A Deep Learning Approach for Detecting COVID-19 and Pneumonia via CXR Images

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Abstract

Nowadays, COVID-19 situation becomes more and more severe, as well as sophisticated in not only Vietnam but also worldwide. That is why we have to take our actions immediately in order to cope with this pandemic. And the very first step in getting through this pandemic is that we have to rapidly identify COVID-19 cases. Thus, in this paper, we will propose a rapidly testing method which has a high productivity in a short time. In details, we will apply deep learning neural networks, e.g. ResNet50, VGG19 to solve this problem. After that, we will proceed analysing pros and cons of those models for a thorough vision about applying artificial intelligence in COVID-19 rapid testing. We will also discuss further about how we apply computational thinking into unfolding this problem via the use of techniques, e.g. Graphic Organizer, hierarchical structure and flowchart.

Index Terms– COVID-19, Computational Thinking, Deep Learning, Chest X-ray (CXR), diagnosis.

1 Introduction

COVID-19 nowadays is a severe situation with not only Vietnam but the whole world as well. Statistics shows that as of 18h GMT+07, Jun 16, 2021, there are more than 177.470.620 cases recorded worldwide, in which 3.839.931 death cases and 161.919.653 recovery cases [1].

To cope with this pandemic, there has been a wide variety of effective methods to diagnose COVID-19 cases rapidly. The most popular one, however, is to diagnose Corona using *Polymerase chain reaction*. Polymerase chain reaction (PCR) is a test to detect genetic material from a specific organism, e.g. virus. And *real-time polymerase chain reaction* (RT PCR) test specified for COVID-19, which is a variation of the traditional PCR, is a molecular test analysing your upper respiratory specimen to search for genetic material (Ribonucleic Acid or RNA) of SARS-CoV-2, the virus that causes the pandemic [16]. Highly productive as RT PCR method is, it requires a great deal of specified machinery and needs to be conducted in specific laboratories. Besides, RT PCR is only used with patients who are doubtfully infected or infected due to its high costs (about 734.000 VND per test - according to *5834 circular*

from the Ministry of Health).

In addition to RT PCR, doctors use *diagnostic imaging* (Chest X-ray Images or CXR Images) to rapidly identify COVID-19 cases. This method is a much faster and cheaper one (just about 100.000 VND per test) in comparison with RT PCR. This method, however, has its own drawbacks. The first cons to be mentioned is that CXR image is never be the only factor to diagnose COVID-19 cases absolutely correct, epidemiological characteristics and clinical manifestations are normally require for an improved accuracy. The other one is the misdiagnosis between COVID-19 and Pneumonia's CXR images. However, this limitation exists only with inexperienced diagnostic imaging doctors which may lead to the medical specified human resource shortage.

So as to improve disadvantages from traditional diagnostic imaging, we now introduce a new approach in minimizing both costs for each COVID-19 test and shortage in medical experts - that is to *use artificial intelligence (AI) for diagnostic imaging via CXR images*. Applying AI can help increase testing speed from half a day to under 5 seconds and provide an effective tool to widespread testing without being afraid of expense raising. Our proposed approach is to use AI for widespread testing at first, then recheck positive cases with RT PCR to cut down testing expense (7 times compared to using RT PCR). Additionally, since AI does not depend on specified human resources in medical science, we can conserve a great number of specialist doctors, especially in diagnostic imaging.

In order to apply AI into diagnosing COVID-19, as well as differentiating between COVID-19 and pneumonia, we have to understand a certain characteristics amount of these two respiratory diseases when observing CXR images only. As we could recognize through the images below:

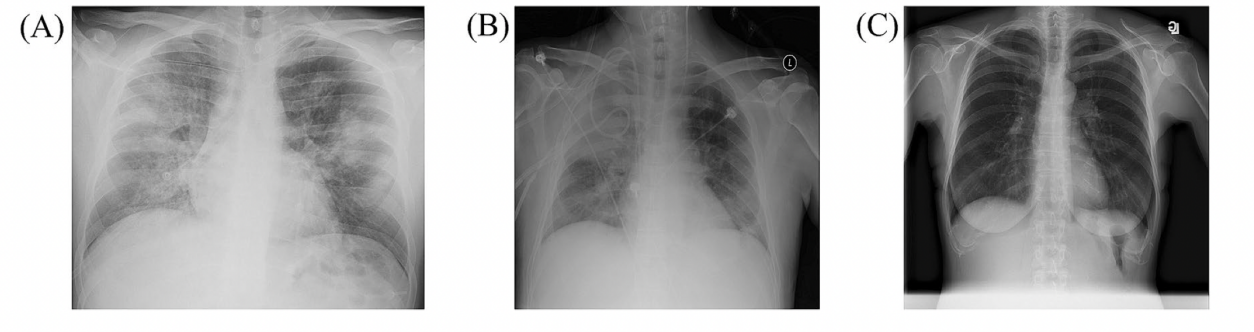

Fig 1. Representative CXR images for 3 cases
COVID-19 (A), Pneumonia (B) and non-respiratory disease (C)

