COVID 19 Detection Through Radiograph Images Using Deep Learning Algorithm

https://www.youtube.com/watch?v=CaSXLJAcebA

Alpas, Michael
Department of Computer Science, UIUC
(309)533-8994
malpas2@illinois.edu

Ahmad, Wasique
Department of Computer Science, UIUC
(414)630-6361
Wasique2@illinois.edu

Singh, Mohit
Department of Computer Science, UIUC
(309)750-7110
Mohits3@illinois.edu

Yadav, Upendra Singh
Department of Computer Science, UIUC
(215)439-4579
Usyadav2@illinois.edu

1. ABSTRACT

The COVID-19 pandemic until this write-up is still causing a major outbreak in all countries around the world. The COVID-19 has led to a historical loss of human life around the world. It gives an unusual challenge to public health, different businesses, and food systems affected by the infection of people by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). It demoralizes tens of millions of people caused by economic and social disruption. Properly mitigating the spread of the COVID 19 virus is very important. There are several ways to do it -- effective infected patient screening is one of them so patients can receive immediate health care. The main screening method for detecting COVID-19 cases in a reverse transcriptase-polymerase chain reaction (RT-PCR) testing can detect SARS-CoV-2 RNA from respiratory specimens (collected through a variety of means such as nasopharyngeal or oropharyngeal swabs). While RT-PCR testing is excellent, it is also a very time-consuming, laborious, and complicated manual process in short supply. [25]

Uncovering this disease from radiography and radiology images is perhaps an efficient alternative way to diagnose the patients. Our team was inspired by earlier works from fellow students, professors, and medical professionals. [15] For this project, we used chest x-rays images from publicly available datasets in which several licensed radiologists evaluated initial images that demonstrated COVID-19 disease. Due to recent development in Machine Learning Models and in the medical imaging field, deep learning methods can be applied to improve the accuracy of diagnosis of COVID-19compared with the gold RT-PCR test and provide valuableinsight for pre-diagnose of patient outcomes.

In this paper, we have proposed a solution that analyzes a broad range of X-ray images [19] of patients using deep learning techniques such as Convolutional Neural Network, pre-trained CNN models ((ResNet50, ResNet101, ResNet152, and InceptionV3), and PyTorch in Amazon SageMaker. We have also hosted our built model in Amazon SageMaker and exposed it as a web service to be consumed by any external third-party system. Our studies' simplicity has also developed a web application that acts as an interface to detect COVID. Any user can upload his X-ray image in a web portal that internally consumes Amazon SageMaker hosted model and can find resultsin few minutes.

2. Introduction

The outbreak of unknown disease started in December 2019, spreading from Wuhan, China.

It was completely unknown at first, but several specialists diagnosed its symptoms similar to coronavirus infection. [16]. As of April 2021, coronavirus cases reached almost 142 million, which has a death toll of close to 3 million, and around 121million recovered from the disease worldwide. [17]

Despite the research efforts around the world, it remains challenging for the early detection of COVID-19 due to limited resources and the amount of data available for research over the past few months.

At present, this pandemic remains to challenge medical systems, governments, and businesses worldwide in many aspects – demands for health care workers, availability of effective vaccines, shortage of medical equipment. In contrast, many healthcare workers and government officials have been infected and threaten everybody despite good progress in managing it.

X-ray imaging is being used as an alternative screening method and done parallel to PCR viral testing. The accuracy of chest X-ray (CXR) in detecting COVID-19 infection relies on radiological expertise due to the complex morphological patterns of lung involvement which can change in extent and appearance over time. If these patterns are detected with high accuracy, it can enable rapid triaging to screen, diagnose, and manage patients with suspected or known COVID-19 infection.

In the particular Convolutional NeuralNetworks (CNN), deep learning techniques have been pounding humans in computer vision and different video processing tasks in recent years.Deep learning algorithms have already been applied to detect and classify Pneumonia and other diseases on radiography.

In this paper, as an effort to improve the current COVID-19 detection using a limited number of publicly available CXR datasets. Our team had the opportunity to apply some of the DeepLearning algorithms we learned from our class.

2.1 Benefit of using Xray images in detecting COVID19.

Rapid Triaging – CXR imaging enables rapid triaging of patients suspected of COVID-19. It can be done in parallel with viral testing (which takes time) to help relieve the high volumes of patients, especially in areas most affected where they have run out of capacity.

