Adversarial Few-shot Domain Adaptation for COVID-19 Medical Image Diagnosis

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1 Research Problem

The outbreak of coronavirus disease 2019 (COVID-19) has caused over 7 million cases and 400 thousands deaths globally by June 10th, 2020 [1]. To diagnose infection, testing includes laboratory assays: a COVID-19 coronavirus reverse transcriptase polymerase chain reaction (RT–PCR) test, and a COVID-19 coronavirus antigen test. However, many countries still lack enough tests which impairs the ability to diagnose early. For example, PCR tests may take days to weeks to complete, and multiple tests are usually required to reduce the risk of false negative. The antigen test is not yet widespread and relies upon testing infrastructure not present in many locations. Thus, an alternative method that is fast and accurate with similar clinical results is needed and of great use for locations with limited resources. Recently, an initial analysis with COVID-19 positive CT imaging has demonstrated that it exhibits multilobular and bilateral and includes both ground-glass opacities and consolidation, often with a peripheral lung distribution [2, 3, 4], which could be employed for fast diagnosis. Given the success of computer vision systems in medical image analysis, a vast amount of research [5, 6, 7, 8] aim to develop deep convolutional neural networks(CNNs) based diagnosis model [9] with CT/X-Ray images.

However, there are several limitations of above mentioned works: (i) lack of large-scale, COVID-19 positive imaging data, and (ii) poor performance on target hospital domain due to domain adaptation [10]. The former is due to the lack of COVID-19 patients' information and privacy issues. The latter happens when you apply your models trained elsewhere to a new hospital, usually domain adaptation methods are required since the data distribution has shifted. Each makes it challenging to generalize to new hospital settings. To address these challenges, we can borrow insights from pretrained pneumonia diagnosis model for COVID-19 diagnosis with only a few labeled samples, *i.e.*, via few-shot learning.

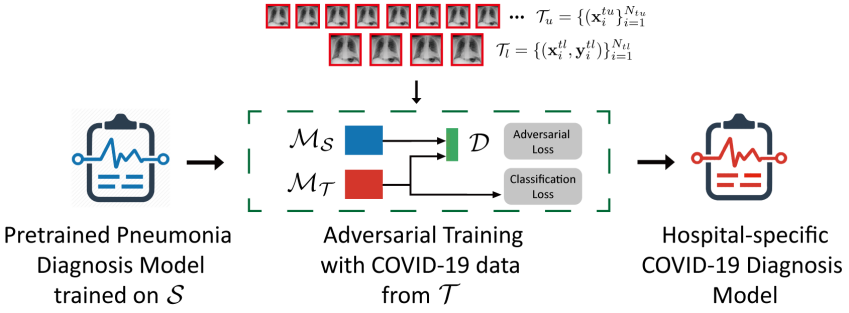

Figure 1: An overview of our workflow.

Formally, our scientific goal is to employ few-shot learning [11, 12] and adversarial training [13] to enable transfer from pneumonia classification models to COVID-19 diagnosis model, as illustrated in Fig 1. We formalize our setting as follows. Let $\mathcal{S} = \{(\mathbf{x}_i^s, \mathbf{y}_i^s)\}_{i=1}^{N_s}$ where $\mathbf{x}^s \in \mathbb{R}^N$ is the labeled data from the source domain, $\mathcal{T}_l = \{(\mathbf{x}_i^{tl}, \mathbf{y}_i^{tl})\}_{i=1}^{N_{tl}}$ denotes the labeled data from target domain, where $\mathbf{x}^{tl} \in \mathbb{R}^M$, and $\mathcal{T}_u = \{\mathbf{x}_i^{tu}\}_{i=1}^{N_{tu}}$ denotes the unlabeled data from target domain. Our goal is to transfer the CNN based model trained on $\mathcal{S}$ to $\mathcal{T}$ and overcome domain shift with a few labeled samples in the target domain.

Previous empirical work has established that using adversarial domain adaptation training typically performs better than the widely adopted fine-tuning process [14].

In our setting, N_{tl} is small, *i.e.*, few-shot. Note that in our experiments, the labeled target dataset could be relatively large, where we use the large number of data for statistical characterization. Meanwhile, our method is meant for application in environments where N_{tl} is indeed small.

2 Project Timeline/Key Milestones and Outcomes

In June, we will first reproduce several related works [15, 14] and apply them on the COVID-19 data set to evaluate the performance as baselines.

In July through September, we will summarize previous experiments on COVID-19 setting and propose our own model based on observations, evaluate our proposed method on both benchmark datasets like MNIST, CUB-200, as well as the COVID-19 dataset. We will assemble our methods, experiments, and findings into a draft for a September conference submission.

From September 2020 to January 2021, we anticipate larger assembled data sets will be available, and will integrate the updated data, perform subgroup analyses, and validate our method to extend our conference manuscript into a journal version.

