.youtube.com/watch?v=Eoiu52cbq7o&feature=youtu.be&ab_channel=MuhammadHassan

Abstract
In 2020, the world has seen a healthcare crisis that nearly brought the world to a stop. The rise of COVID-19 has been rapid and has caused a lot of issues for underdeveloped countries, but also for countries with well-established healthcare systems. A rapid rise in infections combined with shortages and long latency of COVID tests have made it difficult for there to be accurate tracking of infected people. Using chest X-rays have shown to be a promising avenue of diagnosing patients with COVID and provides a quicker method for triaging patients.This project will apply Deep Learning pipeline in an attempt to accurately classify COVID-19 patients from X-Rays taken of normal patients, as well as COVID-19 patients and Pneumonia patients.

1. Introduction

Since December 2019, COVID-19 has put the world on hold as the virus continues to infect people from all nations. Originating in China, the respiratory virus has affected not only the health of the world population, but also the infrastructure and economy of many nations. According to COVID data aggregated by Google, the number of cases reported up until this point has been 53,693,587 resulting in 1,207,501 related deaths worldwide [1]. COVID-19 has similar respiratory symptoms as other viruses like Viral Pneumonia, or have shown to be dormant or non existent. This similarity in symptoms combined with some patients being symptomatic have left people wondering how they can efficiently test for patients who are COVID positive. Issues like this have made it difficult to contain the virus leading to the high infection rate that it is at now.

The current method of testing is a PCR test, which stands for Polymerase Chain Reaction. This test is run after a sample is taken from a person's mouth and nose. Economically, this test has been known to be expensive and take a long time to return results. Not to mention, this testing procedure has been known to have a high false-negative rate which increases the infectiousness of the virus [2]. As a result, health professionals have turned to the use of chest X-Rays to help them diagnose if a patient is COVID positive or negative. As stated above, PCR tests have shown to have a high false negative rate, but coupled with chest X-Rays with patients can give them more confidence in triaging patients that are ill.

X-Ray and CT imaging are already being used in the medical field to help professionals diagnose diseases like brain cancer, or other respiratory diseases such as pneumonia or tuberculosis. For

COVID, AI classification systems present a viable triaging solution for medical professionals, and some models have boasted fairly high accuracy ratings off of existing COVID-19 Chest X-Rays [3]. Deep Learning projects have also been explored to see if Machine Learning can be a viable solution to finding an effective triage method for COVID-19. X-ray imaging is much more efficient and less painful for patients to undergo compared to getting a nasal swab taken. While other diseases such as Pneumonia, or Brain Cancer have extensive X-Ray images available, COVID-19 does not have as many images. Being a fairly new disease, it is difficult to gather a large set of X-Ray images for COVID-19 and this poses a problem for building out an AI/Deep Learning solution for classifying these images [4-5]. Many previous works discuss using Transfer Learning as a means to combat overfitting due to a small dataset in COVID-19 X-Rays [2-7]. Some models are pre trained on images from the ImageNet database, and then utilized in feature extraction from the current set of COVID images [2].

This project seeks to understand the previously utilized methods for COVID-19 classification and propose a working Deep Learning solution to classifying COVID-19 X-Rays from Normal X-Rays and X-Rays from other diseases such as pneumonia. Some issues to be aware of are the COVID-19 imaging datasets available are very limited, and the features of COVID symptoms in these X-Rays are very similar to the features found in other viral/bacterial respiratory diseases such as Pneumonia. This report will quantify the discoveries made while implementing Deep Neural Network solutions to classifying COVID-19 X-Ray images.

2. Experimental Setup

To support the computational requirements of this project, we have chosen an NVIDIA GPU. Specifically the NVIDIA Tesla V100 Tensor Core which is often used for AI and Machine Learning applications. An Ubuntu Server is also utilized to centralize the code and data used in this project.

On the Software side, Apache Spark is utilized in the form of PySpark to take advantage of the Machine Learning tools available in the Spark Ecosystem. In Python, the Keras package as well as SparkDL, Pandas, Numpy and PIL are utilized. Other libraries explored are Thunder for image analysis and loading.

