X-RAY IMAGE ANALYSIS FOR PREDICTING COVID-19

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Abstract : The COVID-19 pandemic is causing a major outbreak in more than 150 countries around the world, having a severe impact on the health and life of many people globally. Oneof the crucial step in fighting COVID-19 is the ability to detect the infected patients early enough, and put them under special care. Detecting this disease from radiography and radiology images is perhaps one of the fastest ways to diagnose the patients. Some of the early studies showed specific abnormalities in the chest radiograms of patients infected with COVID-19. Inspired by earlier works, we study the application of deep learning models to detect COVID-19 patients from their chest radiography images. We first prepare a dataset of Chest X-rays from the publicly available datasets.Images exhibiting COVID-19 disease presence were identified by board-certified radiologist. While the achieved performance is very encouraging, further analysis is required on a larger set of COVID-19 images, to have a more reliable estimation of accuracy rates. The dataset, model implementations (in Keras).

***IndexTerms* – COVID-19, Patients,Dataset, Chest X-rays, Keras.**

I. Introduction

Since December 2019, a novel corona-virus (SARS-CoV-2) has spread from Wuhan to the whole China, and many other countries. ByApril 18, more than 2 million confirmed cases, and more than 150,000 deaths were reported in the world. Due to unavailability of therapeutic treatment or vaccine for novel COVID-19 disease, early diagnosis is of real importance to provide the opportunity of immediate isolation of the suspected person and to decrease the chance of infection to healthy population. Reverse transcription polymerase chain reaction (RT-PCR) or gene sequencing for respiratory or blood specimens are introduced as main screening methodsfor COVID-19. However, total positive rate of RT-PCR for throat swab samples is reported to be 30 to 60%, which accordingly yields to un-diagnosed patients, which may contagiously infect a huge population of healthy people.

Chest radiography imaging (e.g., X-ray or computed tomography (CT) imaging) as a routine tool for pneumonia diagnosis is easy to perform with fast diagnosis. Chest CT has a high sensitivity for diagnosis of COVID-19 and X-ray images show visual indexes correlated with COVID-19. The reports of chest imaging demonstrated multi lobar involvement and peripheral airspace opacities. The opacities most frequently reported are ground-glass (57%) and mixed attenuation (29%). During the early course of COVID-19, ground glass pattern is seen in areas that edges the pulmonary vessels and may be difficult to appreciate visually .Asymmetric patchy or diffuse airspace opacities are also reported for COVID-19. Such subtle abnormalities can only be interpreted by expert radiologists. Considering huge rate of suspected people and limited number of trained radiologists, automatic methods for identification of such subtle abnormalities can assist the diagnosis procedure and increase the rate of early diagnosis with high accuracy. Artificial intelligence (AI)/machine learning solutions are potentially powerful tools for solving such problems.

So far, due to the lack of availability of public images of COVID-19 patients, detailed studies reporting solutions for automatic detection of COVID-19 from X-ray (or Chest CT) images are not available. Recently a small dataset of COVID-19 X-ray images was collected, which made it possible for AI researchers to train machine learning models to perform automatic COVID-19 diagnostics from X-ray images. These images were extracted from academic publications reporting the results on COVID-19 X-ray and CT images. With the help of a board-certified radiologist, we re-labelled those images, and only kept ones a clear sign of COVID-19 as determined by our radiologist. Three sample images with their corresponding marked areas are shown in. We then used a subset of images from ChexPert. dataset, as the negative samples for COVID-19 detection. The combined dataset has around 5000 Chest X-ray images (called COVID-Xray-5k), which is divided into 2000 training, and 3000 testing samples.

II. SCOPE

Medical officials can monitor the society to make health policies. And it also control the Spread of COVID-19 can be minimized. It is highly cost efficient compared to manually detecting the masks.

Current system for detecting COVID-19 using the aforementioned virus and antibody testing modalities is time-consuming and requires additional resources and approval, which can be a luxury in many developing communities. Hence, at many medical centers, the test kits are often unavailable. Due to the shortage of kits and false-negative rate of virus and antibody tests, the authorities in Hubei Province, China momentarily employed radiological scans as a clinical investigation for COVID19.

METHODOLOGY

Deep learning in smart health analytics is a prominent interdisciplinary field that merges computer science, biomedical engineering, health sciences, and bioinformatics. Various medical imaging devices have a dedicated image and signal analysis and processing module, on which deep learning based models can be implemented to provide accurate, real time inferences. Motivated by this, we conceptualize a deep learning-based chest radio graph classification (DL-CRC) framework, which can used for automating COVID-19detection from radiograph images.