Availability of training data - CXR imaging is readily available and accessible in many clinical sites and imaging centers as it is considered standard equipment in most healthcare systems. [25]

Portability - The existence of portable CXR systems means that imaging can be performed within an isolation room, thus significantly reducing the risk of COVID-19 transmission. [25]

Motivated by the urgency to develop solutions to aid the fight against the COVID-19 pandemic, we thought of exploring various deep learning methods, specifically a deep convolutional neural network design using PyTorch framework to detect COVID-19 cases from CXR images that are open source and available to the general public.

3. RELATED WORK

Different Artificial Intelligence tools have produced established and precise results in the applications that use either image-based or other types of data. Apostolopoulos and Mpesiana [4]performed one of the first studies on COVID-19 detection using X-ray images. Their research evaluated the performance of state-of-the-art convolutional neural network architectures proposed over the recent years for medical image classification.

Experimental results show that their proposed model achieved an overall accuracy of 89.6%. More importantly, the precision and recall rate for COVID-19 cases is 93% and 98.2% for 4- class cases (COVID vs. Pneumonia bacterial vs. Pneumonia viralvs. normal). For 3-class classification (COVID vs. Pneumonia vs. normal), the proposed model produced a classification accuracy of95%. The preliminary results of this study look promising, which can be further improved as more training data becomes available.[14]

Their model achieved promising results on a small, prepared dataset, which indicates that the proposed model can achieve better results with using minimum pre-processing of data given more data. Overall, the proposed model substantially make headway the current radiology-based methodology. During the COVID-19 pandemic, itcan be a very effective tool for clinical radiologists and practitioners to aid them in quantification, diagnosis, and follow-up of COVID-19 cases.

4. DATA

While working in the project, we first used below IEEE “covid-chest X-ray dataset” (https://github.com/ieee8023/covid-chest x-ray-dataset)[2].

This data contains 225 COVID-19 chest X-ray images obtained from Cohen data source and available in the above Github link.

This is the first publicly available COVID-19 X-ray image data set; hence, some patients' information is missing in few places.

Dataset contains multiple important metadata fields such as demographic features such as – sex, age, and medical features such as temperature, WBC count, neutrophil count, lymphocyte count, O2 saturation, extubated, intubated, survival and RT_PCR positive. This dataset contains 131 male patients and 64 female patients, and the average age for the group is 58.8±14.9 years.

However, while building the model, we realized that numbers of image data were quite less in this dataset, so we used few more datasets such as “X-Ray Image DataSet” from Ozturk et al. [21]. This dataset contains another 1127 images in three classes: 127 “Covid-19”, 500 ’No_findings’, and 500 “Pneumonia”.

We added one more public image data sets during the model tuning and optimization phase and Chowdhury et al. [22] studies.

The final data set consists of 4412 frontal chest X-ray images in three classes: 698 “Covid-19”, 1851 ’No_findings’, and 1863 “Pneumonia”.

For finally model training, testing and optimization, we have merged these three datasets [1], [21],[22]. After this, we used a random 70% of the dataset for training purposes, 20% for testing purposes and the remaining 10% for validation.

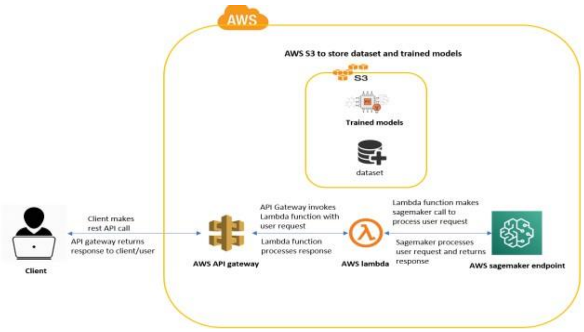
5. APPROACH

The entire project development cycle is divided into two stages. Feature Engineering using CNN (Convolutional Neural Network) and Model Training.[5]

- For PyTorch Model Training, we have used ResNet-50, ResNet152 and InceptionV3 pre-trained models.[6]
- To build the last layer of binary or multi-level classification, we are using the below classifier algorithms.
    - Logistic Regression. [7]
    - Boosted Random Forest Classification.[8]
    - Decision Tree.[9]
- DL Frameworks [10]
    - PyTorch and PySpark

5.1 High Level Architecture

Here is high-level architecture for the project; we used Amazon's simple storage Service (AWS S3) to store datasets and trained models. These models were built and trained using ResNet-50 and InceptionV3. This model(ResNet-50) is hosted in Amazon SageMaker [23] and SageMaker’s endpoint is used in lambda function [24], externalizing Amazon API gateway as a REST endpoint.



