Towards Robust and Adaptable Diagnosis of Pneumonia from Chest X-ray Data: a Self-Supervised approach

Raphael Attias (287613), Riccardo Cadei (321957), Shasha Jiang (321733)
CS-503 Project Proposal

***Abstract*—Chest radiography is a cost effective and powerful investigator method that conveys crucial respiratory information. Rapid and accurate diagnosis is specifically required in most cases, as shown by Covid-19. In this study, we propose a self-supervised learning at test time approach for a robust and adaptable diagnosis of pneumonia on chest X-rays data.**

I. Introduction

According to the World Health Organization (WHO), Pneumonia affects every year children and families worldwide and it is the largest infectious cause of death in children [1]. One key element of its diagnosis is the chest X-rays (CXR) radiography, routinely obtained as standard of care: in fact according to radiologists and general practitioners it appears to contain the most correlated factors with the illness even before observing common symptoms [2] (see Figure 1).

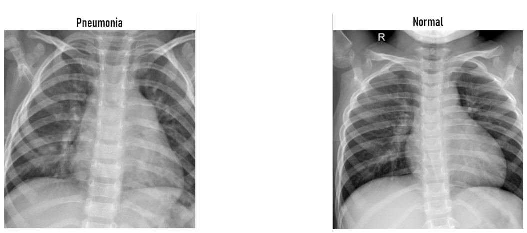

Figure 1. Comparison of chest X-rays between a normal lung and a ill lung.

However, rapid radiologist prediction is not always available for this illness that requires immediate antibiotic treatment and supportive care, and even among senior radiologists disagreements are common, up to a kappa-score equal to 0.395 [3].

There are already several studies combining deep learning and computer vision to extract this information [4] almost in real-time, based on public dataset collected by several hospitals all around the world. The main assumption of these methods is assuming that all the collected images are independent and identically distributed (*i.i.d.*), but it is almost never the case in real world applications: each hospital and machine collect CXR images with different styles (i.e. calibrations and techniques) hiding both spurious features and confounders.

Figure 2 reports the differences in average distribution between the publicly available data from the National Institutes of Health (NIH) [5] and the Guangzhou Women and Children's Medical Center (GMC) [6] which were found out in a recent study proposed by Bellot et al. [3].

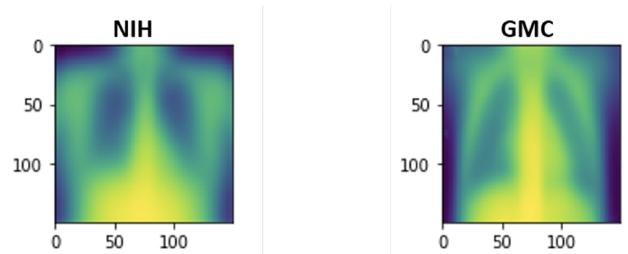

Figure 2. The different average distribution of CXR among the NIH and GMC dataset suggest a strong need to take care of domain shifts.

They then proposed different robust training methods (i.e. IRM [7], REx [8], DIRM [3]) to extract only the invariant features across the different environments (suppressing both spurious features and confounders), improving significantly the ERM baseline in the case of a strong domain shift between training and test set. However, the confouders can still contain several useful information for prediction and they are crucial for an adaptable prediction.

In this work we want to (i) investigate further the advantages/disadvantages of the robust prediction proposed by Bellot et al. [3] evaluating the gap between their approach and an oracle trained only on the targeted domain, (ii) propose a robust and adaptable extension based on Self-Supervised Learning at test time [9].

II. Method and Deliveries

We reconsider the same experiment setup proposed by Bellot et al. [3], combining NIH and GMC datasets in different proportion between training and test set to evaluate the robustness of the models considered.

A. Milestone 1

First we propose to investigate further the gap between the invariant predictors proposed in the original study and an oracle trained only on the target domain (potentially starting from a pre-trained model on the other environments) in order to explicitly quantify the loss of information ignoring the confounders.

B. Milestone 2

Then we propose to use Self-Supervised Learning at test time [9] to extract an invariant latent representation (robust) of CXR images and training the final classifier only at the test time directly on each single environment (adaptable). An alternative proposal is to split the latent representation (learned in an unsupervised way during the training) in two parts: one representing the invariant features and an other representing the confounders, and adapt only the latter at test time.

