Artificial Intelligence In Covid-19 Diagnosis: Using Computer Vision

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Abstract

The corona virus pandemic has now lasted a period of almost 6 months and keeps on steadily spreading despite the measures and precautions that have been put in place. The current approved method of diagnosing Covid-19 in Uganda is the real-time Reverse-Transcription Polymerase Chain Test (RT-PCR test). While it is the 'gold standard' for the detection of some viruses and is characterized by rapid detection, high sensitivity, and specificity, it has a risk of eliciting false positive and false negative results. Since it is not entirely perfect as a diagnostic tool, it is not surprising that the Covid-19 has continued to spread consistently as unsuspected Covid-19 victims spread the virus in their communities. With the help of machine learning and computer vision, the diagnosis of Covid-19 can be improved. Xray images of Covid-19 victims show considerable differences compared to those of non-Covid19 patients. With a computer aided triaging system, the process of separating Covid-19 Xrays from non-Covid19 Xrays can be quickened and the burden on radiologists can be lifted. We will not only be able to streamline higher risk patients to get the immediate help they need, but also communicate how the network works to clinicians, ultimately improving the national standard of care during this period.

1. Introduction

Medical Image Analysis, one of the popular approaches of artificial intelligence in medical image diagnosis of pneumonia Xrays, and malaria infected cells could be very beneficial in the diagnosis of Covid-19. A unique feature of the Covid-19 chest Xrays is the manifestation of a pure ground glass, mixed ground glass opacities to consolidation in bilateral peripheral middle and lower lung zones. This considerably sets it apart from non-Covid19 Xrays, making it a perfect scenario as an image classification machine learning problem.

Machine learning has demonstrated high performance for several image processing applications especially in image classification and image segmentation. With several computer vision architectures that have a high accuracy on the ImageNet dataset, techniques like transfer learning can be used to build tailored models for specific image classification tasks in a few hours from the generic view the pretrained models obtain from the images in the ImageNet dataset. Using a deep learning approach, convolutional neural networks can be used for automatic diagnosis of Covid-19 from Xrays by classifying the Xray images as Covid-19 or non-Covid19 Xray images. Architectures like mobileNet and Resnet50 reported an accuracy of 87% and 89% respectively when tasked with the classification of 2000 test Xrays of Covid-19 and non-Covid19 patients after a few hours of training.

Predictions from these models were got within 30 seconds, something that is considerably faster than the 4 to 8 hours that are needed to get results from the PCR test. With this, health workers can separate out the Covid-19 suspects from the unsuspected as they wait for the results of the PCR test. A proposition is therefore made that artificial intelligence be incorporated in the diagnosis of Covid-19 patients basing on their chest Xrays as the suspects await the results of the PCR test for confirmation. This would therefore give us an edge in identifying the victims who may not be identified using the PCR test with only the victims who test negative for the PCR test and the computer vision model being let to go back into the community.

2. Related Work

The concept of computer-aided diagnosis (CAD) for chest x-rays has been around for the past fifty years, and has made dramatic progress from the rule-based survival prediction from lung X-rays to machine learning approaches to, now, deep learning. Genneken et al made the argument that CAD in radiology is imperative, as the workload of radiologists is quickly becoming unmanageable.

First, computer-aided diagnosis was sought for other types of diagnostic tasks: breast cancer localization by GoogLeNet and skin cancer classification by a network out of Stanford by Esteva et al. Both of these well-designed networks, along with others, have proven that convolutional neural networks can be used very successfully in not just natural image classification, but also medical image classification and segmentation.

