Project Report

of

COVID-19 Diagnosis Using Deep Learning Framework on Chest X-Ray Using FastAI

for Neural Networks

A Project Report is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted by

Paritosh Singh [CO17344]

Under the Guidance of

Dr. Varun Gupta (Professor, CSE Dept.)

CHANDIGARH COLLEGE OF ENGINEERING AND TECHNOLOGY

(DEGREE WING)

Government Institute under Chandigarh (UT) Administration, Affiliated to Panjab University, Chandigarh

Sector-26, Chandigarh. PIN-160019

COVID-19 Diagnosis Using Deep Learning Framework on Chest X-Ray Using FastAI

Paritosh Singh

Chandigarh College of Engineering and Technology (Degree Wing) (Government Institute Under Chandigarh UT Administration | Affiliated to Panjab University, Chandigarh)

Abstract:

The exponential rise of COVID-19 has led to a meteoric rise in the deaths by COVID-19. As the healthcare systems around the world adjust to the realities of the post-pandemic world. With a minuscule number of testing kits and delayed vaccine roll-out, screening and diagnosis of every patient with respiratory illness is an uphill task. One of the key screening approaches being radiology examination using chest radiography. It has been found that patients present abnormalities in chest radiography images that are characteristic of those infected with COVID-19. X-Ray machines are already available in most healthcare systems, and with most modern X-Ray systems already digitized, there is no transportation time involved for the samples either. Application of deep learning models on Chest X-Ray Images can help in identifying patients with a high likelihood of COVID-19. In this manner, we can develop a scalable national identification portal that leads to the identification of COVID cases even in remote areas. In this paper, a new model for automatic COVID-19 detection using raw chest X-ray images is presented. The proposed model is developed to provide diagnostics for classification between COVID, No-Findings and Pneumonia. Implementation of 17 convolutional layers and introduced different filtering on each layer. The model produced a classification accuracy of 80.04% for multi-class cases.

Keywords: COVID-19, deep neural networks, deep learning

Introduction:

As the coronavirus pandemic rapidly sweeps across the world, it is inducing a considerable degree of fear, worry and concern in the population at large and among certain groups in particular, such as older adults, care providers and people with underlying health conditions. As the fear of getting infected deepens so does the fear of getting out of one's house does contributing to deteriorated medical attention to the ones in need as some of the people are too afraid to step into hospitals full of COVID 19 patients. The model we propose can easily dismiss this problem. The patients can have there Chext-X Ray scanned on the national identification portal.

This will help in:

1. Narrowing down of COVID-19 Cases.
2. Prioritizing the ones with high degree of likeliness.
3. Help in COVID-19 testing especially in areas with less number of COVID cases.

As a response to the situation prevailing all over the world it is absolutely necessary to find reliable means for the diagnosis of the needful. This project caters the same issue letting the patient diagnose some of the diseases within the comforts of their own homes.

Related Work:

A lot of research papers have emerged in reponse to COVID-19 pandemic especially in relation to COVID-19 detection in Chest X-Rays. Since the recent sudden surge of COVID-19 infections across the world, many alternative screening approaches [1,2,3,4] have been developed to identify suspected cases of COVID-19. However there are only limited such open-source applications available for use which use chest X-Ray images. Publicly available data on chest X-Rays for COVID-19 are also limited.

Dataset Description and data pre-processing:

