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Detecting COVID-19 in X-ray images with Keras, Tensor Flow, and Deep Learning

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Abstract

COVID-19 found in Wuhan, city in China in the month of December 2019, and since it has immediately become public health problem worldwide. No curable medicine against COVID-19 has been found till now. However, mortality risk in patients could gradually be predicted before disease transmits to critically ill. The corona virus infection surprised the world with its rapid spread and has had a major impact on the lives of billions of people. `The quantification of COVID-19 infection in CT images using deep learning has not been investigated. Clinically there is no automatic tool to quantify the infection volume for COVID-19 patients. Our main aim is to develop a deep learning (DL)-based system for automatic segmentation and quantification of infection regions as well as the entire lung from chest CT scans. And to design AI-based automated CT image analysis tools for detection, quantification, and tracking of Corona virus and perform that they can differentiate corona virus patients from those who do not have the disease. Multiple international datasets, including from Chinese disease-infected areas were included. We create a system that utilizes robust 2D and 3D deep learning models, modifying and adapting existing AI models and combining them with clinical understanding. The candidate infection regions were first segmented out using a 3- dimensional deep learning model from pulmonary CT image set. These separated images were then classified into COVID-19, Influenza-A viral pneumonia and irrelevant to infection groups, together with the corresponding confidence scores using a location-attention classification model. Finally the infection type and total confidence score of this CT case were calculated with Noisy-or Bayesian function.

Keywords: COVID-19, 3-dimensional deep learning model, Influenza-A viral pneumonia, Noisy-or Bayesian function.

1. Introduction

At the end of 2019, the novel corona virus disease 2019 pneumonia (COVID-19) occurred in the city of Wuhan, China.1- 4 On January 24, 2020; the clinical characteristics of 41 patients with COVID-19, indicating that the common onset symptoms were fever, cough, myalgia, or fatigue. All these 41 patients had pneumonia and their chest CT image test showed abnormalities. The complications included acute respiratory distress syndrome, acute heart injury, and secondary infections. Thirteen (32%) patients were admitted to the intensive care unit (ICU), and six (15%) died. The Kok-KH6 team at the University of Hong Kong found the evidence of human-to-human transmission of COVID-19 for the first time [1].

With the rapid development of computer technology, digital image processing technology has been widely applied in the medical field, including organ segmentation and image enhancement and repair, providing support for subsequent medical diagnosis. Deep learning technologies, such as convolution neural network (CNN) with the strong ability of nonlinear modeling, have extensive applications in medical image processing as well. In this study, multiple CNN models were used to classify CT image datasets and calculate the infection probability of COVID-19. The findings might greatly assist in the early screening of patients with COVID-19. Chest CT examination has also shown its effectiveness in follow-up assessment of hospitalized COVID-19 patients. Due to fast progression of the disease, subsequent CT scans every 3-5 days are recommended to evaluate the therapeutic responses. Although CT provides rich pathological information, only qualitative evaluation has been provided in the radiological reports owing to the lack of computerized tools to accurately quantify the infection regions and their longitudinal changes. Thus, subtle changes across follow-up CT scans are often ignored. Besides, contouring infection regions in the Chest CT is mandatory for quantitative evaluation; however, manual contouring of lung lesions is a complex and time-consuming work, and inconsistent delineation could also lead to subsequent assessment discrepancies. Thus, a fast auto-contouring tool for COVID-19 infection is urgently needed in the onsite applications for quantitative disease assessment [2, 3].

We developed a deep learning (DL)-based segmentation system for quantitative infection assessment. The system not only performs auto-contouring of infection regions, but also accurately estimates their shapes, volumes and percentage of infection (POI) in CT scans of COVID-19 patients. In order to provide delineation for hundreds of the training COVID-19 CT images, this is a tedious and time-consuming work, a human-in-the-loop (HITL) strategy to iteratively generate the training samples. This method involves radiologists to efficiently intervene DL-segmentation results and iteratively add more training samples to update the model, and thus greatly accelerates the algorithm development cycle. To the best of our information, there are no resources that have reported the utilization of HITL strategy in detecting COVID-19 symptoms in CT scans [4].