5.2 Methodology Implementation

In high level architecture design of our project, a user uploads a chest Xray image to a web-based portal. This portal is internally connected to AWS API gateway and AWS lambda function. AWS API Gateway invoke lambda function upon receiving the request. Lambda function makes a call to AWS Sagemaker's endpoint which is hosting trained model. After model execution, AWS Sagemaker, provides the response back to Lambda function and then to client web-based application.

ResNet-50, is a 50-layer-deep classic convolutional neural network. It has 5 stages each with a convolution block of 3 convolution layers and an identity block of 3 convolution layers. Like other ResNet models, it uses Skip Connection to pass the residuals to next layer and hence enhances the detection of smaller objects which results in higher accuracy.

Inception V3 neural network is another convolutional neural network which helps in image analysis and detection of finer objects in images. It was developed by a deep learning model community called as GoogleNet in Google.

5.3 PyTorch and AWS SageMaker

PyTorch natively supports ResNet50 and InceptionV3 pre-trained models. We used PyTorch to build the classification models. We adapt the concept of transfer learning, in which the models use all but the last fully connected layer as a fixed feature extractor and then trained a classifier. [18]. The data include images in various sizes and type formats; we resized all the images to the size of 224x224 for ResNet-50 and 299x299 for InceptionV3, normalized them with 0.485 mean and 0.229 standard deviation, and converted them into multidimensional tensors using torchvision.transform package.

We mixed up the dataset images and divided them into batches of 20 using the DataLoader function to feed the PyTorch-based machine learning model. In addition to the two pre-trained models,for the PyTorch framework, we used a cross-entropy loss functionto measure the deviation of the predictions of each class. We also used Stochastic Gradient Descent (SGD) as the optimizer with a learning rate of 0.001 that updates each layer's values and generates probabilities for the target class labels via its SoftMax function behind the scenes.
However, the results were not expected. We then changed the optimization technique to Adaptive Moment Estimation (Adam) method with a learning rate of 3e-5. We applied the train, evaluation, and visualization functions.

We used AWS SageMaker's GPU-powered integrated Jupyter authoring notebook instance to build and train both ResNet-50 and InceptionV3 models using custom PyTorch code.

Our current analysis found that the ResNet-50 model performed better than the InceptionV3 model; we chose tohost the ResNet-50 model using SageMaker hosting services to provide inferences. We used AWS SageMaker Neo to compile and deploy the trained model on a GPU-powered real-time inference instance.
We used AWS S3 storage to store the dataset to train the model, the best-trained model, and the SageMaker Neo compiled model.

To allow the hosted model to be accessible from external applications, we integrated the hosted model with an Internet-facing RESTful API built using Amazon API Gateway and Amazon Lambda function written in Python programming language. API Gateway acts as the 'Entry point' to our serverless User Interface facing web application built in React using AWS Amplify. The User Interface client application is a single-page web application that allows users to upload their Chest X-ray image.

Once a user uploads the image, the request is sent to the POST-RESTful API hosted on AWS API Gateway, which then triggers the Lambda function. The Lambda function forwards the request to the hosted model. The hosted model then provides the data back to the Lambda function, then sent to the APIGateway and finally to the User interface client application.

5.4 Model overview

5.4.1 CNN

A Convolutional Neural Network (CNN, or ConvNet) is a type of deep neural networks, most commonly applied to analyzing visual imagery in deep learning. The name "convolutionalneural network" imply that the network employs a mathematical operation called convolution.
CNN's are used for recognition and image classification becauseof its high accuracy. Examples of CNN in computer vision are face recognition, image classification, etc.
It follows a hierarchical model that builds a network, like a funnel. Finally, it gives out afully connected layer where all the neurons are connected to each other, and the output is processed.
Conv's primary purpose is to extract features from inputimages. In this study, different Conv. Layers can be applied to remove different types of features such as edges, texture, colors, and high-lighted patterns from the images.
A convolution layer is simply a feature detection layer. Every convolution layer has a specific number of channels; each channel detects a particular feature in the image. Each feature to detect is often called a kernel or a filter. The kernel is of a fixed size; usually, kernel sizes 3 x 3 are used.

