CS598 Project Proposal

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ABSTRACT

We are going to reproduce an algorithm that detects pneumonia from an Article "chest X-rays at a level exceeding practicing radiologist [1]", which is proposed by Stanford ML Group. It is also extended to classify multiple thoracic pathologies in the paper. But the precision is lower than predicting single disease. After reproducing, we are going to improve the algorithm in different aspects by modifying the model architecture, introducing attention mechanisms, or combining with other machine learning algorithms.

Keywords

Deep Learning, Convolutional neural networks, Chest X-ray

1. Motivation

X-ray is one of the most popular diagnostic tools to detect varieties of complications for patients' health. It is unsurprising that the need for X-ray is considerable: approximately there are 3.6 billion diagnostic X-ray examinations performed each year across the world. In order to infer the right diagnosis, an experienced radiologist needs to be trained with many years of experience, and the process to read the X-ray examinations also takes time around 5 to 15 minutes. Most importantly, radiologists also may make mistakes. Overall, X-ray is time consuming, error prone as well as requires highly trained while scarce talents.

Fortunately, Deep Learning nowadays is able to land some help to radiologists, mitigating three issues mentioned above. First, a well-trained Deep Learning model is capable of classifying millions of X-ray images within a short period of time while requiring almost no manual effort from input to generate a result. Moreover, a state-of-art Deep Learning model can be more accurate than an experienced radiologist in terms of AUC.

2. Literature Survey

In this literature review, we cover the state-of-the-art (SOAT) results which build a groundwork for us to start. These works provide us important insights and inspirations in X-ray images analysis field. Among the SOAT results, we find there are two main approaches.

2.1 Classification State-of-the-Art

As we will perform the study on the ChestX-ray14 dataset from NIH, we start our survey from the state-of-art result published by NIH together with the dataset's first releasing, which is a weakly-supervised classification and localization CNN model, produced by Wang et al (2017) []. This model uses the whole X-ray images for training without bounding box annotation. Instead, the CNN model modified the ImageNet model by adding a transition layer, a global pooling layer, a prediction layer, and a loss layer to target the local patch of diseases.

After the original dataset ChestX-ray8 expanded to ChestX-ray14, Rajpurkar et al (2017) [1], constructed CheXNet, a 121-layer Dense Convolutional Network instead of using the whole image as input, CheXNet use downscaling images to 224x224 pixels but using image augmentation to add more transformed inputs for ImageNet. The pre-trained weights from ImageNet model are used as the initial value settings to replace the randomized weights, the output of CheXNet exceeds average performance in detecting pneumonia, with modifications on the original binary classification model, it also generally performs better in detecting all 14 diseases compared to previous models, thus achieves the SOAT result. CheXNet also output pathologies from the final convolutional layer to produce bounding box for diseased areas by upscaling the pathologies to the image dimensions.

While both of these previously mentioned works are using a weakly supervised CNN framework, Guan et al (2018) [3] come up with an attention guided CNN model, AG-CNN, their model guided the CNN to target the lesion disease region by feeding both global image to CNN and also cropped attention region and feed it to local branch. The final Classification layer will consume both branches output to produce prediction. The final performance of the model compared to the previous state-of-the-art, improves in the localization but sacrifices the classification performance.

2.2 Localization State-of-the-Art

In the localization field, Candemir et al (2016) [4] structured an automatic organ localization model in chest x-days by comparing the input images' similarity with sample CXR images to locate heart and lung shadows without employing CNN framework.

Rajaraman et al (2020) [5], introduced a model using modality-specific convolutional neural network ensembles, which guided the CNN model to train over wanted features only to better target the abnormal region in the X-ray images. This innovation also helps to make the trained model suitably repurposed from lung segmentation to detecting and localizing abnormalities.

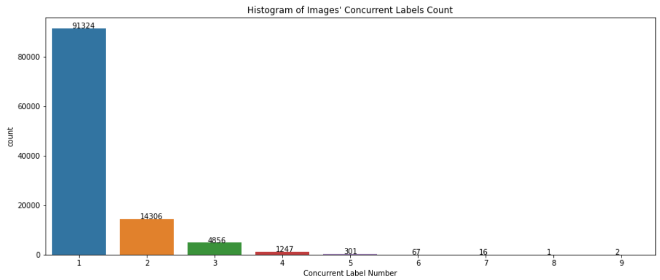
3. Data

In this study, we utilize the ChestX-ray14 dataset which is a publicly available repository published by National Institute of Health. This dataset comprises 112,120 frontal-view X-ray images of 30805 unique patients. There are 14 disease image labels mined from the associated radiological reports using natural language processing.

