Towards Robust and Adaptable Diagnosis of Pneumonia from Chest X-ray Data

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CS-503 Progress Report I

I. Milestone Progress

Less than 6 months ago, DeGrave et al. published on Nature an exhaustive analysis on robustness of AI models for radiographic COVID-19 detection [1]. Their study showed that even state-of-the-art models can rely on confounding factors (spurious 'shortcuts') rather than medical pathology, creating an alarming situation in which the systems appear accurate, but fail when tested in new hospitals. Our project aims to explore possible solutions to suppress these spurious correlations during the learning process, on the top of the preliminary study conducted by Bellot et al. [2].

We started reproducing their Experiment 1, detecting pneumonia from X-Rays images. The datasets of chest X-Rays from the National Institutes of Health (NIH), and the Guangzhou Women and Children's Medical Center (GMC) have been imported and pre-processed to reproduce their experiment setup, not without difficulties: scarce information on the data partition are reported and we already tried to contact the authors for more details. Then we implemented the training routine with vanilla Empirical Risk Minimization and Invariant Risk Minimization. The main limit in their analysis is that they evaluated several robust training routine all on a extremely small Convolution Neural Network: even if it is still interesting from a theoretical point of view, it is not what is used in practice nowadays. We then proposed to compare it with CheXNet, a SOTA Deep Convolutional Neural Network based on DenseNet (see Figure 1).

Finally we configured an account on Microsoft Azure clusters to speed up our (heavy) experiments through their powerful GPUs Nvidia K80 and we are already running the first experiments.

You can already access to our intermediate implementations at the following repository.

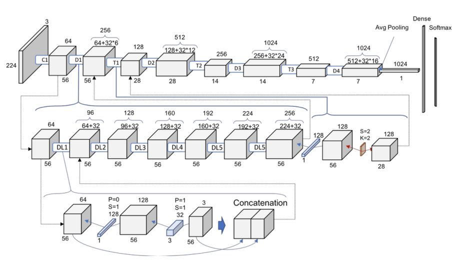

Figure 1: DenseNet module used in CheXNet

II. Discussion & Next Steps

We have already almost completely achieved the goals that we set for the first half of the project. We are now fine-tuning few hyper-parameters and in few days we should be able to visualize the results. We are also considering to extend this analysis with more recent robust training routines (i.e. v-REx [3]) but also novel approaches (i.e. using Contrastive Learning [4]).

Based on these results we will decide on the top of which robust approach we will propose an (even) adaptable model for pneumonia detection on new domains. We are less confident than before in using self-supervised learning (SSL) to extract a causal representation of the input and we are still investigating the literature.

We will design a transfer protocol to evaluate the adaptability of this final model and will try to extract some insights with the lens of causal theory. A possible alternative to SSL for adaptability is to combine the original network trained in a robust way with an additional style encoder to incorporate the suppressed useful confounders (domain specific) [5].

III. Author Contribution Statement

Raphaël took care of collecting the data, preprocess them and reproduce the reference experiment setup. Riccardo took care of implementing the different training routines and other useful functions for testing and visualization of the performances. Shasha set up the Azure environment and located the original datasets. Raphaël set up the first experiments attempts. Riccardo studied the literature for the analysis of the project (robustness). All studied the literature for the second part (adaptability).

References

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