CAPSTONE PROJECT (IIITD-PGD-CSAI OCT 21) PROPOSAL - GROUP 9

PROJECT OBJECTIVE:

Design a DL-based algorithm for detecting pneumonia, i.e. create an architecture which can detect a visual signal (opacity region) for pneumonia in medical images. The neural network needs to locate lung opacities on chest radiographs.

Opacity: Usually the lungs are full of air. When someone has pneumonia, the air in the lungs is replaced by other material - fluids, bacteria, immune system cells, etc. That's why areas of opacities are areas that are grey but should be 'blacker'. When we see them, we understand that the lung tissue in that area is probably not healthy.

It would be a classification task. Each annotated region of opacity is an object by itself. We do not care about its location in the lung-region. If we have even one region of opacity, we would be satisfied and take it to be pneumonia positive. This would be our training data. Our task would be to design a network based on this data, which can predict presence or absence of

SCOPE OF THE PROJECT:

Pneumonia accounts for over 15% of all deaths of children under 5 years old internationally. In 2015, 920,000 children under the age of 5 died from the disease. In the United States, pneumonia accounted for over 50,000 deaths in 2015, keeping the ailment on the list of top 10 causes of death in the country.

While common, accurately diagnosing pneumonia is a tall order. It requires a review of a chest radiograph (CXR) by highly trained specialists and confirmation through clinical history, vital signs, and laboratory exams. Pneumonia usually manifests as an area or areas of increased opacity on CXR.

However, the diagnosis of pneumonia on CXR is complicated because of several other conditions in the lungs such as fluid overload (pulmonary oedema), bleeding, volume loss (atelectasis or collapse), lung cancer, or post-radiation or surgical changes. Outside of the lungs, fluid in the pleural space (pleural effusion) also appears as increased opacity on CXR. When available, comparison of CXRs of the patient taken at different time points and correlation with clinical symptoms and history are helpful in making the diagnosis.

CXRs are the most commonly performed diagnostic imaging study. Several factors, such as positioning of the patient and depth of inspiration, can alter the appearance of the CXR, complicating interpretation further. In addition, clinicians face reading high volumes of images every shift.

This project attempts to improve the efficiency and reach of diagnostic services by attempting to build an algorithm to detect a visual signal for pneumonia in CXRs.

DATA DESCRIPTION:

In this capstone, we are predicting whether pneumonia exists in an image. It is done by predicting bounding boxes around areas of the lung. Samples without bounding boxes are negative and contain no definitive evidence of pneumonia. Samples with bounding boxes indicate evidence of pneumonia.

We have images as our data. The training set contains patient Ids and bounding box / target information. The class data contains detailed information about the positive (Has Pneumonia) and negative classes in the training set, and may be used to build more nuanced models. More parameters:

- 30,227 records total. 9,555 with evidence of pneumonia. And 20,672 with no evidence.
- Data is highly imbalanced towards No Pneumonia, which is what we would normally expect.

Class Information: There are 3 unique values: “Normal”, “Lung Opacity” and “No Lung Opacity / Not Normal”. “No Lung Opacity / Not Normal” indicates that while pneumonia was determined not to be present, there was some type of abnormality on the image, and often this finding may mimic the appearance of true pneumonia.

PLAN:

1. Research and review of available literature on medical imaging with a special focus on pneumonia detection.
2. After a basic EDA, we will first create a base model and study our early results to understand how things are.
3. Then based on our findings, intuition, and past research, we will employ a variety of DL algorithms. Our focus would be on hyperparameter tuning.
4. Since the training data we have is tiny, we will depend on already trained popular models. Transfer learning would be a key.
5. After tweaking numbers, based on our preliminary research and proper counsel from a medical specialist, we will run the data through various networks.
6. Finally, we will make predictions on the test data with the best model based on carefully chosen classification metrics like Accuracy and sensitivity.