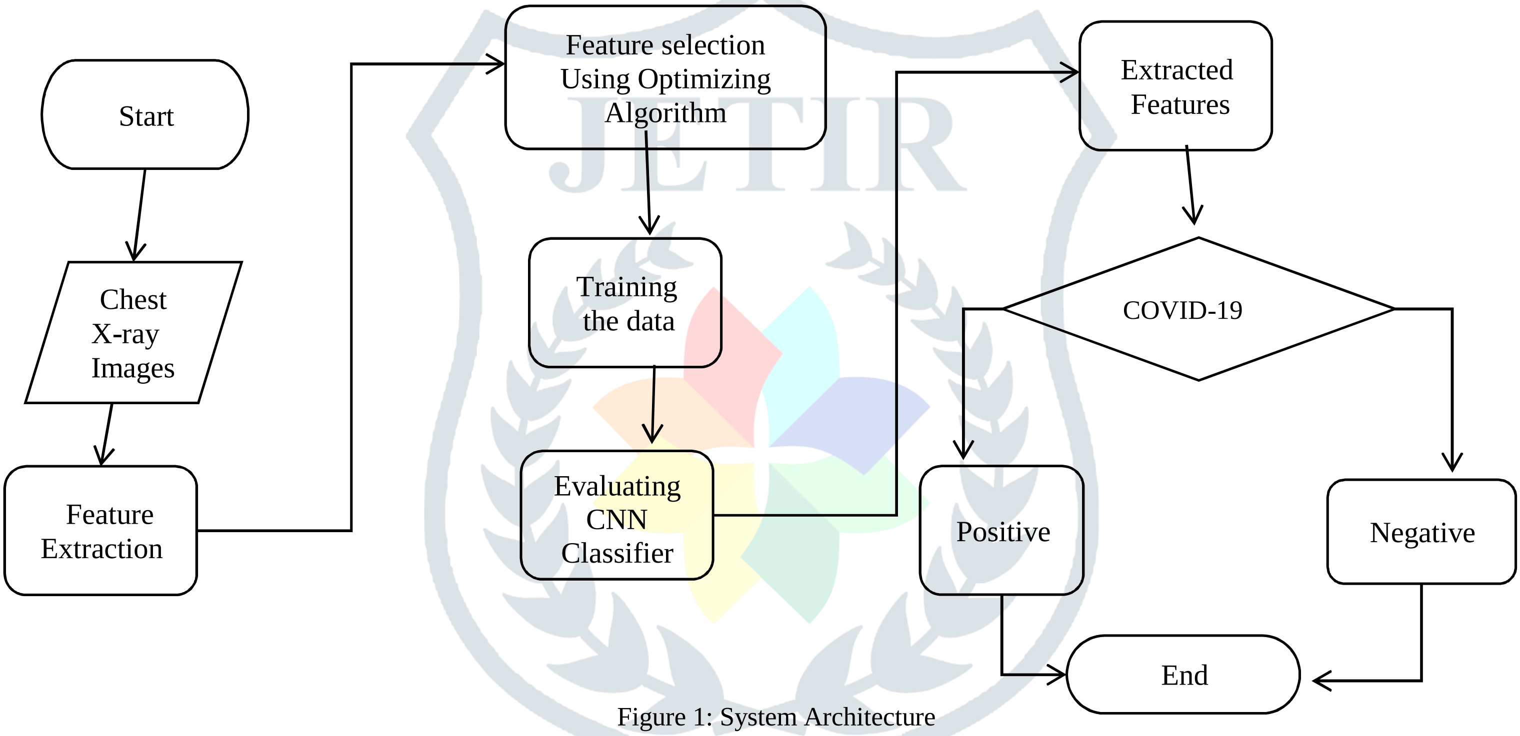


Figure 1: System Architecture

System

CREATEDATASET:

Combining two different datasets of x-ray images into one, to train our model.

PREPROCESSING:

Resizing, gray scaling and reshaping the images into appropriate format to train our model. The final dataset is split into training andtesting dataset with test size of 10%.