The most crucial thing that make CXR images from pneumonia or COVID-19 patients different from normal ones is the appearance of white spots, whether they are a lot of or a few, on particular positions along patients' lungs. Those white spots are recognized as the term of *ground glass opacity* or GGO in medical science. Ground glass opacity is the incompletely consolidated injury in patients' lungs. It has a higher density in comparison with surrounded parenchyma while still enables us to observe underlying structures, e.g. blood vessels or bronchial membranes [12]. A specified doctor in the field of diagnostic imaging could tell that those GGO is the reason for those white spots in the chest radiograph. And a professional radiologist could use these features to differentiate COVID19 with pneumonia patients. Thus, we are capable of using a deep learning network to extract these features, then categorize to give out the appropriate diagnostic results for every cases.

Throughout this research, we use 2 different approaches which are ResNet50 [8] and VGG19 [23] to solve this problem. VGG19 is a deep neural network architecture under-using residual design principals, it is also a compact architecture which has a low diversity of architectures. On the other hand, ResNet50 is a deep neural network harnessing residual design principles and it has a moderate diversity of architectures. This network brings many a high productivity in a large number of researching in classifying X-ray images.

The rest of this paper is organized as follows. First we will talk about related works for this problem on section 2, and discuss about how we apply computational thinking into solving this problem in section 3. And then in section 4, we will discuss further about our approach for this problem. After that, we will talk about our experimental results and how we evaluate the results in section 5. Section 6 and section 7 will respectively display

our proposed improvement to the present problem and our final conclusion to this whole research. Finally, we will give out our assignment for this project in section 8 and introduce ourselves in biography section.

2 Related works

Computer vision has been used into medical diagnosis. It is beneficial into medical fields requiring visual check, e.g. dermatology. Computer vision is used as a diagnostic tool to check whether an abnormal point on skin could be an early signal for skin cancer or not. It is also used to identify inner problems, especially with tissue or blood vessels. And it is often used in ophthalmology to identify diabetic retinopathy for soon prevention of blindness.

It is shown through many researches that medical images help doctors improve identifying the presence of viral pneumonia. In many works, techniques based on deep learning has been developed to identify pneumonia [3][10], different thoracic disorders [21][29][20], skin cancer [11] from medical imaging. Some of these works give us a promising result for such relatively simple architectures [21].

In one research by [24], a simple Convolutional Neural Network (CNN) model was used to identify COVID-19 patients with the help of Computed Tomography (CT) images. In addition, there are many other works about identifying the presence of Corona virus in humans' lungs via CT images [31][22][13]. In the research of Yan et al. [32], supervised AI model was developed to identify Corona virus via the help of CT images with the accuracy of 89%.

However, Huang et al. [9] came into conclusion that CXR images are far better than any other medical images in detecting COVID-19 since its promising results as well as low maintenance cost and the machinery available.

There has been quite a few research conducted by researchers in the field of identifying COVID-19 patients using CXR images [14][28][19][2]. In a work proceeded by Makris et al. [14], trasfer learning was used with Inception-v3 network to classify the healthy, the pneumonia and the COVID-19 via the use of CXR Images. Another paper by Mangal et al. [15] exploited DenseNet and ChexNet architectures to separate healthy subjects, viral pneumonia subjects and COVID-19 ones. Rahimzadeh and Attar [19] applied a combination of Xception and ResNet50V2.Xu et al.'s research used ResNet to identify virus from pneumonia and COVID-19 patients [30]. Unavailable for a big number of imaging data from COVID-19 patients is a tremendous challenge for almost all researchers in this fields to face up to. Improving COVIDGAN to create artistic data was conducted in a work by Waheed et al.

[26], and thus will improve the probability of identifying COVID-19 cases. In a research by Tao [25], they propose a new approach to ensemble 3 modern CNN architectures, which are DenseNet201, ResNet50V2 and InceptionV3, to categorize COVID-19 patients with CXR Images.

In addition to using modern deep learning models, there is now a work by Wang et al. [28] on developing a custom architecture called as COVIDNet to classify COVID-19 patients, pneumonia patients and the healthy. This custom network has achieved the accuracy of categorizing up to 93%.

In this work, we proposed 2 approaches which are VGG19 and ResNet50V2 to classify COVID-19 patients, pneumonia patients and the healthy using CXR images.

3 Applying Computational Thinking to solve the problem

3.1 Project justification

Problem identification

In our first iteration, we did define our problem as detailed as possible. We did give out many a question, e.g. what our problem is? what kind of data we need? which constraint bounds our data ?

Then, in the second one, we proposed the method of using 2 Convolutional Neural Networks, which are ResNet50 and VGG19. This can be achieved via the abstraction section.

Additionally, in the third one, we attach some constraints to our present dataset which are the compulsion of using .jpg as the primary image extension, the combination between different data from different sources, separating training set and validation set appropriately. We also put some constraints about epochs, learning rate, iterations, and ways to save our model into the present problem. We accomplish those through the harnessing decomposition step. Along with the current ones, we did add a new constraint about using pre-trained models from ImageNet [7] in the pattern recognition step.