In a manner analogous to the way in which COVID-19 represents a new strain of corona virus not previously found in humans and presumably representing a mutation of other corona viruses, an AI algorithm can be rapidly created from one or more algorithms that perform a similar task. This is in contrast to the standard way of developing a DL algorithm, entailing several phases: I. Data- collection phase in which a large amount of data samples need to be collected from predefined categories; expert annotations are needed for ground-trusting the data; II. Training phase in which the collected data is used to train network models. Each category needs to be represented well enough so that the training can generalize to new cases that will be seen by the network in the testing phase. In this learning phase, the large number of network parameters (typically on the order of millions) are automatically generated; III. Testing phase in which an additional set of cases not used in training is presented to the network and the output of the network is tested statistically to determine its success of categorization [5].

Respiration is a core physiological process for all living creatures on earth. A person's physiological state as well as emotion and stress may be reflected by representation of some respiratory parameters. Therefore, we should pay attention to respiration. Integrated different respiratory signs, respiratory patterns are able to more comprehensively resemble the conditions of respiratory activity. Many clinical studies suggested that abnormal respiratory patterns can predict a few specific diseases, providing relatively detailed hints for clinical treatments. Unfortunately, these abnormal respiratory patterns occur in a way difficult for people to notice themselves. If we could develop a system capable of remotely and unobtrusively detecting these unnoticeable abnormal breathing patterns under various scenarios, people who have the diseases may be diagnosed at earliest possible time.

Deep learning has been extensively used in many fields. In terms of respiratory pattern detection, the convolution neural networks (CNN) achieve the identification of deep breathing. Therefore, the classification of respiratory signals extracted by the non-contact measurement system with the aid of deep learning is a study worth trying and of much significance. In the above study, all the data sets required for model construction were obtained, though, by assessing the respiratory activities of the test subjects.

This approach for capturing different types of respiratory patterns yields a limited set of data. There is no more training data to support; the neural network might not be able to give full play to its advantages. Again, researchers often present literatures that the classification models generally adopt the general network architecture in the field of deep learning without specific designs for respiratory pattern classification. At the same time, the network is not optimized according to the characteristics of the collected data. During the epidemic prevention and control period, our study can be helpful in prognosis, diagnosis and screening for the patients infected with COVID- 19 (the novel corona virus) based on breathing characteristics. According to the latest clinical study, the respiratory pattern of COVID-19 is varying from the respiratory patterns of flu and the common cold. One significant symptom that occurs in the COVID-19 is Tachypnea. People infected with COVID-19 have more fast respiration. Our study can be utilized to distinguish various respiratory patterns [6-8].

Accurate detection of the unexpected abnormal respiratory pattern of people in a remote and unobtrusive manner has great significance. In this work, we innovatively capitalize on depth camera and deep learning to achieve this goal. The challenges in this task are twofold: the amount of real-world data is not enough for training to get the deep model; and the intra-class variation of different types of respiratory patterns is large and the outer-class variation is small. In this paper, considering the characteristics of actual respiratory signals, a novel and efficient Respiratory Simulation Model (RSM) is first proposed to fill the gap between the large amount of training data and scarce real-world data. Subsequently, we first apply a GRU neural network with bidirectional and attentional mechanisms (BI-AT-GRU) to classify 6 clinically significant respiratory patterns (Eupnea, Tachypnea, Bradypnea, Biots, Cheyne-Stokes and Central-Apnea).

2. Methods and Materials

We will learn how to automatically detect COVID-19 in a hand-created X-ray image dataset using libraries of machine learning like Keras, Tensor Flow, and Deep Learning etc.

- Sample an open source dataset of X-ray images of patients who have tested positive for COVID-19 (corona virus).
- Sample "normal" (i.e., not infected) X-ray images from healthy patients
- Train a CNN to automatically detect COVID-19 in X-ray images via the dataset we created
- Evaluate the results from an educational perspective

How could COVID-19 be detected in X-ray images?