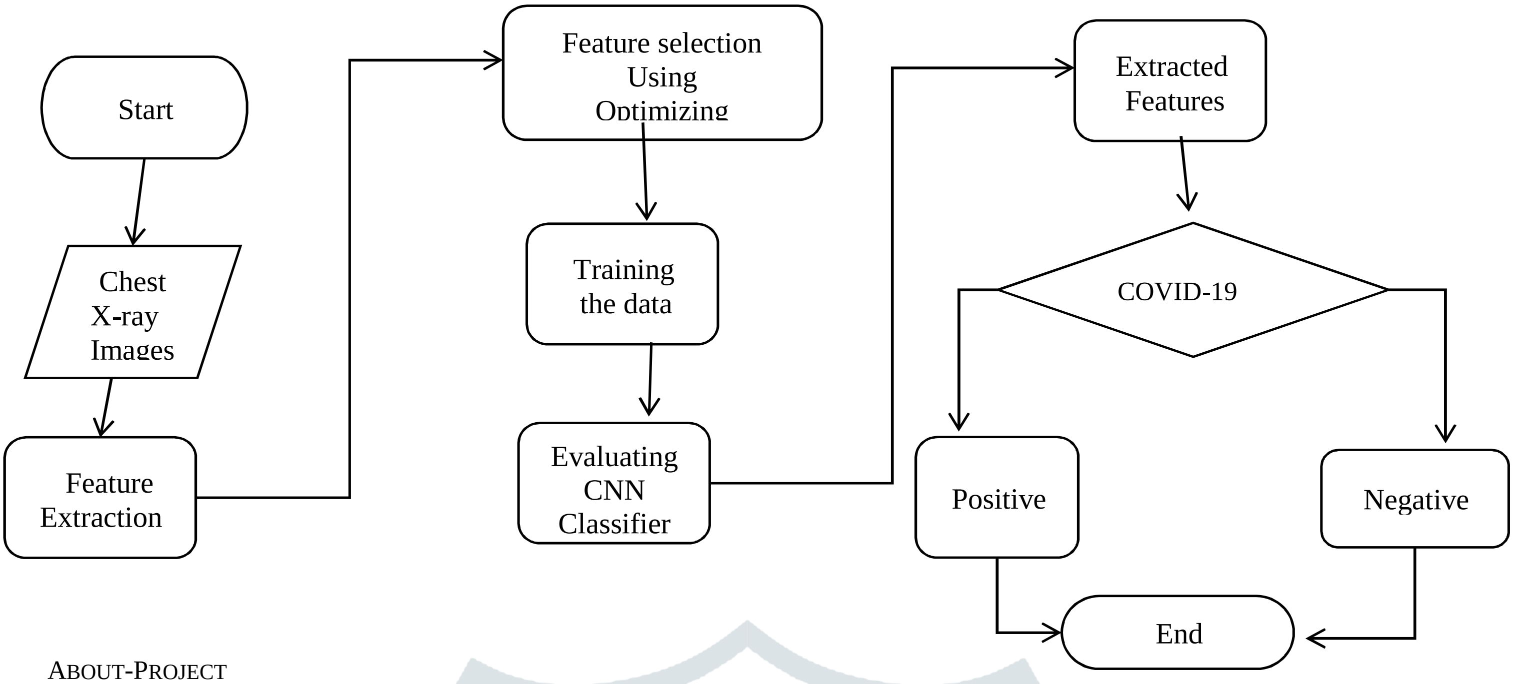
TRAINING:

Use the pre-processed training dataset to train our model using CNN algorithm.

USER:

Register

The user needs to register and the data stored in MySQL database.



ABOUT-PROJECT

In this application, we have successfully created an application which takes in an X-ray image and predicts if it belongs to a COVID-19 positive person or not.

LOGIN

A registered user can login using the valid credentials to the website to use a application.

UPLOADIMAGE

The user has to upload an image which needs to be tested for covid-19.

PREDICTION

The results of our model is displayed as either positive or negative for covid-19 period.

LOGOUT

Once the prediction is over, the user can logout of the application.

III. **Convolution Neural Networks:**

Step1: Convolution Operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks

Step2: Pooling Layer:

In this part, we'll cover pooling and will get to understand exactly how it generally works. Our nexus here, however, will be a Specific type of pooling; max pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part will end with a demonstration made using a visual interactive tool that will definitely sort the whole concept out for you.

STEP 3: FLATTENING:

This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

STEP 4: FULL CONNECTION

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

IV. CONCLUSION

In this application, we have successfully created an application which takes in an X-ray image and predicts if it belongs to a COVID-19 positive person or not. This application saves a lot of time and is very cheap to operate. This application can also be easily scaled up to handle large amount of tests which generally happens during a pandemic. Faster prediction also results in faster treatment and low chances of contagion to the public.

V. FUTURE WORK

In future this application can be extended to a real time model, where X-ray of people are taken and the results are generatedimmediately which can be very useful in airports when people travels to different countries.

VI. REFERENCES

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