And ultimately, we use improved information of using a given code from Github to change image extension and to combine different datasets in the last iteration.

Decomposition

In the first iteration, we found out 4 sub-problems to the original one. And with these 4 sub-problems, we continued to break down into 8 sub-problems in the second iteration. These sub-problems are all crucial for us to understand more as well as help us to find the solution to our problem.

Pattern recognition

Pattern recognition plays a decisive role for us in this problem to figure out the solution. We found out the solution via this step in our very first iteration. Then pattern recognition helps us to adjust our deficiency about resources and not to mention about giving us a hand to make our model training step more effectively.

Abstraction

Since we did clarify our problem as much as possible from the very beginning, we only use abstraction in the first and the second iteration. The first one points out for us to recognize the correlation between the quantity of images and the imbalance among classes, hence we could raise our algorithm effectiveness. Meanwhile, the second iteration helps us to recognize the irrelevance between the patient ID and data source into solving the problem, then we get them rid of our datasets.

Abstraction contributes to focusing on important information and ignoring meaningless or irrelevant information to the problem.

3.2 Graphic Organiser

3.2.1 Iteration 1

Input: 1 CXR image
Output: probability of that image is COVID-19, Pneumonia or normal.

Parameters and constraints: size of input image is 224x224 at minimum, image and medical details are clear, sufficient and non-eclipsed, CXR images have to be straight-forward, the maximum tilt for the image is 10 degree angle at most and categorized by a specified diagnostic imaging doctor.

Dataset: COVIDx dataset comprises of 20 000 images and labels from different patients in 5 sources: Cohen et al. [6], Chung [4], Chung [5], Radiological Society of North America [17],

and Radiological Society of North America [18]

Evaluating criteria: F1 score, PPV(Precision), Sensitivity (Recall), Accuracy.

Decomposition
We do not use this step in this iteration.

Pattern recognition
We do not use this step in this iteration.

Abstraction
We do not use this step in this iteration.

3.2.2 Iteration 2

Input: 1 CXR image
Output: the probability of that image is COVID-19, Pneumonia or normal

Parameters, constraints: the size of the input image is 224x224 at minimum, image and medical details are clear, sufficient, and non-eclipsed, CXR images have to be straight-forward, the maximum tilt for the image is a 10-degree angle at most and categorized by a specified diagnostic imaging doctor.

Use deep learning to solve problems: ResNet50 or VGG19 to extract features (dependent on the features' quality), put them into a Fully Connected Neural Network to classify.

Dataset: COVIDx dataset comprises of 20 000 images and labels from different patients in 5 sources: Cohen et al. [6], Chung [4], Chung [5], Radiological Society of North America [17], and Radiological Society of North America [18]

Evaluating criteria: F1 score, PPV(Precision), Sensitivity (Recall), Accuracy.

Decomposition

- We can not use our current image since the file extension is .mri, how can we handle this ?
- How to synthesize and balance dataset ?
- Split dataset into train set, test set, and valid set ?

- Resize the original image to put into the model
- How many epochs to stop training process ?
- How to save when our model is good while training?
- Can we tune the learning rate in training process ?

Decomposition
We do not use this step in this iteration.

Pattern recognition

Use VGG19 and ResNet50 pre-trained model on image net to reduce training time.

Abstraction

We do not have to worry about patient ID in our dataset since there is only a CXR image for each patient.

3.2.3 Iteration 3

Input: 1 CXR image
Output: the probability of that image is COVID-19, Pneumonia or normal.

Parameters and constraints:
the size of the input image is 224x224 at minimum, image and medical details are clear, sufficient, and non-eclipsed, CXR images have to be straight-forward, the maximum tilt for the image is a 10-degree angle at most and categorized by a specified diagnostic imaging doctor. We will not pay attention to the patient ID in our datasets.

Our input data has the extension as .jpg and there must be a combination between datasets.

Use deep learning to solve problems: ResNet50 or VGG19 to extract features (dependent on the features' quality), put them into a Fully Connected Neural Network to classify. Both ResNet50 and VGG19 will reuse the pre-trained model's weights to cut down on our training time.

The training set that is split from our dataset is also divided into 90% training set and 10% validation set. We have to check whether our dataset is imbalanced or not. If yes, then we

have to get rid of some redundant images to ensure 3 dataset's classes are balanced. We also need to resize our images with a corresponding size to our model. Let us define x, y, z as our hyper-parameters. If the loss on validation set is steady or increasing on x epochs, then our model will stop. Our learning rate will drop down an amount of y, if the loss on validation set stays stable or rises after z epoch. We would save our model when the loss is minimal on validation set.
Dataset: COVIDx dataset comprises of 20 000 images and labels from different patients in 5 sources: Cohen et al. [6], Chung [4], Chung [5], Radiological Society of North America [17], and Radiological Society of North America [18]

Evaluating criteria: F1 score, PPV(Precision), Sensitivity (Recall), Accuracy.