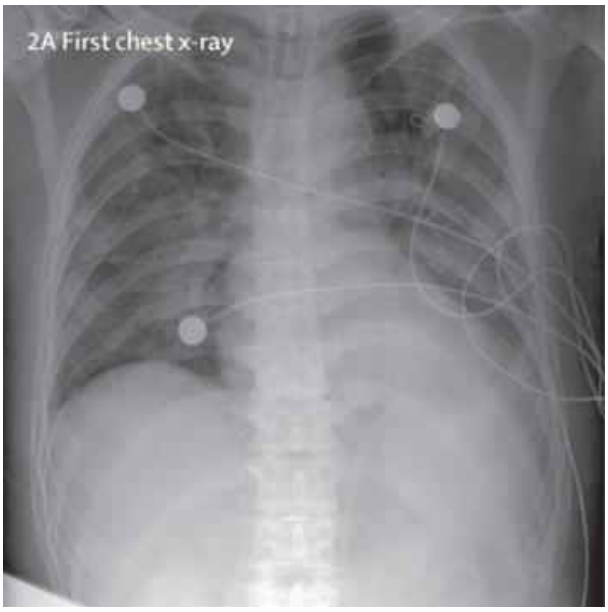

Figure 2.1 shows the example of an X-ray image taken from a patient with a positive test for COVID-19. Using X-ray images we can train a machine learning classifier to detect COVID-19 using Keras and TensorFlow.

Our COVID-19 patient X-ray image dataset -

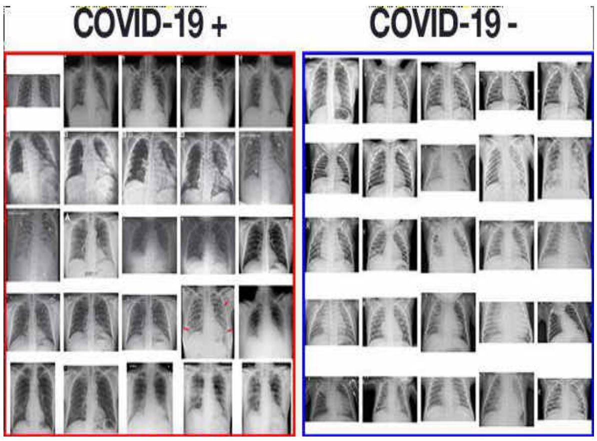

Fig 2.2: CoronaVirus (COVID-19) chest X-ray image data. On the left we have positive (i.e., infected) X-ray images,

whereas on the right we have negative samples. These images are used to train a deep learning model with Tensor Flow and Keras to automatically predict whether a patient has COVID-19 (i.e., corona virus).

In total, that left me with **25 X-ray images of positive COVID-19 cases (Figure 2, *left*). The next step was to sample X- ray images of** *healthy* **patients.** To do so, we used [Kaggle's Chest X-Ray Images (Pneumonia) dataset] and sampled **25 X- ray images from healthy patients (Figure 2,** *right*). There are a lot of problems with Kaggle's Chest X-Ray dataset, namely noisy/incorrect labels, but it served as a good enough starting point for this proof of concept COVID-19 detector.

Project structure:- Detecting COVID-19 in X-ray images with Keras, Tensor Flow, and Deep Learning

```
$ tree --dirsfirst --filelimit 10
├── Dataset
│ ├── covid [25 entries]
│ └── normal [25 entries]
├── build_covid_dataset.py
├── sample_kaggle_dataset.py
├── plot.png
└── covid19.mode
```

Our corona virus (COVID-19) chest X-ray data is in the dataset/ directory where our two classes of data are separated into Covid /and normal/. Instead, we will review the train_covid19.py script which trains our COVID-19 detector.

Implementing our COVID-19 training script using Keras and Tensor Flow:- Now we've reviewed image dataset along with the corresponding directory structure for project, and move on to fine-tuning a Convolution Neural Network to automatically diagnose COVID-19 using Keras, Tensor Flow, and deep learning. Additionally, we use scikit-learn, the de facto Python library for machine learning, matplotlib for plotting, and OpenCV for loading and preprocessing images in the dataset.

Our three **command line arguments** include:

- --dataset: The path to our input dataset of chest X-ray images.
- --plot: An optional path to an output training history plot. By default the plot is named plot.png unless otherwise specified via the command line.
- --model: The optional path to our output COVID-19 model; by default it will be named covid19.model.
- Extract the class label (either covid or normal) from the path.
- Load the image, and preprocess it by converting to RGB channel ordering, and resizing it to *224×224* pixels so that it is ready for our Convolution Neural Network.
- Update our data and labels lists respectively.