In the world of chest X-ray classification tasks, Rajkomar et al used GoogLeNet along with image augmentation and pre-training on ImageNet to classify CXR images as either frontal or lateral with 100 percent accuracy. While this is not directly clinically relevant, it is an important proof on concept of the use of deep learning on chest X-ray images. Anavi et al sought to create a network that could, given a query image, rank the other chest X-ray images in its database by similarity to the query. They found that a 5 layer convolutional neural network was much more effective than similarity based on image descriptors. Such a network could be used to help clinicians search for past cases easily and help inform their current or future diagnosis. In 2016, Shin et al used a CNN to detect specific diseases in chest X-rays and assign disease labels. They then used a recurrent neural network to describe the context of the annotated disease based on the features of the CNN and patient metadata. They were only able to achieve validation accuracy of 69.8% on this ambitious task. This performance may be largely due to their relatively small data set size of 7470 images, the challenges of multi-class classification and incorporating textual data from patient records. Most recently, in 2017, Wang et al, successfully designed a CNN to diagnose specific diseases by detecting and classifying lung nodules in Chest X-ray images with high accuracy.

While these approaches function as very good proofs of concept, and may in and of themselves be useful for assisted diagnosis, they are not easily generalizable to different diseases as new training data and labels must be obtained to retrain models for each specific sub-question. This project is among many already done in the field of classifying chest X-rays as normal versus abnormal to assist primary healthcare physicians and radiologists to move more quickly and effectively rather than render radiology obsolete. The predictions given by the model are not in by themselves going to classify the images to specific categories of disease, until a much more versatile framework that is applicable to the much larger general population is built.

3. Dataset

The Xrays images used were collected from IEEE Medal for Innovations in Healthcare Technology, which has been collecting CT scans and X-rays of Covid-19 patients since March 2020. The CT scans and Xrays have been collected from multiple publications including the NEJM, PMC, JAMA to mention but a few. For this project, 4044 Covid-19 images and 5500 Non-Covid19 images were used to train the computer vision model. Each image is labeled 0 (Covid-19 Xray) or 1 (Non-Covid-19 Xray). Original images were 1468 x 1010 pixels.

4. Methods

4.1 Preprocessing

There are many sources of variance in chest X-ray data which negatively affect the performance of downstream classification tasks using feature-based methods or neural networks. Major sources of variance include contrast variance, positional variance and view angle variance (e.g. Anterior-Posterior vs Medial Lateral). For this project, all the images were re-sized down to 224 x 224 pixels and preprocessed using the preprocessing techniques used in the ResNet50 architecture.

4.2 Data augmentation

Since the dataset was small compared with usual image classification problems, the images were augmented to prevent overfitting in the model. Each training image, before being input into a neural network, was cropped, rotated 0, 90, 180, 270 degrees, flipped left to right. Lastly, each image had some random small amount of Gaussian noise added to each pixel value.

4.3 Network architectures

The Convolutional neural network was run on Google's GPUs through Google's Colaboratory. The data was split into training and validation sets using an 80-20 split. The validation data was then split into the true validation data and test data using a 80-20 split. The CNN model performance was assessed using the true validation data. Overfitting was assessed by comparing the binary cross-entropy loss and accuracy on training vs true validation data. Loss was calculated as follows;

$$L = -\frac{1}{n}\sum_{i=1}^{n} y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i))$$

Default hyperparameter settings were as follow: Learning rate = 0.0001, Regularization = L2, Batch Size = 32, and Dropout = 0.2.

4.4 ResNet50

Residual Networks reformulate the concept of learning to learn residuals with respect to each layer rather than functions directly. This means each layers try to learn RES where RES is the final loss minus the output of the previous layer. These networks are easier to optimize than traditional ones, and this approach, I use the first 175 layers without experiencing classical problems like vanishing gradients. Initially, the model is evaluated using the weights from the imageNet dataset - performs poorly. When the last 75 layers are trained, the accuracy on the test data increases by about 2.5 times. On top of the 175 layers, I added a Global Average Pooling layer and finally a dense layer with 1 unit.