3. Approach

3.1. Preprocessing

The data is taken from 2 sources:

- COVID Chest X-ray Dataset: This dataset is a public repository on GitHub with a collection of X-ray and CT scans compiled from various sources like other public datasets or hospitals. The groups of imaging show X-Rays that are positive for COVID-19 as well as other bacterial and viral Pneumonias like MERS and SARS. [10]

- COVID-19 Radiography Database: This dataset is another public database filled with images of COVID-19 X-rays as well as normal X-rays and Pneumonia X-Rays. There are 219 COVID images, 1341 Normal Images, and 1345 Pneumonia Images. This database is currently made public on Kaggle for use. [11]

The data is preprocessed to resize each image to a uniform pixel width and height of 224 x 224. The images are also subject to a random flip along the vertical axis to introduce features and symptoms across the imaging of the lungs.

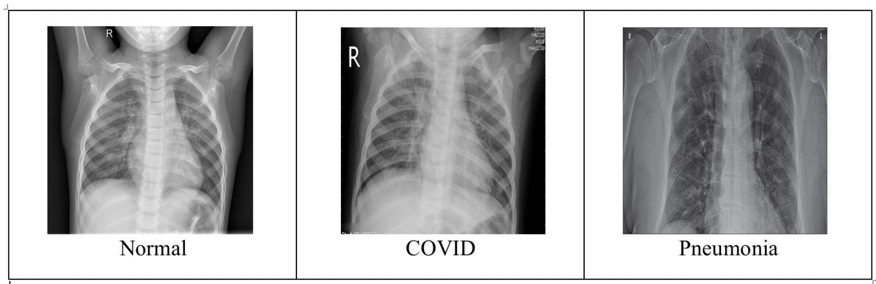


Figure 1: X-ray images of a Normal Chest, COVID Symptom Chest, and Pneumonia Symptom Chest.

3.2. CNN for Image Classification

We utilized a proposed CNN by Ozturk et. al. in processing the images and returning a classification. This model utilizes the FastAI python library which preprocesses the images by resizing them and splits the inputs into an 80:20 split for a training and testing set respectively.

A modified Darknet model is utilized to create the CNN for classification. The model uses 17 convolution layers with maxpool layers [8].

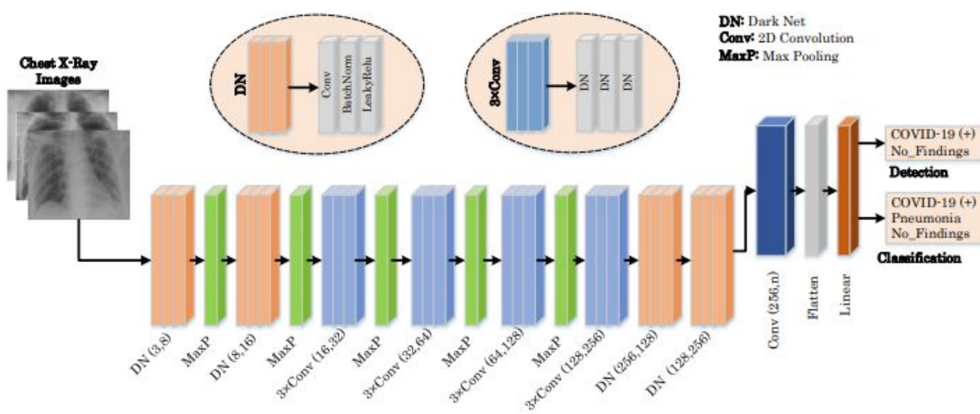


Figure 2: Proposed CNN for Image Classification by Ozturk et. al

This initial model is used to classify the images that we have obtained in our dataset. Ozturk et. al. only used a total of 125 COVID-19 X-Ray Images. Through the datasets mentioned above, we had access to more images so we increased the number of images to 305 COVID -19 X-Ray images. Ozturk et. al. also used 500 normal and 500 pneumonia X-Rays as inputs to this CNN model. To address the accuracy, we will be looking at recall, precision, and the f1-score.

3.3. Keras CNN for Image Classification

Another attempt was made in utilizing PySpark and Keras Deep Learning tools to get better accuracy than the modified DarkNet model in the section above. Images were loaded into Spark dataframes using PySpark and SparkDL. Image features were extracted and inserted into a CNN model created utilizing Keras and trained with an 80:20 training to test split. The model had 13 Convolutional Layers, each followed by a Leaky Relu activation function and a max pooling layer. A dense layer is applied at the end with a softmax function to classify the images. Another layer for Dropout was added to help alleviate the effect of overfitting. To analyze the effectiveness of this pipeline, we looked at the time to completion, and accuracy measures such as recall and precision. Loss was measured through cross entropy and keras used an Adam optimizer.

