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Detection of Lung Inflammation using Transfer Learning

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ABSTRACT

Covid19 is a destructive infection that has killed millions of people across the world. Elderly people and individuals with genuine fundamental ailments or past instances of pneumonia seem, by all accounts, to be at more danger of growing more genuine intricacies from the infection. Serious types of the infection can cause lung inflammation, prompting danger of death. The challenge here is to speed up the determination of the onset or the ongoing pneumonia infection.This paper proposes a Transfer learning based Deep Learning model for automated way of using X-ray imaging for early diagnosis of COVID19/pneumonia infection. We initially train the system using an 8-layer CNN model and a 13-layer CNN model and then compare it with ResNet model which is based on transfer learning for higher accuracy.
Keywords: Covid19, Lung inflammation, Deep Learning, X-ray, CNN model, ResNet model.

I. INTRODUCTION

Deep learning has reached a stage where we can use it to have human-level accuracy in segmenting and analyzing an image. Due to this, the deep learning has wide usage in a range of industries and medical industry in not far behind in utilizing its potential. A lot of diagnosis in medical industry happens though the means of imaging be it X-Rays, Sonography, CT-Scans, MRI Scans etc. It can be widely used in the detection of tumors and lesions in patients. [1] [2]
In this paper, we detect inflammation of lungs by giving the X-Ray images as input. The dataset is taken from the Gangzhou Women and Children's Medical center. These images are transformed to make them legible for training using Python Transforms. This dataset is then used to create a 8 layer CNN model and a 13 layer CNN model. Then we use transfer learning-based technique of reusing a pretrained model where we use ResNetmodel (Residual Network) and train it on the data set available.
Once these models are trained, we evaluate the models for loss and accuracy. We compare the loss and accuracy of these 3 models and determine which is the most efficient one. The models trained can be used for detecting lung inflammation/pneumonia by giving the X-Rays in the test data set. Even though deep learning still cannot replace doctors in medical diagnosis, it can provide support to experts in the medical domain, including examining chest X-Rays for signs of pneumonia. Inflammation of the lungs which is commonly known as Pneumonia can be caused by bacteria, viruses, and fungi. It can strike people of any age, even healthy

individuals. It can be life-threatening to infants, people with certain diseases, and people with impaired immune systems. [3] Researchers have proposed different artificial intelligence (AI)-based solutions for different medical problems recently. With convolutional neural networks (CNNs), researchers have been able to achieve successful results in a wide range of medical problems, like breast cancer detection, brain tumor detection & segmentation and disease classification in X-ray images [4] A deep CNN model such as ResNet requires a lot of data to train from scratch, since it contains millions of trainable parameters, so a small dataset wouldn't suffice to generalize the model. In Transfer Learning [5], a pre-trained CNN model is reused to take advantage of its weights as initialization for another CNN model tailored to a different purpose using the model's weights.

II. METHODOLOGY

The methodology used in this Paper is depicted below:Fig.1

We use the algorithm provided under Pytorch based package called TORCH.

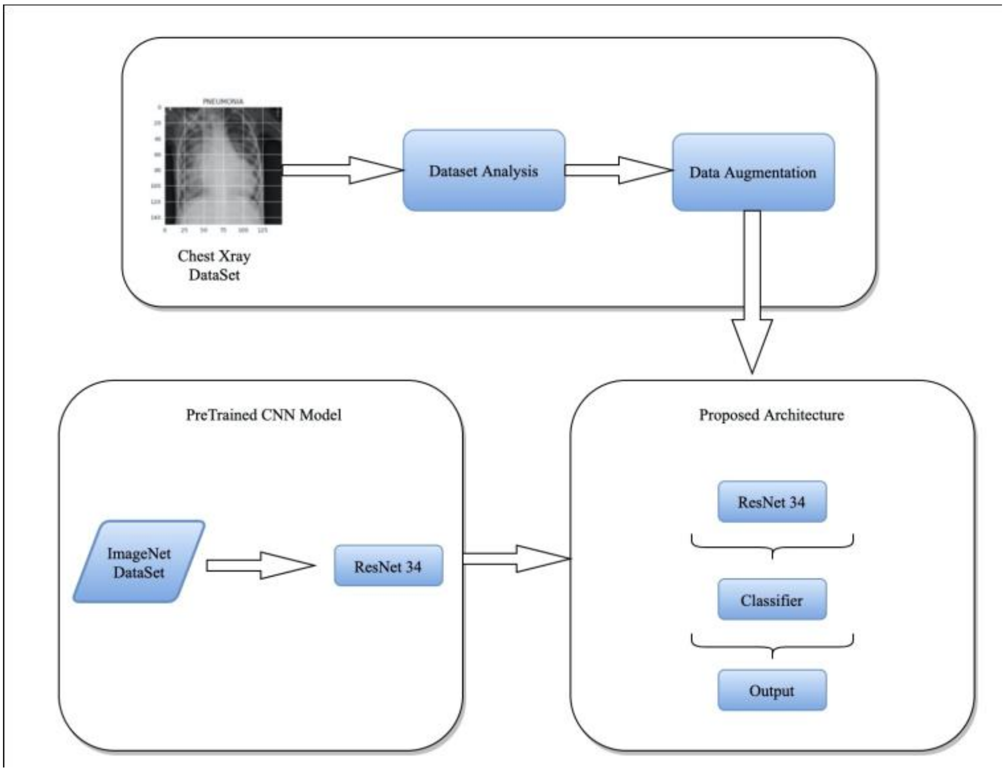

Fig:1. Methodology Used

The torch package contains data structures for multi-dimensional tensors and defines mathematical operations over these tensors. Additionally, it provides many utilities for efficient serializing of Tensors and arbitrary types, and other useful utilities. Class Used: torch.nn. Conv2d