3.1 Data Exploration

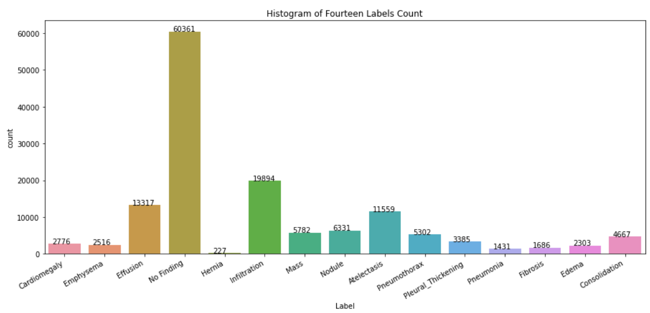
3.1.1 Images' concurrent Label

Through our initial exploration, we notice each image can have multi-labels. The following figure shows that about 82% images have only one label associated, while 12% images are associated with multiple labels.



3.1.2 *Label Distributions*

Secondly, we check the distribution of all labels (14 disease + no finding) in the annotation dataset. It turns out these labels occur roughly at clinical prevalence with normal to abnormal ratio at 42: 58.



3.2 Data Limitations

Only frontal-view X-ray images are available in the dataset, but sometimes accurate diagnoses require lateral view because 15% of the lung can be hidden by cardiovascular structures and the diaphragm. In addition to that, some diseases do require other symptoms to get accurate results, but due to privacy concerns, patient history is not allowed to be used in data, which results in lower performance.

3.3 Next Steps

In the next steps, our data preprocessing will focus on both X-ray images' downscaling and also the adjudication of image labels.

4. Approach

The high-level technical approach for the project is exploring the advancing Deep Convolutional Neural Network and Recurrent Neural Network in with CXR datasets.

Based on the state-of-the-art works we learnt, we will perform processes like augmentation, downscaling and cropped the attention regain defined by bounding box to provide quality and sufficient input images to our model.

Further we will try to train our own semi-supervised Deep Convolutional Neural Network with targeted features ensemble.

We will try to improve the current state-of-the-art result in classification performance in the AG-CNN [3] framework by modifying the architecture, exploring different attention mechanisms, and combining our CNN model with other popular chest Xray prediction algorithms like Localization models [6], modality-specific convolutional neural network ensembles [5], Multi-label Softmax Loss, MSML [7] and so on.

In the model evaluation steps, we will produce success metrics like AUC, accuracy, recall, speedup in running time by disease types to compare with other state-of-the-arts result.

Potential Improvements:

- Improve AUC for each single disease.
- Improve the minimum AUC crossing 14 diseases.
- Improve the average AUC crossing 14 diseases.
- Speed up the model with similar prediction performance
- Simplify the model Architecture with similar prediction performance.
- Identify other disease types other than the existing 14 diseases.

5. Experimental Setup

We set up our initial coding lab environment with a free-tier Google Colab platform. We pulled our data from the public URL of NIH ChestX-ray14 to a shared google drive. From Colab, we can easily mount the folders from Google Drive and use it as an external storage for reading and writing.

Inside Colab, we are using Jupyter Notebook with Python version 3.7.10 to have a similar set up as our homework lab environment.

To make good use of the Colab free-tier resources we will carefully plan our batch data size to feed our model and the number of epochs when training our model.

Hardware		Software	
CPU Model Name	Intel(R) Xeon(R)	Lab Environment	Google Colab
CPU Freq	2.20GHz	Data Storage	Google Drive
No. CPU Cores	2	Coding Language	Python 3.7.10
CPU Family	Haswell	Python Packages	Pandas, Numpy, Seaborn, PyTorch, cv2, sklearn, keras
Available RAM	12GB		
GPU	Tesla T4		
GPU Memory	16GB		

6. Timeline

We list the detail of tasks' contents and deliverables for each task in the following charts with specified deadlines. We hope to perform data processing and model building in two rounds. We will focus on structuring the framework in the draft round and adding fine touch in the report round.

Step	Tasks	Deliverable	Deadline 1st Drafting Round	Deadline 2nd Report Round
1	Define cohort, target, features	The definition settings of input, output for the model	4.1.2021	-
2	Clean and process the data; Generate the Data Loader to absorb images and csv tables	Customized dataset class and load data function	4.4.2021	-
3	Develop and train the model	Complete framework and model	4.10.2021	4.25.2021
4	Evaluate and tune the model performance	Model with expected performance	4.14.2021	4.25.2021
5	Visualize the result and prepare the paper draft	Paper draft without formatting	4.17.2021	4.28.2021
6	Finalize paper format	Formatted paper	4.18.2021	4.30.2021
7	Prepare PowerPoint for presentation	PowerPoint Slides	-	5.1.2021
8	Recording Video and Upload	Presentation Video	-	5.2.2021
9	Finalize submitting package	Submit NetID-chestXray.zip	-	5.8.2021

7. REFERENCES

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