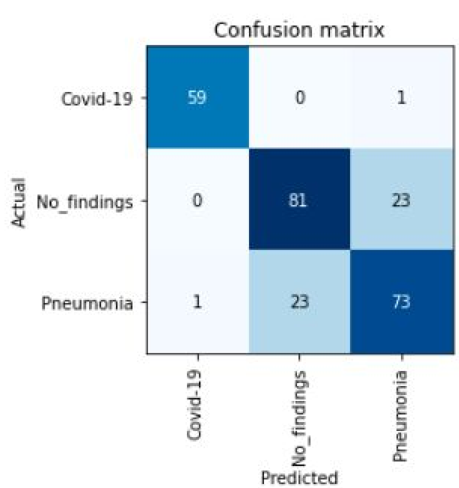
4. Experimental Results

4.1. DarkCovidNet

The dataset we supplied was run through a modified version of the DarkCovidNet CNN model proposed by Ozturk et. al. The data was pre-processed as an initial input to this model. We found that the model was fairly accurate in classifying the three classes from the X-ray images in the validation set which had 261 images in it.

	Precision	**Recall**	**F1-Score**
COVID-19	0.98	0.98	0.98
No-Findings	0.78	0.78	0.78
Pneumonia	0.75	0.75	0.75

Table 1: Results of the Improvised DarkCovidNet with images provided



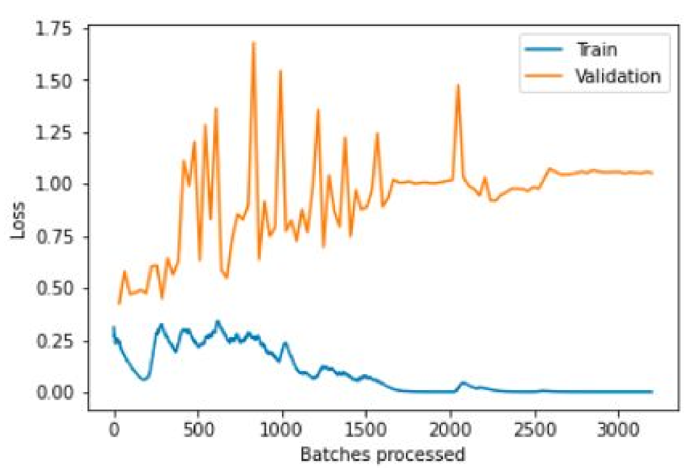


Figure 3: Confusion Matrix and Loss Charts for DarkCovidNet

The results of the original DarkCovidNet are shown in table 2 below.

	Precision	**Recall**	**F1-Score**
COVID-19	0.96	0.86	0.91
No-Findings	0.89	0.94	0.91
Pneumonia	0.88	0.85	0.87

Table 2: Results of the original DarkCovidNet with images provided for comparison

Once optimal results were obtained, in order to optimize the training time, we added lung segmentation to the preprocessing step. The following are the results obtained with lung segmentation.

	Precision	**Recall**	**F1-Score**
COVID-19	0.95	0.70	0.81
No-Findings	0.68	0.70	0.69
Pneumonia	0.56	0.63	0.59