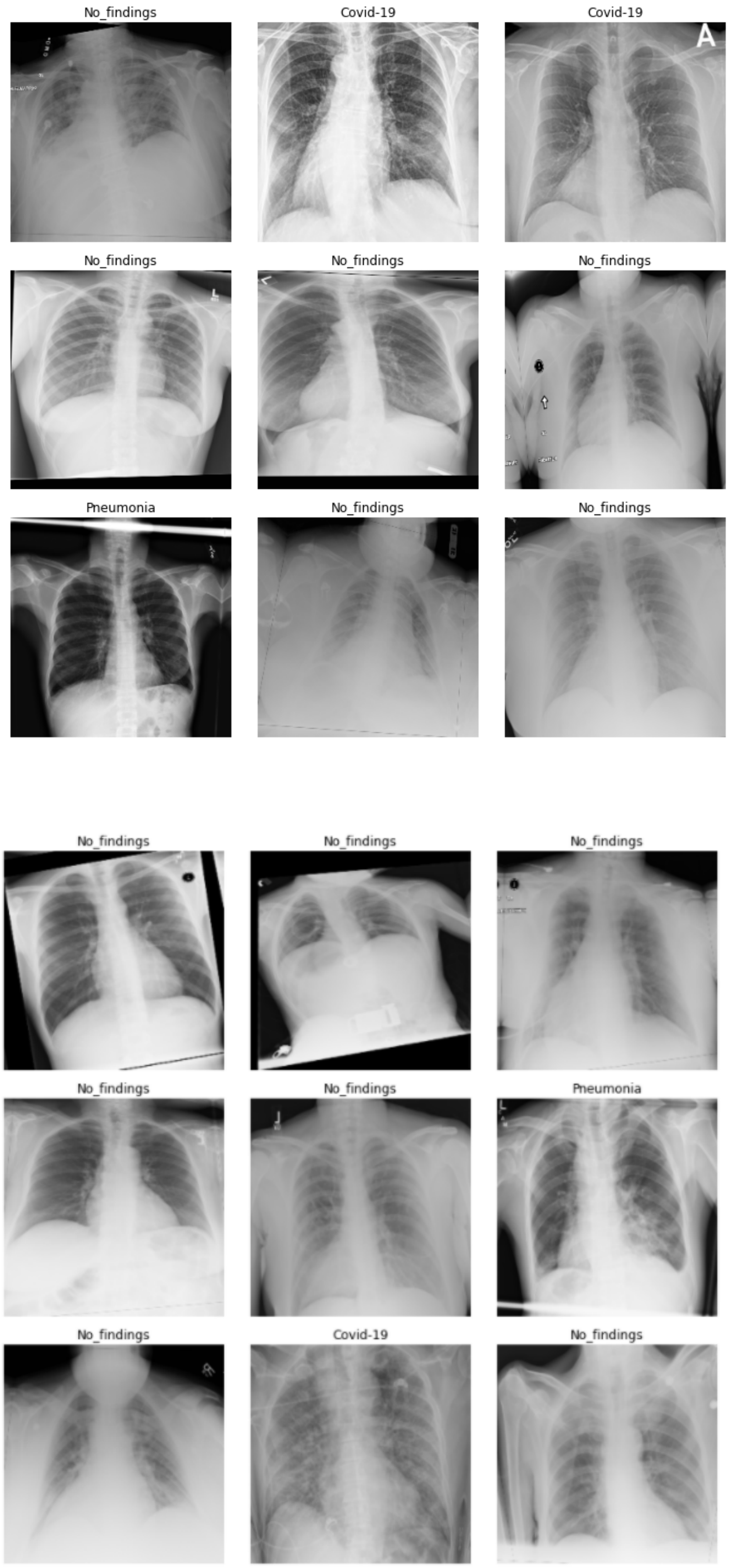
For COVID-19 Images. The following public open dataset of chest X-ray and CT images of patients which are positive or suspected of COVID-19 or other viral and bacterial pneumonias was utilized.[5] Data was collected from public sources as well as through indirect collection from hospitals and physicians. All images and data will be released publicly in this GitHub repo.

The total images of each type was:

1. COVID: 125 Images
2. No-Findings: 500 Images
3. Pneumonia: 500 Images

Dataset was further partitioned into test, tain and validation sets for each category

- Total Number of images in training: 778
- Total Number of images in validation: 30
- Total Number of images in test: 317



<u>COVID 19 Image Dataset exapmle</u>

Proposed Model:

The proposed model has 17 convolution layers. Each layer has one convolutional layer followed by BatchNorm, and LeakyReLU operations, while each 3 Conv layer has the same setup three times in successive form. The batch normalization operation is used to standardize the inputs, and this operation has other benefits, such as reducing training time and increasing stability of the model.