Decomposition
We do not use this step in this iteration

Pattern recognition
Use a given code on Github to combine dataset and change file extension.

Abstraction
We do not use this step in this iteration.

3.2.4 Iteration 4

Input: 1 CXR image
Output: the probability of that image is COVID-19, Pneumonia or normal.

Parameters, constraints
The size of the input image is 224x224 at minimum, image and medical details are clear, sufficient, and non-eclipsed, CXR images have to be straight-forward, the maximum tilt for the image is a 10-degree angle at most and categorized by a specified diagnostic imaging doctor. We will not pay attention to the patient ID in our datasets.

Our input data has the extension as .jpg and there must be a combination between datasets. This can be resolved using a given code on Github.

Use deep learning to solve problems: ResNet50 or VGG19 to extract features (dependent on the features' quality), put them into a Fully Connected Neural Network to classify. Both ResNet50 and VGG19 will reuse the pre-trained model's weights to cut down on our training

time.

The training set that is split from our dataset is also divided into 90% training set and 10% validation set. We have to check whether our dataset is imbalanced or not. If yes, then we have to get rid of some redundant images to ensure 3 dataset's classes are balanced. We also need to resize our images with a corresponding size to our model. Let us define x, y, z as our hyper-parameters. If the loss on validation set is steady or increasing on x epochs, then our model will stop. Our learning rate will drop down an amount of y, if the loss on validation set stays stable or rises after z epoch. We would save our model when the loss is minimal on validation set.

Dataset: COVIDx dataset comprises of 20 000 images and labels from different patients in 5 sources: Cohen et al. [6], Chung [4], Chung [5], Radiological Society of North America [17], and Radiological Society of North America [18]

Evaluating criteria: F1 score, PPV(Precision), Sensitivity (Recall), Accuracy.

Decomposition
We do not use this step in this iteration.

Pattern recognition
We do not use this step in this iteration.

Abstraction
We do not use this step in this iteration.
Moreover, we use Figure 1 to demonstrate the connection between a big problem with smaller ones, which is a result of decomposition step. Besides, we also use Figure 2 to illustrate our overall solution.

4 Methods

In this paper, we harness the power of two neural networks which are VGG19 [23] and ResNet50 [8]. Both network architectures are proved their productivity through real application. In addtion, we use COVIDx dataset - which is a widely used dataset in recent research about COVID-19 nowadays.

4.1 COVIDx Dataset

COVIDx Datset [27] is a dataset synthesized from many a different source, which are in details: Cohen et al. [6], Chung [4], Chung [5], Radiological Society of North America [17], and Radiological Society of North America [18]. Additionally, this dataset also provides an image extension transfer tool: from .mri into .jpg. And the author moreover provide a code to support data pre-processing and getting rid of unnecessary part for synthesized data.

The dataset consists of more than 20.000 CXR images from different patients and divided into 2 sets which are training set and testing set. They are also separated into 3 classes which are pneumonia (train: 5963, test: 105), COVID-19 (train: 4649, test: 274) and the healthy (train: 8751, test: 100).

Our model will get an input of one CXR image and will give out an output as the probability of that image falling into each class which is pneumonia, COVID-19 and healthy, respectively.

4.2 Detailed implementation

Both deep learning neural network we proposed which are VGG19 and ResNet50 are all pre-trained on ImageNet [7]. Afterwards, we proceed training process on COVIDx dataset with Adam as the optimization algorithm and the learning rate's strategy as reducing if the loss on validation set does not improve at all in a long period (patience).

With VGG19, the hyper-parameters using for training are learning rate = 5e-4, epoch numbers = 13, batch size = 32, factor = 0.1, patience = 3 and the resolution for input image is 480x480.

Meanwhile with Resnet50, we proceed the training into 2 separated times:

- Hyper-parameters for the first time are learning rate = 5e-4, epoch numbers = 14, batch size = 32, factor = 0.1, patience = 3 and input image's resolution is 224x224.
- Hyper-parameters for the second time are learning rate = 5e-3, epoch numbers = 50, batch size = 32, factor = 0.1, patience = 3, input image's resolution is 224x224.

Besides, we also cut down on some image in pneumonia and normal class to ensure the balance among numbers of images of 3 classes. This project of us is constructed and evaluated primarily based on Keras deep learning library and Tensorflow framework. You can review our method which is published on Github vokhanhan25 or ngctnnnn.