Table 3: Results of the DarkCovidNet with lung segmentation

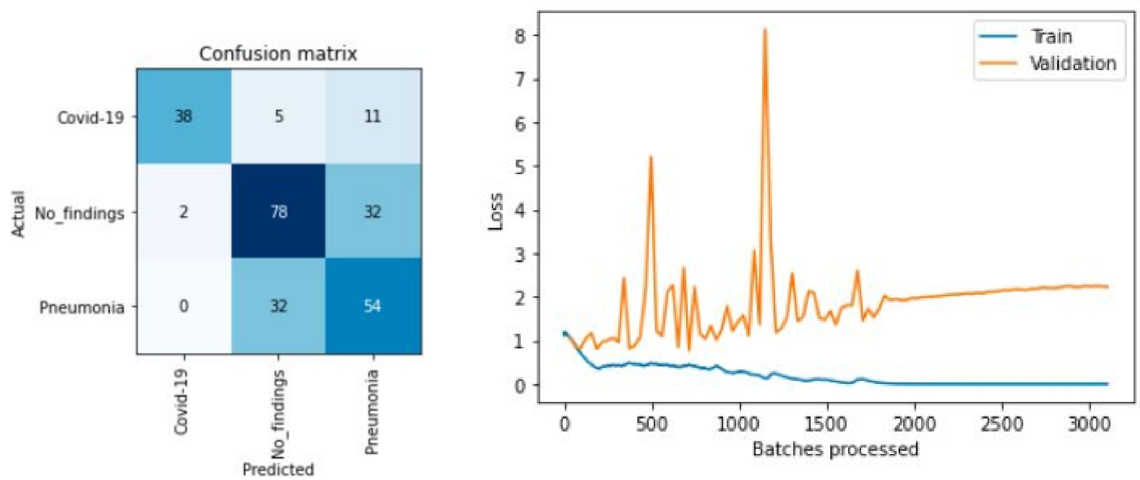


Figure 4: Confusion Matrix and Loss Charts for Lung Segmented DarkCovidNet

	Without Lung Segmentation	**With Lung Segmentation**
Time (Mins)	18 Mins	6 Mins

Table 4: Time comparison for CNN to complete training with and without Lung Segmentation

4.2. Keras CNN with PySpark

In our PySpark and Keras pipeline, we utilized 3192 images as the training set and 799 images as the testing/validation set. The CNN was trained for 100 epochs and took about 48 minutes to complete training. The Loss Charts and Accuracy Charts are shown below for the training and validation sets used to fit the CNN. The precision, recall and F1-Score is also shown for each of the classifications.

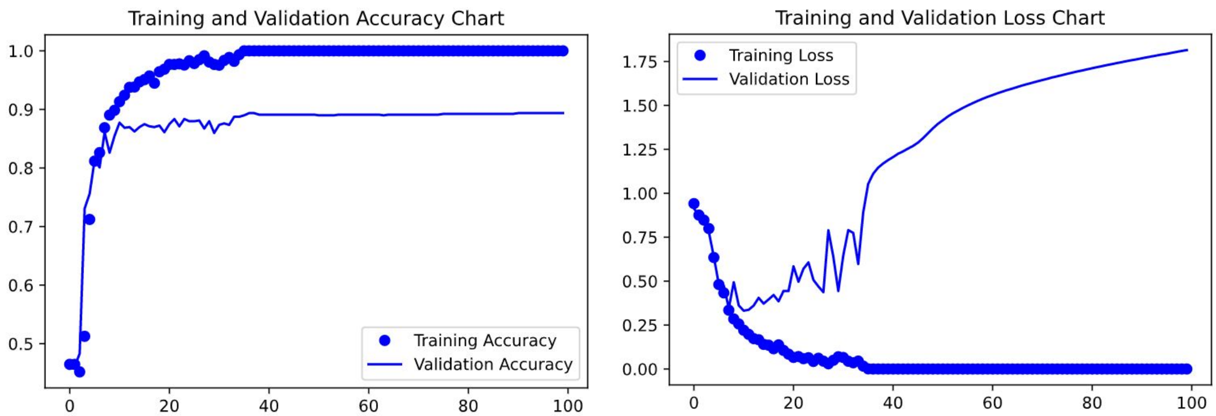


Figure 5: Loss and Accuracy Charts for Keras CNN

	Precision	Recall	F1-Score
COVID-19	0.86	0.75	0.80
No-Findings	0.90	0.92	0.91
Pneumonia	0.90	0.89	0.89

Table 5: Results of Keras CNN

5. Discussion

The DarkCovidNet CNN offers a fairly accurate model in classifying the COVID-19 images. For the images that are preprocessed with just random flips and rotations, we see high precision and recall. However, looking at the loss chart, there is evidence of overfitting as well. Our method of preprocessing does show higher recall and precision compared to the results of the original DarkCovidNet CNN. The lung segmentation we implemented also showed signs of overfitting, but significantly improved the time of the model. 100 epochs took 6 minutes with segmentation, while the normal preprocessed images took 18 minutes. Compared to the 48 minutes it took the Keras CNN model. The lung segmentation gave high precision but low recall meaning it didn't pick up all the covid images but accurately classified the ones it did.

For the Keras CNN, it was noticed that the CNN had high accuracy for the training and validation sets reaching 99% and 89%, respectively. The model performed worse than DarkCovidNet CNN models and it took longer. From the loss charts shown in the figure above, we can see that there is evidence of overfitting in the model. As the CNN is trained through the epochs, we can see an increase in loss and barely any change in accuracy so training the model for more epochs results in more overfitting. Adding a dropout layer to the CNN helped in reducing the effect of overfitting, but it is difficult to overcome this entirely due to the small sample size of COVID-19 images. The Keras CNN with 13 convolution layers performs slightly worse than the DarkCovidNet CNN in classifying the three types of images.