In a CNN, the input is a tensor with a shape: (number of inputs) x (input height) x (input width) x (input channels). After passing through a convolutional layer, the image becomes abstracted to a feature map, also called an activation map, with shape: (number of inputs) x (feature map height) x (feature map width) x (feature map channels). A convolutional layer within a CNN generally has the following attributes:[26]

- Convolutional filters/kernels are defined by a width and height (hyper-parameters).

- The number of input channels and output channels (hyper-parameters). One layer's input channel must equal the number of output channels (also called depth) of its input.

- Additional hyperparameters of the convolution operation, such as: padding, stride, and dilation.

5.4.2 Logistic Regression

Logistic regression is a supervised classification algorithm that is used when the value we are going to predict can be divided into categories. Logistic regression transforms its output using the logistic sigmoid function calculates its weights and biases to return a probability value which can then be mapped to two or more discrete classes. [7]
As Pneumonia and COVID detection is a classification problem, we can use logistic regression to return a probability score between 0 and 1, with 0 representing a normal lung and 1 representing infected lungs.

5.4.3 Random Forest

As its name implies, a random forest consists of many individual decision trees that operate as an ensemble. It uses bagging and feature randomness when building each individual tree to try to create an uncorrelated forest of trees whose prediction by committee is more accurate than that of any individual tree. [11]

A Boosted Random Forest is an algorithm consisting of two parts; the boosting algorithm: AdaBoost and the Random Forest classifier algorithm [12], which consists of multiple decision trees. A decision tree builds models that are similar to an actual tree. The algorithm divides our data into smaller subsets, simultaneously adding branches to the tree. The outcome is a tree consisting of leaf nodes and decision nodes. A decision node has two or more branches representing the value of each feature (like age, symptom1, etc.) tested, and the leaf node holds the result value on the patient's perspective condition (target value).

Multiple classifier decision trees (ensemble of classifiers) eliminate the risk of failure of a single decision tree to correctly predict the target value. Thus, the random forest averages theresult provided by multiple trees to give the final product.

5.4.4 PyTorch

PyTorch is an open-source machine learning library based on the Torch library that implements a dynamic computational graph, which allows you to change the way your neural network behaves on the fly and capable of performing backward automatic differentiation. It provides two high-level features:[6]

- Tensor computing (like NumPy) with solid acceleration via graphics processing units (GPU)

- Deep neural networks built on a tape-based automatic differentiation system.

5.5 Performance Criteria

A variety of performance criteria are used to evaluate the performance of classification models, namely classification accuracy, precision, recall, F1 score, sensitivity, and specificity. The two suitable criteria that can be used to report model performance are Sensitivity and Specificity, widelyused in the medical field.

The cross-validation estimator can be used and also can be created a confusion matrix, as shown in the table below.

Confusion Matrix

	Predictive Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

- TP (true positive) is a number of anomalies and was identified with the correct diagnosis.
- TN (true negative) is an incorrectly measured number of regular instances.
- FP (false positive) is a Type 1 error, a set of regular instances that are classified as an abnormality diagnosis.
- FN (false negative) is a Type 2 error, a list of abnormalities observed as an ordinary diagnosis. [27]

Accuracy is defined by the rate of correctly classified images.

$$Accuracy = TP + TN / (TP + TN + FP + FN)$$

Precision is used to compare the TP predicted values and FP predicted values.

$$Precision = TP / (TP + FP)$$

Recall is defined as the ratio of the total number of correctly classified positive patients to the total number of positive patients. It should be as high as possible.

$$Recall = TP / (FN + TP)$$

F1 score: we use this to compare the low precision and high recall of two models. It measures the Recall and Precision values simultaneously. It uses the mean in place of the arithmetic mean by penalizing more extreme values.

$$F1\ score = 2 * (precision * recall) / (precision * recall)$$

5.6 Experimental Setup

For this experiment, we are using the following technology stack – Docker, Jupyter Notebook, and PyTorch. To manage the dependencies, we leveraged containerized environment using Docker. This container will be responsible forhosting a Jupyter notebook environment, and for our base image, we will install Python libraries such as PyTorch, Numpy, and Pandas. The Docker image will be saved in the teams' Docker Hub. The advantage of this kind of setup is that team members willhave a ready-to-go consistent working environment to focus on the assigned tasks.

