Active Learning to Minimize the Risk from Future Epidemics

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***Abstract*—For any future epidemics (e.g., Covid-19), typical deep learning (DL) models are of no use as they require a large amount of data for training. Moreover, data collection (with annotations) typically takes months (and even years) in public healthcare. In such a context, active learning (or human/expert-in-the-loop) is the must, where a machine can learn from the first day with the minimum possible labeled data. In unsupervised learning, we propose to build pre-trained DL models that iteratively learn independently over time, where human/expert intervenes/mentors only when it makes mistakes and for limited data. To validate such a concept, deep features are used to classify data into two clusters (0/1: Covid-19/non-Covid-19) on two different image datasets: Chest X-ray (CXR) and Computed Tomography (CT) scan of sizes 4,714 and 10,000 CTs, respectively. Using pre-trained DL models and unsupervised learning, in our active learning framework, we received the highest AUC of 0.99 and 0.94 on CXR and CT scan datasets, respectively. Our results are comparable with the fully trained (on large data) state-of-the-art DL models.**

***Index Terms*—Active learning, future epidemics, Covid-19, CT scans, Chest X-rays**

I. Introduction

Future epidemics are inevitable, and Covid-19 is an example with ∼759,408,703 infections and 6,866,434 death cases (as of March 7, 2023, source: WHO). For such sudden disease emergencies, state-of-the-art prediction models are of no use for two reasons: i) they require large dataset (and labeled) to train, and ii) they behave differently when there exist unavoidable uncertainties [3]. Furthermore, increasing the dataset size alone does not guarantee to make the system robust [1]. Therefore, we need an intelligent tool that can learn with human experts without having to wait for a complete and/or labeled dataset [2], and we call it Active Learning (AL).

In this paper, the proposed AL (or expert-in-the-loop machine learning) learns from the first day with the minimum possible labeled data, which is inspired from concept of mentoring or interactive learning [13]. Mentoring refers to the inclusion of the expert, so AL iteratively improves the performance until it has sufficient knowledge to make independent decision(s).

II. Active learning and implementation

With AL, it is possible for models to learn iteratively over time without having prior knowledge on any specific event(s). Due to which, it helps models adapt new data without forgetting their existing limited knowledge. In a setting where a continuous flow of data occurs (at epidemics), it is important to exploit the real-time data with an expert mentoring the decision(s) until machine is ready to be independent (if required) [2]. In a nutshell, on a limited data used for mentoring (M), the primary idea is to see when a function $h(s_i)$ needs to be updated; $h(s_i) = 1$ if a machine commits a mistake and 0, otherwise, where $h(s_i)$ and $s_i \in M$ denote the function for activating the expert's intervention and unknown data, respectively. In Fig. 1, we describe our AL framework, where expert's intervention happens in a closed loop feedback format. As we run our framework, $h(s_i)$ gets activated $\forall s_i \in M$ when the machine commits mistakes, where $M \in$ dataset, D. To avoid algorithmic complexity, we employ k-way (two-class problem: Covid-19/non-Covid-19) few-shot learning mechanism, where few-shot refers to support sets belonging to two clusters (an outcome of unsupervised clustering). In our AL framework, with deep features (from three different pre-trained models: VGG16, ResNet101, and DenseNet169), unsupervised clustering follows indices such as Dunn's index, Davies-Bouldin index, and Silhouette index using Euclidean, Manhattan, and Cosine distance metrics. This applies to both modalities: CXRs and CT scans, and the code/implementation is available: https://github.com/2ai-lab/Active-Learning.

III. Experiments

In AL framework, we are primarily looking how much mentoring is required to make our model independent to make decisions. For this, in other words, we are required to see when to stop mentoring. We setup our experimentation (Lawrence Supercomputer: NSF.1626516) as follows (see Table I): a) Start with limited known samples: 40 CXRs and 200 CT scans; b) Define a set of mentored subsets of dataset: $\mathcal{M}_{\text{type}} = \{M_i\}_{i=1,\ldots,n}$, and type refers to modality type, CXR and CT scans; and check, for every M_i, whether the machine commits mistakes. Mentoring stops when number of mistakes are insignificant. In total, we have 4,714 CXRs and 10,000 CT scans[1] [2] [3] [4],

[1]https://github.com/agchung/Figure1-COVID-chestxray-dataset
[2]https://github.com/agchung/Actualmed-COVID-chestxray-dataset
[3]https://www.kaggle.com/tawsifurrahman/covid19-radiography-database

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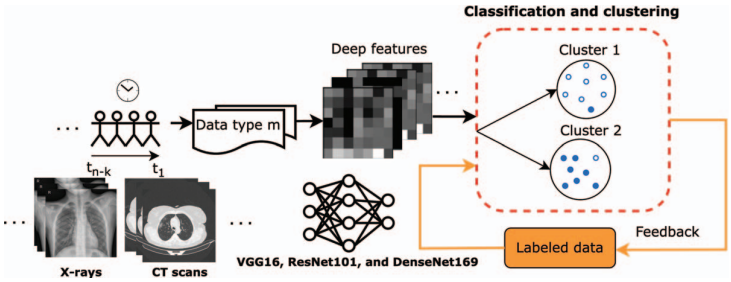

Fig. 1: Active learning schema for two different modalities: chest X-ray and CT scan. Deep features are used to classify between Covid-19 and non-Covid-19 cases in an unsupervised clustering mechanism, and the machine gets updated from the expert's intervention when it commits a mistake.

TABLE I: Cumulative avg corrections on a different subsets of mentored data (M_1 - M_4) in both cases: CXR and CT scan.

