Project Ideation

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Problem Statement

Pneumonia can be a fatal disease, and early diagnoses are essential to improve survivability as the healthcare systems are strained with the current pandemic. They are causing timely diagnoses of pneumonia cases to be diminished. Using machine learning, the group will aim to create a model that can correctly diagnose cases of pneumonia from X-ray images - making use of Artificial Intelligence in the diagnoses of pneumonia could decrease the workload from medical staff, freeing up more time.

Problem Motivation

Unfortunately, pneumonia can be a fatal disease, and it is a severe lung infection affecting one or both lungs (Fenwick, 2021). Childhood pneumonia at the moment is the foremost individual cause of death in children before the age of five years old (Rudan et al., 2008). Nonetheless, it is correspondingly dangerous for elderly people also where the mortality rate was the highest (L. Trotter, M. Stuart, George and Miller, 2008).

The project's motivation is that this problem is an essential aspect of the current crisis facing the world nowadays; People have been creating models to determine cases of pneumonia for a while, but earlier models failed to stand up to the accuracy of a doctor.

The initial diagnosis of pneumonia gains paramount importance for saving countless human lives. It is indispensable to concentrate on the early detection of this condition since there is no adequate classification of diagnostic methods for early disclosure; the above reasons are a great justification for why this project has focused on this theme *(Kallander, H Burgess and A Qazi, 2015).*

Additionally, our X-ray diagnoses model can be used daily to detect pneumonia, which will significantly enhance healthcare delivery time and develop the availability of acknowledged and agile expertise of professionals *(Rajpurkar et al., 2017).*

Literature Review

In literature, pneumonia is a common theme, as well as a massive problem in society. This study aims to concentrate on one of the most well-known diseases, in which the principal intention is the focus around early detection. Due to the outbreak of the COVID-19 worldwide, pneumonia resulting from the disease must be crucially diagnosed simultaneously with its underlying analyses. *(Mahmud, Rahman and Anowarul Fattah, 2020*)

The most well-known imaging examination tool in usage is X-Rays. The paper by Farukh concludes that CT-Scans and X-rays in investigating the lungs in COVID-19 are believed to be some of the most efficient and prevalent techniques implemented by researchers. However, X-ray imaging is preferred over CT, primarily due to the quality, output time and reduced exposure rate. *(Farukh et al., 2020), (Panwar et al., 2020).*

There are various sorts of pneumonia, such as bacterial, viral, and mycoplasma pneumonia, which science has attempted to confront for decades. *(D. John, Ramanathan and E. Swischuk, 2001), (Ruuskanen, Lahti, C Jennings and Murdoch, 2011)*

Many projects are operating on early detection, but regrettably still without sufficient resolution. It would be massively beneficial to review the existing solutions and relevant literature to evaluate the significance of this dilemma. Due to the massive progression of the machine learning aspect, it is much more manageable to reduce the high mortality rate from early detection.

One of the most well-known solutions is the project implemented by the SMLG (Stanford Machine Learning Group). Their idea focuses on chest X-Rays detecting pneumonia by using CNN (convolution neural networks). Our model for detecting pneumonia also uses CNN, making it a fair comparison. In their project, CheXNet is a 121-layer CNN. SMLG did this project to produce a specific analysis of X-rays images that produce the output about the likelihood of pneumonia disease using a heatmap that would localize the infected areas and calculate the probability of Pneumonia *(Rajpurkar et al., 2017).*

While our project also aims to detect pneumonia. The Stanford model uses a larger dataset compared to ours. While a fair comparison can be made regarding pneumonia cases, the Stanford model also classifies an additional 16 lung diseases, while our group will only classify two, which are normal and pneumonia. The 128-layer CNN that SMLG created is close to the project we will work on but differs in the number of classifications. Their data visualization is much more straightforward, which is an example of the improvements of their model. However, their data visualization originates from additional CSV files, allowing them to draw a box around the precise coordinate.

Densenet, our CNN model, Xception, VGG19, Resnet50, and InceptionV3 are all combined in the ensembled model. Unfortunately, our model performed worse in the small test, with 84 percent accuracy compared to Densenets' 93 percent accuracy. However, our model perfomes in compare to the other models with the optional data with 93 percent accuracy. It was reasonable to comprehend the advantages and disadvantages of both initiatives. Various projects have already proposed several biomedical image detection techniques.

An automated pneumonia classification model based on deep learning and convolutional neural networks is another well-known example of the solution. The proposed method operates on a deep transfer learning algorithm to extract features from the X-ray image that automatically define the existence of the disease and report whether it is a case of pneumonia. *(Farukh et al., 2020)* In this project, different models were used, such as ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3; The final test accuracy was 98.43%. As a result, the proposed model, as stated by the owners, can be used for a fast diagnosis of pneumonia and can assist radiologists in the diagnosis process. Finally, as an outstanding achievement of this project is data, there were 5136 images used in the training set and 700 images in the test set and the Guangzhou Women and Children's Medical Center pneumonia dataset.

One of the consistent advantages of this project in comparison with ours would be the model's accuracy. The unseen project data got around 2.3% more accuracy than the one we produced. Their accuracy got 98.4%, while ours got around 95%-96%. In terms of the CheXNeXt, our model could be tweaked to diagnose additional lung problems, but we kept it simple by limiting it to two groups normal and pneumonia.

Nonetheless, it is worth mentioning the groundbreaking project that is CheXNeXt, a convolutional neural network that can simultaneously detect the existence of 16 different pathologies in frontal-view chest radiographs, including pneumonia, pleural effusion, pulmonary masses, and nodules. *(Rajpurkar P. et al., 2018)*

Based on a literature search, it was remarked that numerous if not all systems described in this report have the potential to be valuable in clinical practice. However, no meaningful increase of development was recognized in sensitivity, availability, and capability to identify various types and shapes of nodules in the studied interval. Furthermore, models that focus on detecting pneumonia approaches are not intended to completely replace qualified clinicians in medical diagnosis; instead, they are intended to complement clinical decision-making. Challenges were presented for prospective analysis, especially for this project.

Project Statement

Based on the literature reviews, the group will proceed to create a basic CNN model as a starting point to gauge the accuracy. Once the baseline model has been implemented, the group has decided to use additional models, which are ResNet50, Inception, Xception. VGG19 and Densenet then using TensorFlow built-in ensembling to create a combined model for the detection of pneumonia.

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