The containerized setup is a simple solution. However, in the event that greater processing power is needed due to the limitationof team member's individual laptops – we discussed possiblyleverage AWS Elastic Container Service or AWS Fargate for managed serverless compute for containers.

6. RESULTS

To evaluate the efficacy, accuracy of our model, we used the F1 score, accuracy, sensitivity, and confusion matrix.

We tried multiple pre-trained CNN models and finally selected ResNet50 and Inception V3 as the best models which showed promising results. See table below:

Model Names	Precision	Recall	F1 Score	Accuracy
Small Dataset ResNet-50	0.94	0.93	0.935	0.93
InceptionV3	0.88	0.89	0.884	0.88
Large Dataset ResNet-50	0.97	0.97	0.97	0.97
InceptionV3	0.94	0.93	0.934	0.93

7. DISCUSSION

As per the above results, both CNN-trained models ResNet-50 and InceptionV3 are showing promising results. We are getting approximately 97% accuracy in ResNet-50 model and 93% accuracy in InceptionV3 model.

The above results indicate that ResNet-50 model is more effective and accurate in predicting outcomes.

This could be explained by the underlining architecture of Inception V3 and ResNet-50 models. InceptionV3 model has an issue with vanishing gradient problem. On the other end, ResNet50 uses skip connection to propagate information over layers and enhances the detection of smaller objects in the image, which led to improving accuracy in detecting the results.

While developing this project, we thought of hosting this project locally in a docker image. Still, due to very slow performance and umpteen issues related to the environment, we finallydecided to move to the AWS environment. Our teammates learned most AWS services such as AWS SageMaker, AWS S3 etc.

Another challenge we had in selecting CNN models -- we selected multiple CNN models, trained them, and tested and checked the misclassification rate; it took a lot of time and effort to decide the correct CNN model.

In our next step, we will fine-tune our model, use n-fold cross-validation, and see how it will improve accuracy.

7.1 Optimization

For optimizing the results in PyTorch framework, at first, we have used a cross-entropy loss functions to measure the prediction of each class. Along with the cross-entropy function, we also used Stochastic Gradient Descent (SGD) as the optimizer with a learning rate of 0.001, which updates each layer's value and generates probabilities for the target class labels via its SoftMax function.

We could not achieve good accuracy after using the cross-entropy loss function and SGD optimization. We changedthe optimization technique to ADAM (Adaptive Moment Estimation) method with learning rate 3e-5. Using cross-entropy Loss function and ADAM optimizer with a learning rate of 3e-5, we improved the results with more than 90%accuracy.

8. CONCLUSION

In this paper, the results showed that the Convolutional Neural Network with minimized convolutional and fully connected layers can detect COVID-19 with reasonable accuracy.

As a result, we can say that deep learning algorithms such as CNN are capable of analyzing Xray images and easy detection of COVID-19 decease. We used cloud computing architecture – AWS SageMaker and demonstrated how it can host machine learning models.

Definitely, advanced work can be done to further enhance the accuracy of the COVID-19 detection models. We are confident that bringing more real-time data will further develop the detection models. Also, it would be interesting to get data of patients that has been infected by COVID-19 and showed excellent improvement after the vaccine.

9. CONTRIBUTION

Each team member read several research papers, which helped us build our ideas and strategy. Individuals had a chance to analyze the dataset and developed the needed models, and we used the AWS Services for our development environment. Also, several tasks were assigned to individuals – Michael's focus was making the containerenvironment completed in the 1st week of April. Together, members could read different research papers and shared learning approaches for our project. Mohit did coordination, and the draft was completed on April 20th.

Wasique and Upendra worked on Deep Learning algorithms based on the research papers we read and did the setup of AWS. After individual tasks, everyone contributed to the analysis and coding.

Everybody contributed for reviewing, proof-reading our drafts and final paper together with the presentation.

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