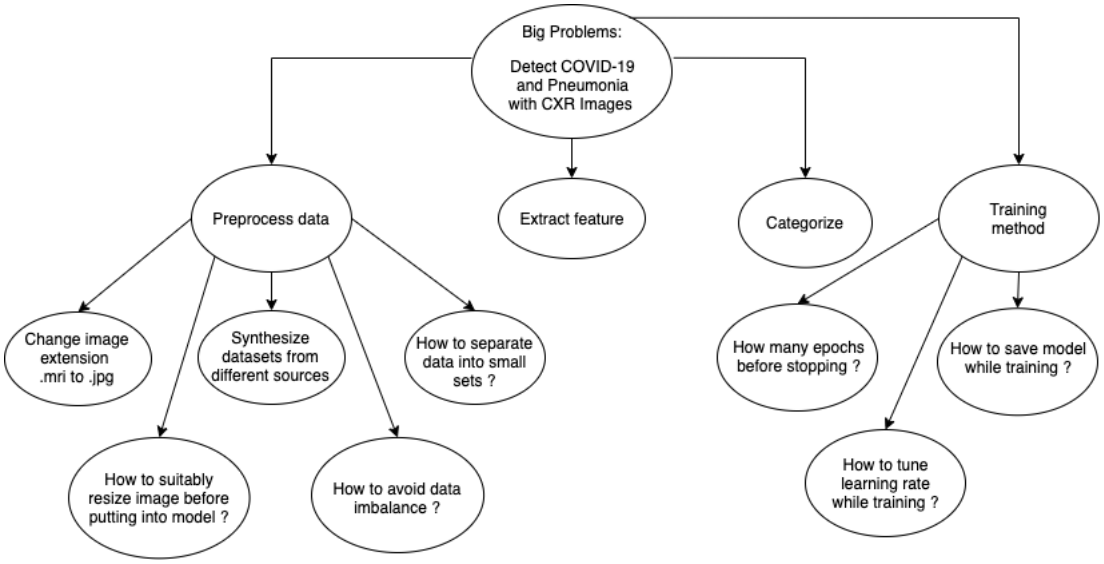

Figure 1: Hierarchical structure

	Precision	Recall	F1-score	Support
COVID-19	0.97	0.67	0.79	274
Normal	0.56	0.96	0.71	100
Pneumonia	0.74	0.85	0.79	105

Table 1: Results on ResNet50 (14 epochs)

	Precision	Recall	F1-score	Support
COVID-19	0.96	0.80	0.88	274
Normal	0.73	0.86	0.79	100
Pneumonia	0.71	0.90	0.79	105

Table 2: Results on ResNet50 (50 epochs)