Detecting COVID-19 in X-ray images with Keras, Tensor Flow, and Deep Learning-

```
[[0. 1.]
[0. 1.]
[0. 1.]
…
[1. 0.]
[1. 0.]

[1. 0.]]
```

Each encoded label consists of a two element array with one of the elements being "hot" (i.e., 1) Versus "not" (i.e., 0). From there, we construct a new fully-connected layer head consisting of POOL => FC = SOFTMAX layers and append it on top of VGG16. Here we generate a confusion matrix and use the confusion matrix to derive the accuracy, sensitivity, and specificity and print each of these metrics. We then plot our training accuracy/loss history for inspection, outputting the plot to an image file. Finally we serialize our tf.keras COVID-19 classifier model to disk.

Training our COVID-19 detector with Keras and Tensor Flow:- With our train_covid19.py script implemented, we are now ready to train our automatic COVID-19 detector.

3. Results

Automatic COVID-19 diagnosis from X-ray image results: As you can see from the results above, our automatic COVID- 19 detector is obtaining ~90-92% accuracy on our sample dataset based solely on X-ray images — no other data, including geographical location, population density, etc. was used to train this model. We are also obtaining 100% sensitivity and 80% **specificity** implying that:

- Of patients that do have COVID-19 (i.e., true positives), we could accurately identify them as “COVID-19 positive” 100% of the time using our model.
- Of patients that do not have COVID-19 (i.e., true negatives), we could accurately identify them as “COVID-19 negative” only 80% of the time using our model.

As our training history plot shows, our network is not over fitting, despite having very limited training data. Being able to accurately detect COVID-19 with 100% accuracy is great; however, our true negative rate is a bit concerning — we don’t want to classify someone as “COVID-19 negative” when they are “COVID-19 positive”. We also want to be really careful with our false positive rate — we don’t want to mistakenly classify someone as “COVID-19 positive”, quarantine them with other COVID-19 positive patients, and then infect a person who never actually had the virus. When it comes to medical computer vision and deep learning, we must always be mindful of the fact that our predictive models can have very real consequences — a missed diagnosis can cost lives.

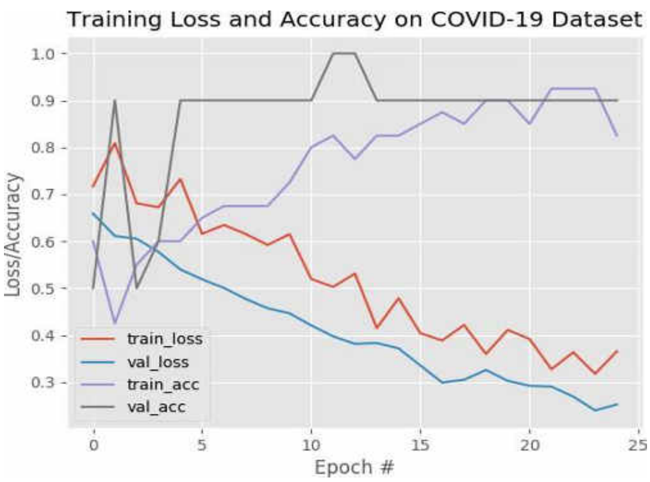

Fig 3.1: This deep learning training history plot showing accuracy and loss curves demonstrates that our model is not over fitting despite limited COVID-19 X-ray training data used in our Keras/TensorFlow model.

4. Discussion

Limitations, improvements, and future work:- We simply don’t have enough (reliable) data to train a COVID-19 detector: Hospitals are already overwhelmed with the number of COVID-19 cases, and given patients rights and confidentiality, it becomes even harder to assemble quality medical image datasets in a timely fashion. I imagine in the next 12-18 months we’ll have more high quality COVID-19 image datasets; but for the time being, we can only make do with what we have. Furthermore, we need to be concerned with what the model is actually “learning”. And finally, future (and better) COVID-19 detectors will be multi-modal. Right now we are using only image data (i.e., X-rays) — better automatic COVID-19 detectors should leverage multiple data sources not limited to just images, including patient vitals, population density, geographical location, etc. Image data by itself is typically not sufficient for these types of applications.

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