LeakyReLU is a variation of the ReLU operation used to prevent dying neurons. Unlike ReLU or sigmoid activation functions, which have zero value in the negative part of their derivatives, LeakyReLU has a small epsilon value to overcome the dying neuron problem.

Sequential

Layer (type)	Output Shape	Param #	Trainable
Conv2d	[8, 256, 256]	216	True
BatchNorm2d	[8, 256, 256]	16	True
LeakyReLU	[8, 256, 256]	0	False
MaxPool2d	[8, 128, 128]	0	False
Conv2d	[16, 128, 128]	1,152	True
BatchNorm2d	[16, 128, 128]	32	True
LeakyReLU	[16, 128, 128]	0	False
MaxPool2d	[16, 64, 64]	0	False
Conv2d	[32, 64, 64]	4,608	True
BatchNorm2d	[32, 64, 64]	64	True
LeakyReLU	[32, 64, 64]	0	False
Conv2d	[16, 66, 66]	512	True
BatchNorm2d	[16, 66, 66]	32	True
LeakyReLU	[16, 66, 66]	0	False
Conv2d	[32, 66, 66]	4,608	True
BatchNorm2d	[32, 66, 66]	64	True
LeakyReLU	[32, 66, 66]	0	False

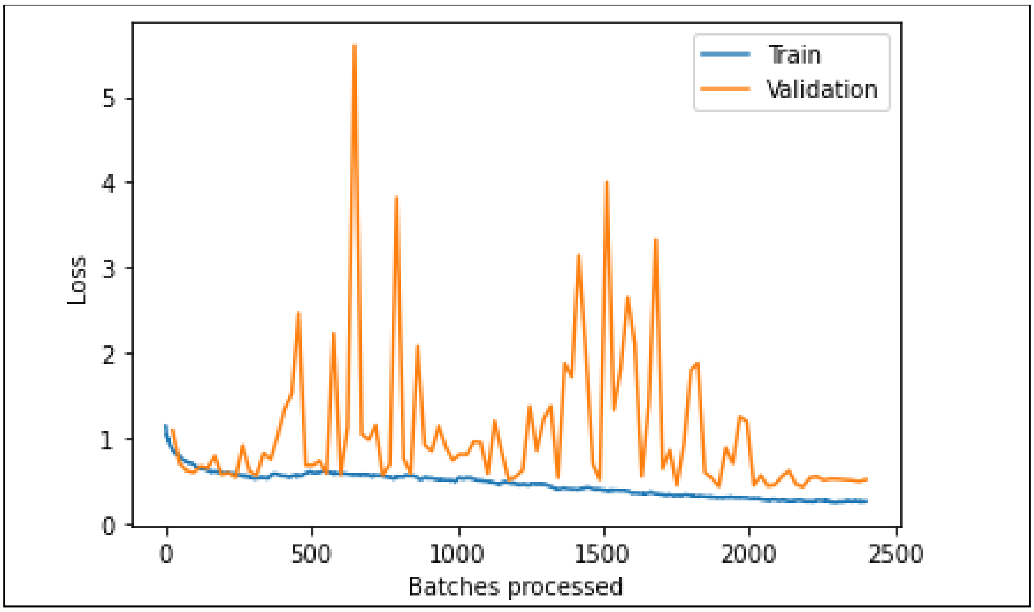
MaxPool2d	[32, 33, 33]	0	False
Conv2d	[64, 33, 33]	18,432	True
BatchNorm2d	[64, 33, 33]	128	True
LeakyReLU	[64, 33, 33]	0	False
Conv2d	[32, 35, 35]	2,048	True
BatchNorm2d	[32, 35, 35]	64	True
LeakyReLU	[32, 35, 35]	0	False
Conv2d	[64, 35, 35]	18,432	True
BatchNorm2d	[64, 35, 35]	128	True
LeakyReLU	[64, 35, 35]	0	False
MaxPool2d	[64, 17, 17]	0	False
Conv2d	[128, 17, 17]	73,728	True
BatchNorm2d	[128, 17, 17]	256	True
LeakyReLU	[128, 17, 17]	0	False
Conv2d	[64, 19, 19]	8,192	True
BatchNorm2d	[64, 19, 19]	128	True
LeakyReLU	[64, 19, 19]	0	False
Conv2d	[128, 19, 19]	73,728	True
BatchNorm2d	[128, 19, 19]	256	True
LeakyReLU	[128, 19, 19]	0	False
MaxPool2d	[128, 9, 9]	0	False
Conv2d	[256, 9, 9]	294,912	True
BatchNorm2d	[256, 9, 9]	512	True
LeakyReLU	[256, 9, 9]	0	False
Conv2d	[128, 11, 11]	32,768	True
BatchNorm2d	[128, 11, 11]	256	True
LeakyReLU	[128, 11, 11]	0	False
Conv2d	[256, 11, 11]	294,912	True
BatchNorm2d	[256, 11, 11]	512	True
LeakyReLU	[256, 11, 11]	0	False
Conv2d	[128, 13, 13]	32,768	True
BatchNorm2d	[128, 13, 13]	256	True
LeakyReLU	[128, 13, 13]	0	False
Conv2d	[256, 13, 13]	294,912	True