We plan to submit to an academic conference (AAAI/ICLR) in Fall 2020. A journal version will be submitted to the Journal of Machine Learning Research in Winter 2020-21.

3 Additional Information

3.1 Data Type

Medical images such as CTs and X-ray. In the future, we may also add other clinical information to further improve the system.

3.2 Details about Dataset

We are using a public COVID-19 dataset(https://github.com/ieee8023/covid-chestxray-dataset). This is a open dataset of chest X-ray and CT images of patients who are positive or suspected of COVID-19 or other viral and bacterial pneumonias(MERS, SARS and ARDS). We are investigating the use of local data sources for validation purposes, though our current request is for training models based on the data linked above. Also, we pay close attention to any newly released COVID-19 dataset and are ready to include it into our experiments.

Another dataset we may be using is COVID-CT dataset from UCSD(https://github.com/UCSD-AI4H/COVID-CT), which contains 349 CT images containing clinical findings of COVID-19 from 216 patients and 463 non-COVID-19 CTs.

And we are in conversation with local hospitals to see if we can get private data from their database. However, due to privacy issues, the process may take several months. Thus, at the beginning time of this project, we will focus on above public datasets.

3.3 Team Composition and Preparedness

The team is composed of two PhD students and an assistant professor from Carnegie Mellon University, with research interests on machine learning for health care. The list of members is as follows.

Xuejian Wang is a second-year PhD student with experiences in deep learning field, and has published in venues like KDD, AAAI, ECML-PKDD, TKDD, etc.

Cheng Cheng is a second-year PhD student with interests in deep learning and health informatics.

Dr. Jeremy Weiss, Assistant Professor of Health Informatics, is the PI for this project. He holds an MD and PhD in Computer Science with research interests at the intersection of machine learning for health care.

With this mixed background spanning, we believe we can contribute to combating COVID-19 from machine learning perspective with solid medical applications.

References

[1] World Health Organization et al. Coronavirus disease 2019 (covid-19): situation report, 142. 2020.

[2] Michael Chung, Adam Bernheim, Xueyan Mei, Ning Zhang, Mingqian Huang, Xianjun Zeng, Jiufa Cui, Wenjian Xu, Yang Yang, Zahi A Fayad, et al. Ct imaging features of 2019 novel coronavirus (2019-ncov). *Radiology*, 295(1):202–207, 2020.

[3] Adam Bernheim, Xueyan Mei, Mingqian Huang, Yang Yang, Zahi A Fayad, Ning Zhang, Kaiyue Diao, Bin Lin, Xiqi Zhu, Kunwei Li, et al. Chest ct findings in coronavirus disease-19 (covid-19): relationship to duration of infection. *Radiology*, page 200463, 2020.

[4] Xueyan Mei, Hao-Chih Lee, Kai-yue Diao, Mingqian Huang, Bin Lin, Chenyu Liu, Zongyu Xie, Yixuan Ma, Philip M Robson, Michael Chung, et al. Artificial intelligence–enabled rapid diagnosis of patients with covid-19. *Nature Medicine*, pages 1–5, 2020.

[5] Linda Wang and Alexander Wong. Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest radiography images. *arXiv*, pages arXiv–2003, 2020.

[6] Charmaine Butt, Jagpal Gill, David Chun, and Benson A Babu. Deep learning system to screen coronavirus disease 2019 pneumonia. *Applied Intelligence*, page 1, 2020.

[7] Mucahid Barstugan, Umut Ozkaya, and Saban Ozturk. Coronavirus (covid-19) classification using ct images by machine learning methods. *arXiv preprint arXiv:2003.09424*, 2020.

[8] Fei Shan, Yaozong Gao, Jun Wang, Weiya Shi, Nannan Shi, Miaofei Han, Zhong Xue, and Yuxin Shi. Lung infection quantification of covid-19 in ct images with deep learning. *arXiv preprint arXiv:2003.04655*, 2020.

[9] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[10] Hidetoshi Shimodaira. Improving predictive inference under covariate shift by weighting the log-likelihood function. *Journal of statistical planning and inference*, 90(2):227–244, 2000.

[11] Li Fei-Fei, Rob Fergus, and Pietro Perona. One-shot learning of object categories. *IEEE transactions on pattern analysis and machine intelligence*, 28(4):594–611, 2006.

[12] Michael Fink. Object classification from a single example utilizing class relevance metrics. In *Advances in neural information processing systems*, pages 449–456, 2005.

[13] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.

[14] Saeid Motiian, Quinn Jones, Seyed Iranmanesh, and Gianfranco Doretto. Few-shot adversarial domain adaptation. In *Advances in Neural Information Processing Systems*, pages 6670–6680, 2017.

[15] Zelun Luo, Yuliang Zou, Judy Hoffman, and Li Fei-Fei. Label efficient learning of transferable representations acrosss domains and tasks. In *Advances in Neural Information Processing Systems*, pages 165–177, 2017.