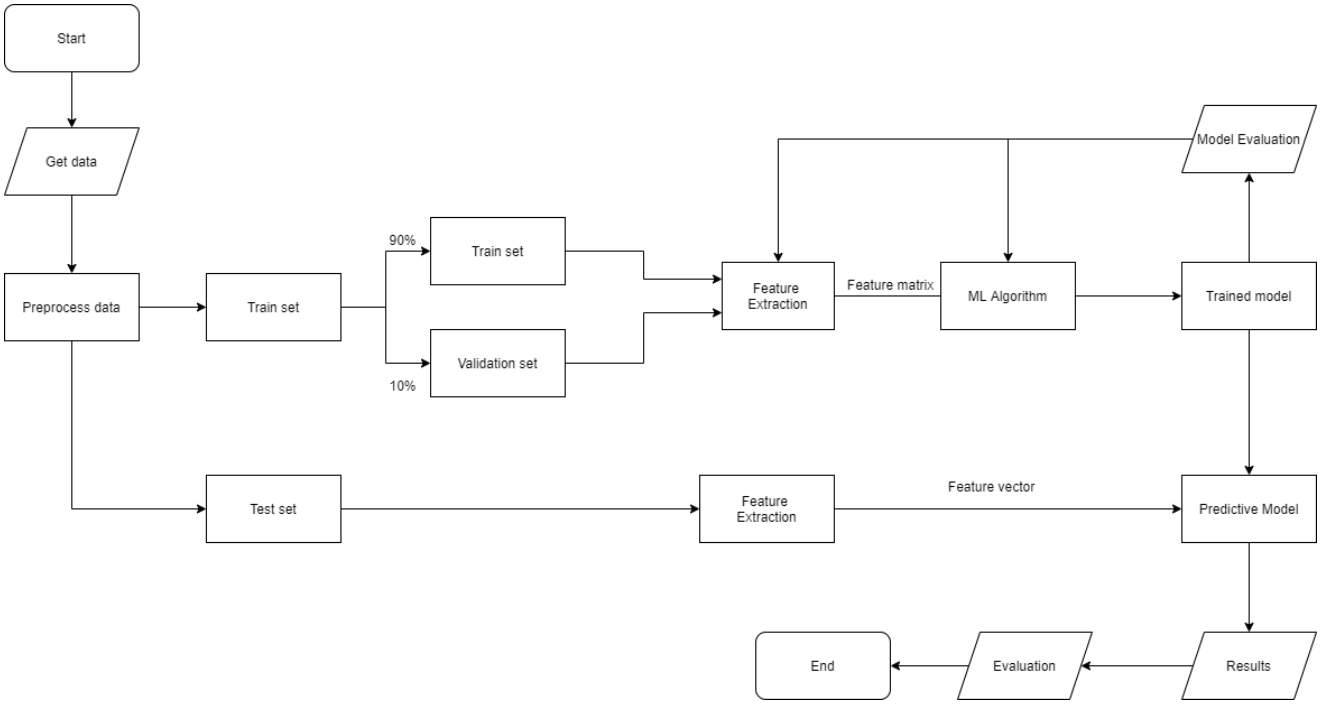

Figure 2: Overall solution's flow chart

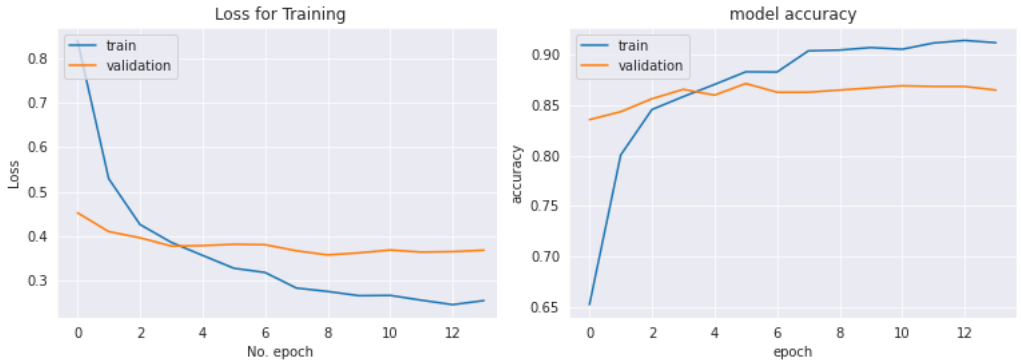

Figure 3: Loss for training of ResNet50 (14 epochs)

Figure 4: Model accuracy of ResNet50 (14 epochs)

Figure 5: Loss for training of ResNet50 (50 epochs)

Figure 6: Model accuracy of ResNet50 (50 epochs)

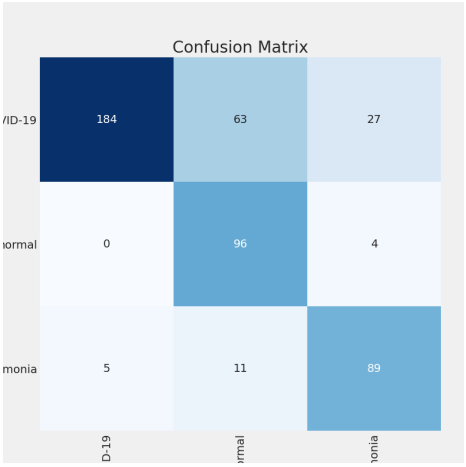

Figure 7: Confusion matrix of ResNet50 (14 epochs)

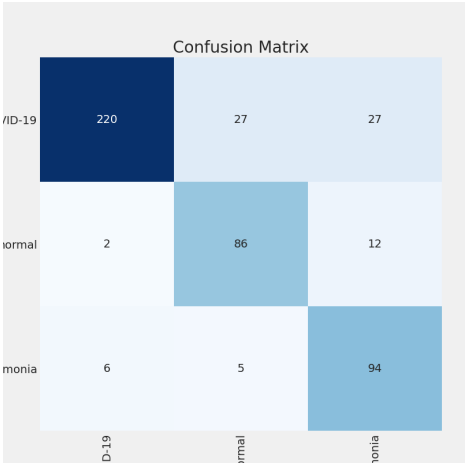

Figure 8: Confusion matrix of ResNet50 (50 epochs)

	Precision	Recall	F1-score	Support
COVID-19	0.99	0.82	0.90	274
Normal	0.7	0.96	0.81	100
Pneumonia	0.8	0.86	0.83	105

Table 3: Results on VGG19

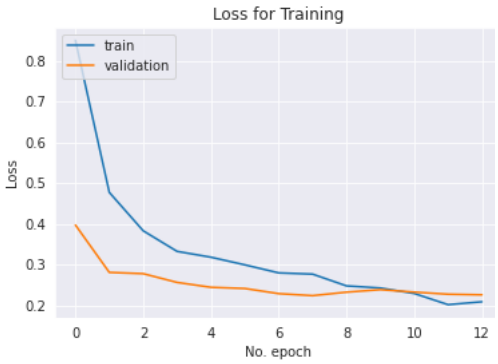

Figure 9: Loss for training of VGG19

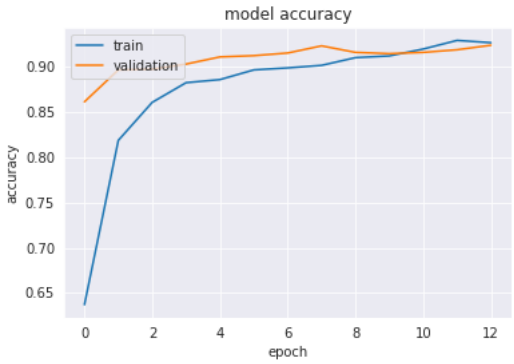

Figure 10: Model accuracy of VGG19

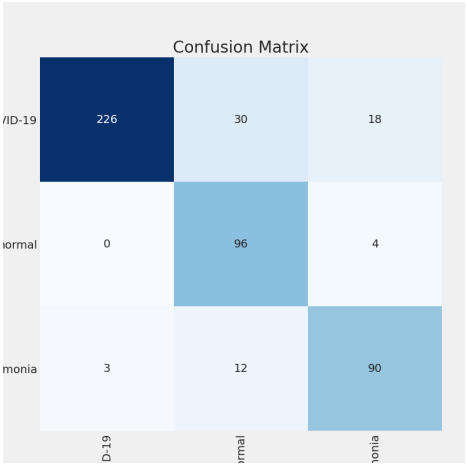

Figure 11: Confusion matrix of VGG19

5 Experimental results and evaluation

We provided a demo video for the experiment.