BatchNorm2d	[256, 13, 13]	512	True
LeakyReLU	[256, 13, 13]	0	False
Conv2d	[3, 13, 13]	6,912	True
ReLU	[3, 13, 13]	0	False
BatchNorm2d	[3, 13, 13]	6	True
Flatten	[507]	0	False
Linear	[3]	1,524	True

Total params: 1,167,586
Total trainable params: 1,167,586
Total non-trainable params: 0
Optimized with 'torch.optim.adam.Adam', betas=(0.9, 0.99)
Loss function : CrossEntropyLoss

```
model = nn.Sequential(
    conv_block(3, 8),
    maxpooling(),
    conv_block(8, 16),
    maxpooling(),
    triple_conv(16, 32),
    maxpooling(),
    triple_conv(32, 64),
    maxpooling(),
    triple_conv(64, 128),
    maxpooling(),
    triple_conv(128, 256),
    conv_block(256, 128, size=1),
    conv_block(128, 256),
    conv_layer(256, 3),
    Flatten(),
    nn.Linear(507, 3)
)
```

Results and Discussions:

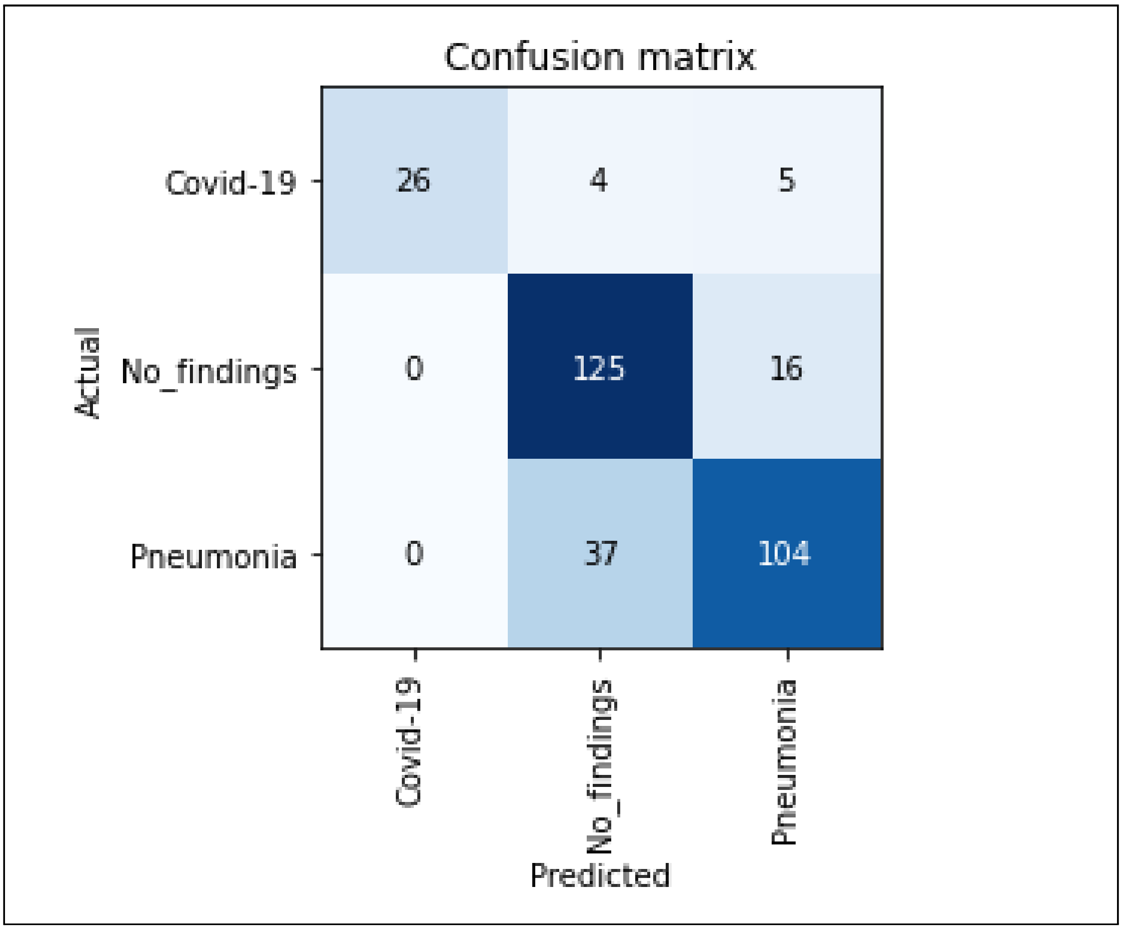


Loss v/s Batches Processed

The proposed method has high precision value of detecting COVID-19 X-Rays.

	precision	recall	f1-score	support
Covid-19	1.00	0.74	0.85	35
No_findings	0.75	0.89	0.81	141
Pneumonia	0.83	0.74	0.78	141
accuracy			0.80	317
macro avg	0.86	0.79	0.82	317
weighted avg	0.82	0.80	0.80	317

Precision, Recall, F1-Score and Support



The proposed model is developed to provide diagnostics for classification between COVID, No-Findings and Pneumonia. Implementation of 17 convolutional layers and introduced different filtering on each layer. The model produced a classification accuracy of 80.04% for multi-class cases.

Conclusions:

We have presented some initial results on detecting COVID-19 positive cases from chest X-Rays using a deep-learning model. The results look promising, though the size of the publicly available dataset is small. We plan to further validate our approach using larger COVID-19 X-ray image datasets and clinical trials. Also, such models can be used to diagnose other chest-related diseases including tuberculosis and pneumonia. A limitation of the study is the use of a limited number of COVID19 X-ray images. We intend to make our model more robust and accurate by using more such images from our local hospitals.

References:

1. COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from chest X-ray images (https://arxiv.org/pdf/2003.09871.pdf)
2. A Critic Evaluation of Methods for COVID-19 Automatic Detection from X-Ray Images (https://arxiv.org/ftp/arxiv/papers/2004/2004.12823.pdf)
3. COVID-19 Pneumonia Diagnosis Using a Simple 2D Deep Learning Framework With a Single Chest CT Image: Model Development and Validation (https://www.jmir.org/2020/6/e19569)
4. Prognostic Modeling of COVID-19 Using Artificial Intelligence in the United Kingdom: Model Development and Validation. (https://www.jmir.org/2020/8/e20259)
5. Dataset https://github.com/ieee8023/COVID-chestxray-dataset/