All these approaches will be compared with the robust training proposed by Bellot et al. [3] using the same experiment set up.

III. Related Work

The COVID-19 pandemic has motivated the research to focus more than ever in the development of systems to predict pneumonia. Deep Learning models have been shown to be powerful tools in predicting pneumonia from CXR images, with sensitivity results often surpassing 85% and reaching up to 98.81% on certain datasets [10], [11]. However, as far to our knowledge, only a recent study [3], considered a dataset composing the data collected from different hospitals. Its focus is to create a robust model even under strong domain shifts between training and test set. This is a crucial aspect, since in real world the data are more and more heterogeneous and there could be a lot of benefits both if we are able to elaborate them all together, either if we are able to tackle this heterogeneity in the test data. Our proposal differs from this study since we aim to create a model not just robust but also adaptable to the new environments using self-supervised learning, which was already showed to get surprising performances (99.2% sensitivity) on the on homogeneous data [12], [13].

IV. Discussion

This study aims to investigate further robustness and transferability in deep learning models for diagnosis of Pneumonia from CXR data. Our hope is to find out useful insights towards a Causal Representation Learning of these images.

We are not extremely confident with the second part of this project, and if our approach will be adaptable and able achieve the state-of-the-art on the task, but we strongly agree that the problem above mentioned is a fundamental open problem both in theoretical machine learning and in application and it deserves more study attention.

References

[1] World Health Organization, https://www.who.int/news-room/fact-sheets/detail/pneumonia, 2019.

[2] A. M. Speets, A. W. Hoes, Y. van der Graaf, S. Kalmijn, A. P. E. Sachs, and W. P. T. M. Mali, "Chest radiography and pneumonia in primary care: diagnostic yield and consequences for patient management," *European Respiratory Journal*, vol. 28, no. 5, pp. 933–938, 2006. [Online]. Available: https://erj.ersjournals.com/content/28/5/933

[3] A. Bellot and M. van der Schaar, "Accounting for unobserved confounding in domain generalization," *arXiv preprint arXiv:2007.10653*, 2020.

[4] W. C. Daniel S. Kermany, Michael Goldbaum, "Identifying medical diagnoses and treatable diseases by image-based deep learning: Cell," https://www.cell.com/cell/fulltext/S0092-8674(18)30154-5, 2019, (Accessed on 10/15/2021).

[5] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. Summers, "Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in *IEEE CVPR*, vol. 7, 2017.

[6] D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan *et al.*, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1131, 2018.

[7] M. Arjovsky, L. Bottou, I. Gulrajani, and D. Lopez-Paz, "Invariant risk minimization," *arXiv preprint arXiv:1907.02893*, 2019.

[8] D. Krueger, E. Caballero, J.-H. Jacobsen, A. Zhang, J. Binas, D. Zhang, R. Le Priol, and A. Courville, "Out-of-distribution generalization via risk extrapolation (rex)," in *International Conference on Machine Learning*. PMLR, 2021, pp. 5815–5826.

[9] Y. Sun, X. Wang, Z. Liu, J. Miller, A. Efros, and M. Hardt, "Test-time training with self-supervision for generalization under distribution shifts," in *International Conference on Machine Learning*. PMLR, 2020, pp. 9229–9248.

[10] "Pneumonia detection in chest x-ray images using an ensemble of deep learning models," https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0256630, (Accessed on 10/15/2021).

[11] "Deep learning approaches for detecting pneumonia in covid-19 patients by analyzing chest x-ray images," https://www.hindawi.com/journals/mpe/2021/9929274/, (Accessed on 10/15/2021).

[12] I.-Y. L. C. Park, J.; Kwak, "A deep learning model with self-supervised learning and attention mechanism for covid-19 diagnosis using chest x-ray images," file:///Users/raphael-attias/Downloads/electronics-10-01996-v2.pdf, 2021, (Accessed on 10/15/2021).

[13] J. P. P. D. Matej Gazda, Jakub Gazda, "Self-supervised deep convolutional neural network for chest x-ray classification," https://arxiv.org/pdf/2103.03055.pdf, 2020, (Accessed on 10/15/2021).