As observing at Figure 9 and Figure 10, we can see that VGG19 achieved a relatively good result in the early time which is more than 90% in around epoch 2 and epoch 3. After that, it slowly increased its result to 92% and stopped increased until early convergence in epoch

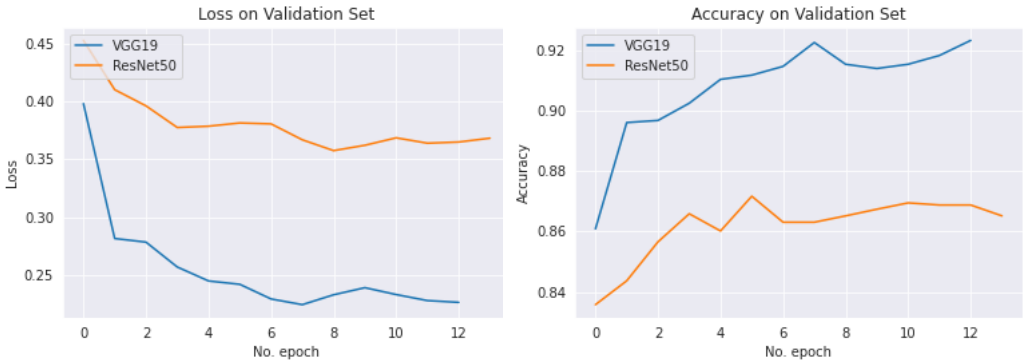

Figure 12: Comparison between ResNet50 and VGG19 on Validation set

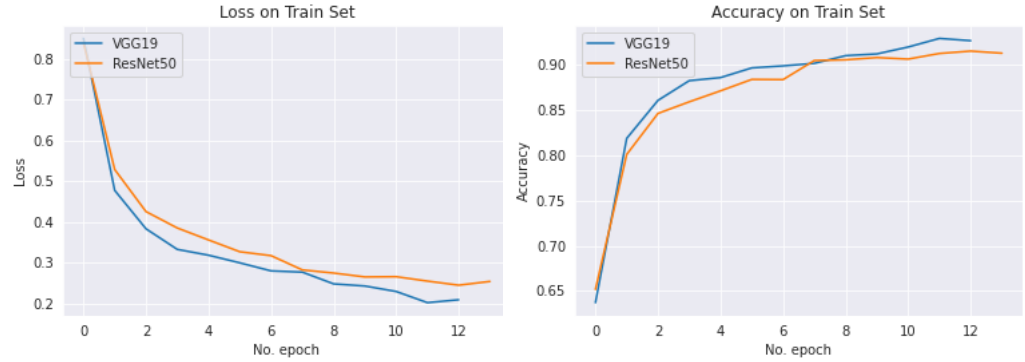

Figure 13: Comparison between ResNet50 and VGG19 on Train set

12. We can figure out that the diagonal on VGG19's confusion matrix (Figure 11) is pretty impressive. However, in Table 3, it sometimes take the wrong way in which most of its misclassifying are COVID-19 patients and the healthy. This also means that it would achieve an almost absolute precision once it identifies the patient as COVID-19.

ResNet50's result, on the other hand, falls short of our expectation. Despite the fact that researches consider ResNet is better than VGG19 in many a conclusion since ResNet allows

Architectures	Number of parameters (M.)	Accuracy	Resolution
VGG19 [27]	20.37	83%	
VGG19	29.76 trainable + 20.25 non-trainable	86%	480 x 480
ResNet50 [27]	24.97	90.6%	
ResNet50 (14 epochs)	25.93 trainable + 23.77 non-trainable	77%	224 x 224
ResNet50 (50 epochs)	25.93 trainable + 23.77 non-trainable	84%	224 x 224
COVID-net [27]	11.75	93.3%	480 x 480

Table 4: Comparison between precision and number of parameters among models

Architectures	Non-respiratory disease	Pneumonia	COVID-19
VGG19 (Wang et al.,2020)	98%	90%	58.7%
VGG19	96%	86%	82%
ResNet50 (Wang et al.,2020)	97%	92%	83%
ResNet50 (14 epochs)	96%	85%	67%
ResNet50 (50 epochs)	86%	90%	80%
COVID-net (Wang et al.,2020)	95%	94%	91%