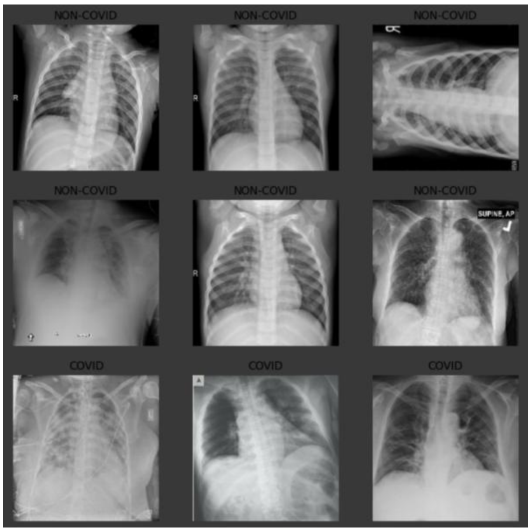

Figure 1: Some of the images in the training dataset

5. Results

Using the unaltered weights of the ResNet50 network trained on imageNet, the accuracy on the validation data was 37.9%
After training the last 3 layers on the model that I added on the training data, the final training accuracy was 91.23% and and the final validation accuracy was 85.84%.

After training the last 75 layer of the base model for 10 more epochs, the final training accuracy improved to 96.68% and final validation accuracy was 90.62%. When evaluated on the test dataset, the model achieved an accuracy of 87.23%

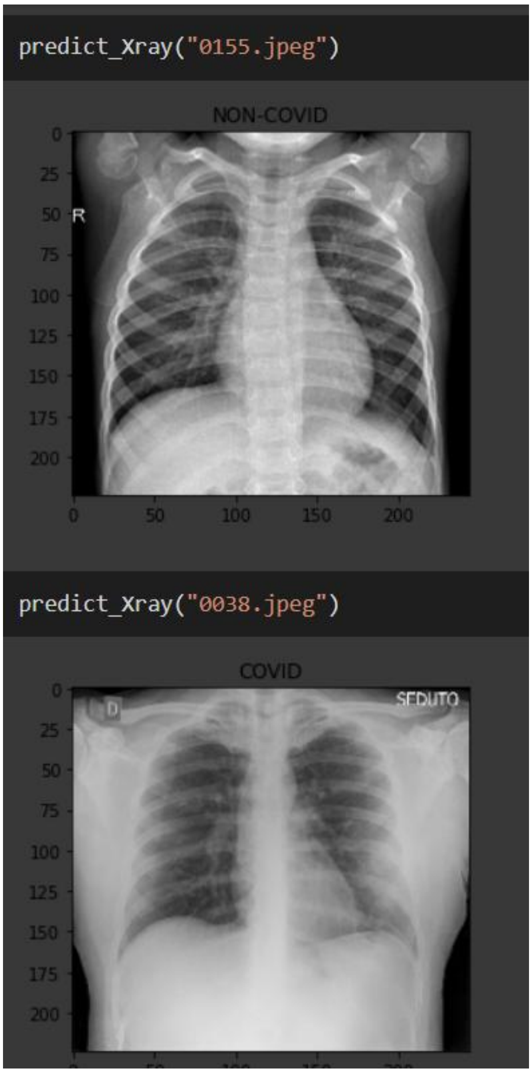

Figure 2: Predictions on random images obtained from different publications

6. Conclusion

It is evident that with a computer vision model, the ability to identify Covid-19 Xrays will be improved, made faster and thus diagnosticians and health workers at the front line of the Covid-19 battle will have a tool they can rely on.
The main downside has been the limited amount of data to train the model on. If more Xray images are obtained to train the model, there is likely to be a bigger increase in accuracy and the model can generalize better to real life test data.
Although this model has not been evaluated on real life data and may in by itself not be ready for clinical adoption, it promises a future classification network that can classify Normal Covid-19 Xrays and Non-Covid Xrays. This can provide primary healthcare physicians and radiologists with valuable information to significantly decrease time-to-diagnosis and greatly improve the current standard of care.

From this, I propose that once this tool is fully tested on real life data, it is used alongside the PCR test so that unsuspected Covid-19 victims can be identified basing on their Xrays for further testing.

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