	Labeled data	Mentored data	Avg. corrected counts
CXRs (4,714)	40	160 (M_1)	**18.75**
	40	360 (M_2)	**32.58** (18.75+ 15.80)
	40	760 (M_3)	**50** (18.75 + 15.80 + 17.42)
	40	1510 (M_4)	**72.58** (18.75 + 15.80 + 17.42 + 22.58)
CT scans (10,000)	200	200 (M_1)	**50.77**
	200	600 (M_2)	**132.97** (50.77 + 82.20)
	200	1400 (M_3)	**275.50** (50.77 + 82.20 + 142.53)
	200	3000 (M_4)	**511.22** (50.77 + 82.20 + 142.53 + 235.72)

[5]. To validate our model, common evaluation metrics such as accuracy, specificity, sensitivity, and area under the ROC curve (AUC) are used. Three pre-trained DL models: VGG16, ResNet101, and DenseNet169 are used to classify Covid-19 and non-Covid-19 samples in an unsupervised clustering framework that follows criteria of the respective clustering indices: Dunn, Davies-Bouldin, and Silhouette. Clustering indices help us analyze how well data has been learned.

Table II depicts the best classification results on each model with the number of data samples that required mentoring (Best results are included due to page limitation). For CXR, best performances were observed in M_2, M_1, and M_3 for VGG16, ResNet101, and DenseNet169, respectively. Similarly, for CT scans, all the models had the best performance in M_4. VGG16 had the highest AUC (0.94), specificity (0.90), and accuracy (0.87). Table III shows the comparison of our results with the state-of-the-art methods. Comparable performances were observed for CXR, however, lower scores were observed for CT scans due to less mentoring.

IV. Conclusions

In this paper, we have implemented AL (or expert-in-the-loop machine learning) on classifying Covid-19 from non-Covid-19 samples. Using pre-trained DL models and unsupervised learning, we have received the highest AUC of 0.99 and 0.94 on CXR and CT scan datasets, respectively. Our results are comparable with the fully trained (on large dataset) state-of-the-art DL models.

TABLE II: Best classification results on different models.

	Model	Mentored data	AUC	ACC	SPEC	SEN
CXRs	VGG16	M_2	0.99	0.98	0.99	0.97
	ResNet101	M_1	0.99	0.98	0.98	0.98
	DenseNet169	M_3	0.99	0.96	0.99	0.99
CT scans	VGG16	M_4	0.94	0.87	0.90	0.85
	ResNet101	M_4	0.93	0.85	0.88	0.83
	DenseNet169	M_4	0.93	0.85	0.80	0.89

TABLE III: Comparison with state-of-the-art methods.

	Authors	Methods	AUC	ACC	SPEC	SEN
CXRs	Santosh [6]	ChexNet	0.99	0.98	0.98	0.99
	Mahmud [10]	CovXNet	0.96	0.97	0.94	0.97
	Asnaoui [11]	Inception ResNet V_2	-	0.92	0.96	0.92
	Ucar [12]	Bayes-SqueezeNet	–	0.98	0.99	-
	Ours	Active Learning	0.99	0.98	0.99	0.97
CT scans	Gunraj [5]	COVID-NET CT-2	-	0.98	0.99	0.99
	Loddo [7]	VGG19	-	0.98	0.99	0.97
	Jia [8]	Modified ResNet	-	0.99	-	0.99
	Zhao [9]	ResNet V_2	-	0.99	0.99	0.99
	Ours	Active Learning	0.94	0.87	0.90	0.85

References

[1] KC Santosh and S Ghosh. "Covid-19 imaging tools: How big data is big?." J of Med Syst 45 (2021): 71.

[2] KC Santosh. "AI-driven tools for coronavirus outbreak: need of active learning and cross-population train/test models on multitudinal/multimodal data." J of Med Syst 44 (2020): 1-5.

[3] KC Santosh. "COVID-19 prediction models and unexploited data." J of Med Syst 44.9 (2020): 170.

[4] Kermany et al. "Labeled optical coherence tomography and chest x-ray images for classification." Mendeley data 2.2 (2018): 651.

[5] Gunraj et al. "Covid-net ct-2: Enhanced deep neural networks for detection of covid-19 from chest ct images through bigger, more diverse learning." Frontiers in Medicine 8 (2022): 3126.

[6] Santosh et al. "CheXNet for the Evidence of Covid-19 Using 2.3 K Positive Chest X-rays." Recent Trends in Image Processing and Pattern Recognition: 4th International Conference, RTIP2R 2021, Msida, Malta, December 8-10, 2021, Revised Selected Papers. Cham: Springer International Publishing, 2022.

[7] Loddo et al. "Deep learning for COVID-19 diagnosis from CT images." Applied Sciences 11.17 (2021): 8227.

[8] Jia et al. "Classification of COVID-19 chest X-Ray and CT images using a type of dynamic CNN modification method." Computers in biology and medicine 134 (2021): 104425.

[9] Zhao et al. "Deep learning for COVID-19 detection based on CT images." Scientific Reports 11.1 (2021): 1-12.

[10] Mahmud et al. "CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization." Computers in biology and medicine 122 (2020): 103869.

[11] Asnaoui et al. "Using X-ray images and deep learning for automated detection of coronavirus disease." Journal of Biomolecular Structure and Dynamics 39.10 (2021): 3615-3626.

[12] Ucar et al. "COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images." Medical hypotheses 140 (2020): 109761.

[13] RM Monarch. Human-in-the-Loop Machine Learning: Active learning and annotation for human-centered AI. Simon and Schuster, 2021.