We use Maxpooling and ReLu in between the layers. Maxpooling reduces the dimensions of the image, due to this the network will look at expanded areas of the image and this reduces the number of parameters associated which reduces the computational load. ReLu, Rectified Linear Unit is the most commonly used activation function in deep learning models. The function returns 0 if it receives any negative input, but for any positive value xx it returns that value back. So it can be written as f(x)=max(0,x)f(x)=max(0,x).

```
evaluate(model2, test_dl)
```

```
{'val_loss': 0.6960327625274658, 'val_score': 0.375}
```

Fig 2.CNN 8 Layer – Loss & Accuracy values

We add two additional functionalities to the above 8 layer model called Batch Normalization & Dropout

```
evaluate(model3, test_dl)
```

```
{'val_loss': 0.6847389340400696, 'val_score': 0.625}
```

Fig 3.CNN 13 Layer – Loss & Accuracy values

Because of batch normalization and dropout layers along with a few more layers, this 13-layer CNN model proves to be a better alternative than the CNN 8-layer model. It is now able to categorize more than 50% of the images in the testing dataset properly. However, this is still not as good it has to be for using in the real world comfortably.

We solve this problem by leveraging the optimization technique of transfer learning. Here we repurpose complex models trained for one purpose for another. Here we will use a pretrained residual network ResNet that is trained on the ImageNet dataset & repurpose that to our chest x-rays dataset. We use a 34-layer residual network with dropout in the final layer and check how well it compares to the previous models.

Transfer Learning is a supervised learning technique. It works by reusing parts of an earlier trained model on a fresh network which is tasked for altogether a different problem. Transfer learning significantly reduces the time required for feature based specific engineering and its corresponding training. First, a source model needs to be selected. Ideally the one which can train with a large set of data. Many researchers or labs release their pre-trained models for further use in the industry and research [10]

Second, we need to decide which layers of the pretrained model to be used in our system. The idea is to build a framework which is bare minimum better than an amateur model which gives way for new feature learning. Top layers tend to focus on more finely tuned to a particular problem whereas deeper layers are reused for more typical problems.

Finally, now we trained the newly built model on the new dataset. The benefit is that the model tends to converge faster and with less data and requires lesser computational cost.

We utilize ResNet(Residual Network) in our paper. Let's us understand the architecture of ResNet34 at high level. Deeper neural networks are harder to train which gave rise to ResNet. It is basically a residual learning framework which facilitate the training of networks that are significantly deeper than those used previously. [11]

```
{'val_loss': 0.7321296334266663, 'val_score': 0.7948718070983887}
```

Fig 4. ResNet34 Transfer Learning – Loss & Accuracy Values on CPU

III. RESULTS AND DISCUSSION

A model evaluation accuracy of about ~80% on a CPU based computing which is definitely an improvement from the prior two models. This shows the power & efficiency of using transfer learning to solve common image problems. Although the accuracy of the test has increased significantly, it is debatable whether this is sufficient for real-world implementation. The efficiency further increases when the model is run on a GPU based machine.

We tested for 20 X-Ray images and out of 20, it successfully identified 19 of them and 1 was identified incorrectly. This leaves us with an accuracy of 95% on the test data.

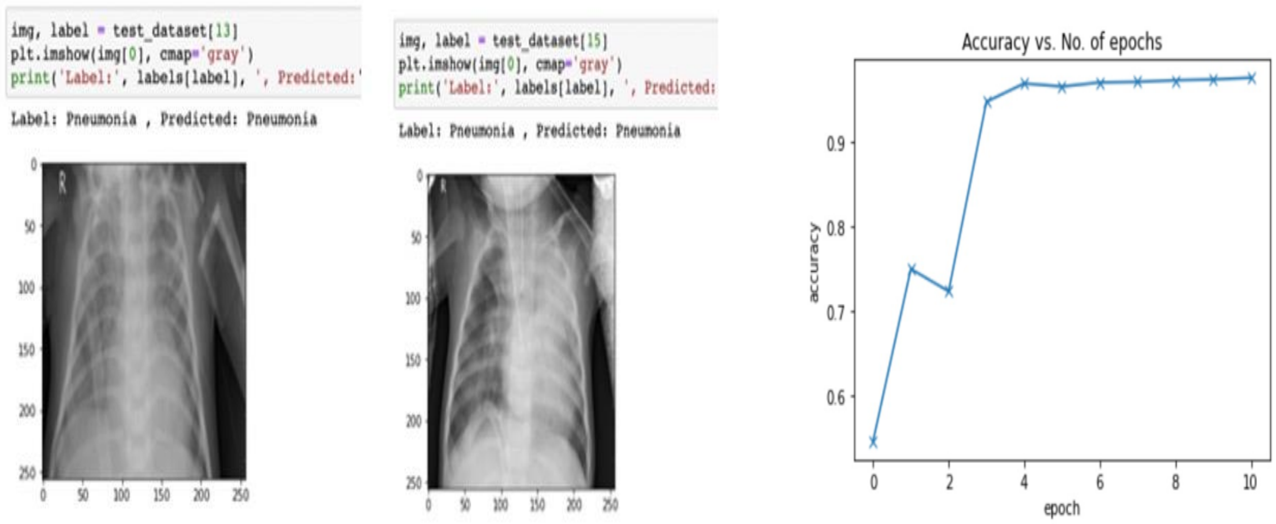

Fig 5: Test Results & Accuracy vs No. of Epochs for ResNet34

IV. CONCLUSSION

The proposed paper speed up the determination of the onset or the ongoing pneumonia infection.This paper proposes a Transfer learning based Deep Learning model for automated way of using X-ray imaging for early diagnosis of COVID19/pneumonia infection.

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