A further enhancement of the model that was researched was the lung segmentation. Lung segmentation significantly reduced the training time of the model, but did not produce the best results. The recall was lower for the lung segmentation images which meant but still had high precision. Lung segmentation shows promising results for training an efficient CNN.

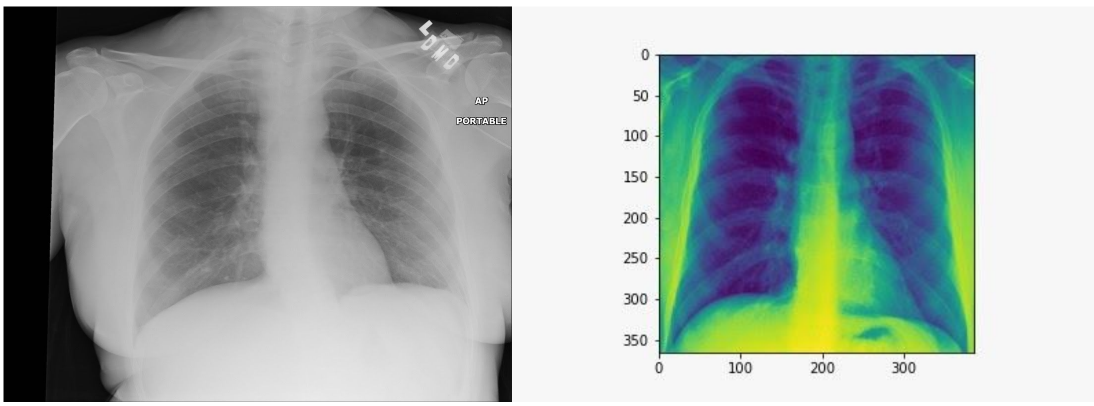


Figure 5: Original Image (Left), Segmented Lung (Right)

While we were not able to completely address the small sample size and the overfitting of the model, in future works, we would proceed by utilizing transfer learning to extract features from the images. There are many transfer learning models available that are trained on larger image sets and using those pretrained weights in combination with these CNN models could help us improve our accuracy in classifying the COVID-19 images. Some pretrained models include ResNet50, VGG16 or InceptionV3. Another benefit of utilizing a pre-trained model as a feature extractor is it takes less time overall to build a classification model. To train the Keras CNN, it took 48 minutes to train it for 100 epochs. Using a pre-trained model like the ones listed above would greatly diminish the time because the models do not have to be trained from scratch. Another area to look into is further preprocessing the images by augmenting the images with a small rotation. Oftentimes, many images are augmented by creating multiple images with a different set of rotations and including that would help our overfitting problem. Adding rotations would mean increasing the areas that could possibly have COVID-19 symptoms in the X-Ray images.

6. Conclusion

Implementing a Deep Learning Neural Network to accurately classify COVID patients will vastly change the way that healthcare professionals diagnose and triage patients. The current modified DarkCovidNet model is able to achieve an accuracy of 96-98% with no feature extractor or Transfer Learning model incorporated. Lung segmentation also seems to produce a faster training time for the CNN and Transfer Learning with another pre trained CNN could surely improve the results and time. Similarly, the Keras CNN developed off of the features from the PySpark dataframe offers an accuracy of 86%. One issue that still remains is the small size of the COVID-19 image set, but utilizing transfer learning with a pretrained model could help overcome that issue. All in all, training a CNN model can be a useful tool in helping healthcare professionals triage COVID-19 patients.

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Team Effort:

Name	Tasks
Kim Jaeyong	• Worked on drafting intro to proposal • Worked on literature review for preprocessing • worked on coding the preprocessing pipeline • Explored CovidXray detection on spark
Muhammad Hassan	• Explored possibilities of performing preprocessing on spark • Finalized consolidated feedback from the team and finalized project proposal, progress report and Final paper • Worked on preparing PPT slides summary of the paper • Presented the project summary through a recorded video
Omar Mohammadi	• Worked on literature review for CNN & evaluation metrics • worked on coding the CNN & evaluation metrics • Explored to optimize performance speed of CNN • Explored utilizing lung segmentation to improve performance of covid classifier