Table 5: Comparison among models based on sensitivity

Architectures	Non-respiratory disease	Pneumonia	COVID-19
VGG19 (Wang et al.,2020)	83.1%	75%	98.4%
VGG19	70%	80%	99%
ResNet50 (Wang et al.,2020)	88.2%	86.8%	98.8%
ResNet50 (14 epochs)	56%	74%	97%
ResNet50 (50 epochs)	73%	71%	96%
COVID-net (Wang et al.,2020)	90.5%	91.3%	98.9%

Table 6: Comparison among models based on PPV

us to train in a more effectively way on a big neural network with more parameters and with a deeper network, ResNet in this paper does not reflect that fact. As in Figure 4 and Figure 3, loss and accuracy converged pretty soon which is about 85% then it crossed over a plateau and then early stopping. As we observe Figure 7 about ResNet's confusion matrix, we

are acknowledged that our model confuses a lot about COVID-19 patients with the healthy. This is a surprising news as we tend to be afraid our model might be bewildered about the COVID-19 and the pneumonia instead of the healthy. As in the Table 1, we could witness that ResNet only has the accuracy of 77% and it drops a large number of real COVID-19 cases (this is easily proved through the recall ratio of 67% on COVID-19 class).

It was due to the bad result at ResNet50 that we came into decision of tuning some parameters, e.g. patience, learning rate, early stopping and epoch. This accidentally leads to a mess in Figure 5 and Figure 6. After that, as we brought the best model on validation set to run on test set, we were surprised by the results: the result on validation set is pretty the same as the last training step, the accuracy, however, increased up to 84% - which is 7% higher than previous result. Our ResNet are no longer bewildered from COVID-19 to the healthy as the previous one anymore. Besides, results on Table 2 also show that other results are all above 70% which is an acceptable level. And the best thing is that it misses just a few pneumonia patients (which achieves the recall ratio of 90% on pneumonia class).

In order to evaluate the quality of our models, we applied some evaluating method, e.g. precision, positive predictive value (PPV), sensitivity and F1-socre. As shown in Table 4, the precision of our VGG19 model is 86%, this result is better than Wang et al. 2020 3%. On the contrary, our ResNet50 has a poor performance, this can be understood since the resolution of our input image is just 224x224 instead of 480x480 which is due to hardware's limitation.

Next, we proceed comparision based on sensitivity. Our VGG19 has surpassed the VGG of Wang et al. 2020 on this scale. In addition, other numbers in this table on our ResNet50 (epoch) and VGG19 also get a flying color result, which are all above 80%. Achieving such a high sensitivity result is the top importance as considering that this model drops out few patients on each classes as well as we do not want an accurate model but still missing out COVID-19 cases in the present pandemic worldwide.
We also found an impressive result on PPV scale, which shows that our VGG19 model did achieve the best productivity among the results at Table 6. In contrast, the results from ResNet50 and VGG19 on other class are just at an acceptable level, from 70%.

6 Improvement

In order to raise persuasiveness into real-life application, we are about to conduct the problem of identifying objects. Drawing bounding boxes would help our model to be more trustworthy once we could point out which parts of patients' lungs are abnormal.

In addition, there is many a patient who, although, catches COVID-19, there is no typical symptoms for this disease. Categorizing those who have no typical symptoms into a same class with those who have typical ones might make our model be less accurate and be easier to mis-classify from those who are healthy. Thus, we would split COVID-19 patients into 2 separated classes: typical symptoms and atypical ones.

Moreoever, to increase the accuracy, we also exploit other information from patients, e.g. age, gender, race, weight, or even epidemiological characteristics and clinical manifestations. Those additional information would help us a lot into sorting out COVID-19 patients.

7 Conclusion

In this project, we did conduct classify Chest X-ray images into 3 classes which are COVID-19, pneumonia and non-respiratory disease via the use of VGG19 and ResNet50. The result shows that using VGG19 could help us to find a positive result and we could apply this model into pandemic situation nowadays.

8 Project assignment

An Vo	**Tan Ngoc Pham**
Solution designing	Report writing
Solution implementing	Demo building
Solution evaluating and comparing	Data pre-processing
Graphic Organizer and flowchart designing	Hierarchical structure designing

Biography

An Vo

An Vo graduated in 2019 at Phan Ngoc Hien High school for the gifted, Ca Mau province, specified for Mathematics - Informatics. From 2019, he has been studying at University of Information Technology, Vietnam National University HCMC, faculty of Computer Science, class of KHCL2019.1.

He received several prizes at provincial, Southern and National Olympics in Informatics. Besides, he has also achieved himself three scholarships from Office of Student Affairs, UIT - VNU HCM and two scholarships from Office of Excellent Programs, UIT - VNU HCM.

Tan Ngoc Pham

Tan Ngoc Pham graduated in 2019 at Nguyen Du High school for the gifted, Dak Lak province, specified for English. From 2019, he has been studying at University of Information Technology, Vietnam National University HCMC, faculty of Computer Science, class of KHCL2019.2.

He received several prizes at provincial and National Olympics in English and second prize in the National Olympics in English is among the top prizes of him.

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