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| PREDICTING COVID-19 STATUS FROM CHEST X-RAY IMAGES |
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| **IFN 646 – BIOMEDICAL DATA SCIENCES** |

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## I. INTRODUCTION

In December 2019, a new virus known as “2019 novel corona-virus” or “Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)” that has been firstly identified from Wuhan, China and its infectious disease is called COVID-19. Until 14th October 2020, more than 37.7 billion confirmed cases have been results in 235 countries, areas and territories according to announcement of WHO (2020).Currently, early symptom diagnosing is highly importance to self-isolate the suspected people and decrease the risk of spreading to public community’s health due to lack of specific treatment or vaccine for this virus.

In many countries, to detect suspected COVID-19 individuals, governments have applied reverse transcriptase–polymerase chain reaction (RT-PCR) or collecting pharyngeal swabs or blood specimens to detect people who is suspected as positive with COVID-19 (Wang et al., 2020). According to Department of Heath of Australia Government (2020),it may take 1 or 2 days to get the results of PCR and while people is waiting for their testing result, they need to perform self-isolation at home. Compared to chest radiography, X-Ray imaging is a method which is easy to apply and fast diagnosis for pneumonia. In the research of Kanne et al. (2020), the author reported that radiography images are able to visualize the correlation with COVID-19. The symptoms of COVID-19 are reported to be as following, ground-glass (57%) and mixed attenuation (29%) (Kong and Agarwal as cited in Minaee et al., 2020), the pulmonary vessels are edged by ground glass pattern make it becomes more difficult to appreciate visually reported in the research of Feng et al. (2016). In addition, Asymmetric patchy or diffuse airspace opacities are also reported for COVID-19 (Rodrigues et al., 2020). These abnormalities are only be observed by expert radiologists. However, the ratio between trained radiologists and suspected cases is imbalance and with the number of suspected cases continues to increase, an automatic method for identification of such subtle abnormalities to assist with diagnosis is crucial. Therefore, Artificial Intelligence (AI) solutions are promising methods which are significant for solving such problems.

The pandemic that caused by COVID-19 has raised an alarm to the way people react to diseases and viruses. Although machine learning was applied to support medical image classification, this traditional approach was not powerful enough to win against the race of detecting COVID-19 amid the escalation of the epidemic. Thus, instead of following a two-step procedure including feature extraction and recognition, we use an end-to-end deep learning framework. The approach will directly predict the COVID-19 based on raw X-Ray images of lungs without requiring feature extraction. Deep learning model, or more specifically Convolutional Neural Networks (CNN) have been proved that outstrip traditional AI approaches in the field of computer vision in recent years, and have been applied widely to solve various problems, such as classification, segmentation, face recognition and image enhancement (Bhosle et al., 2018; Li et al., 2018).

Additionally, we adopt the approach of training traditional Convolutional Neural Network on COVID-19 dataset of Wang et al. (2020), and evaluate the performance of models on predicting COVID-19 detection. However, since the medical images of COVID-19 are not widely published, there is a limited number of available publicity images. We collected and prepared a dataset of around more than 2,000 images (using images from two datasets). In addition, we performed a detail experimental analysis evaluating the performance of the model in different approaches. Thus, in order to improve and measure the performance of COVID-19 detection experiment, we apply 2 following strategies*:*

* We apply different techniques to transform the images in the effort of data augmentation, such as flipping and small rotation, to increase the number of samples.
* We also calculate the confidence interval of the performance metrics on the respective models. In addition, we provide Area Under the Curve (AUC) to summarize the performance of models in our report.

The data availability including codes and dataset are now published on Git (<https://github.com/ifn-646/x_ray_project>)

## II. COVID-19 X-ray DATASET

The COVID-19 X-ray dataset consists of chest X-rays from two datasets:

1. **Covid-19 Radiography Dataset (dataset A)** which contains a total of 219 Covid-19 Positive images and 1341 Covid-19 Negative test images are separated in two labelled folders.

2. Another dataset is the **Covid-Chest Xray-Dataset (dataset B)**, which was recently published and is comprised of a set of images from published sources regarding COVID-19 topics collected by <https://github.com/ieee8023/covid-chestxray-dataset> , Cohen et al. (2020). This dataset is compiled of a blend of CT images along with chest X-rays (Figure 1.1).

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***Figure 1.1. X-ray and CT Scan Proportion***

This pool of data is unceasingly updated, and meta-data such as age, findings, sex, survival and hospitalization status are also recorded. Part of the COVID-19 images used for this project contains the images that derived from this dataset. We have only kept the PA view images for COVID-19 prediction (Figure 1.2).

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***Figure 1.2. Views of Recorded Images***

The resolution should be mentioned regarding this dataset, as it varies widely. The lower-resolution COVID-19 images are below 400 x 400, while some of the higher ones are exceeding 1900 x 1400. The models produce accurate results regardless of this disparity in image quality. Although exceptional image quality should be strived for, it is a focus in the machine learning realm to create systems that are able to operate well regardless of differing image qualities. The dynamic ranges also differ as they are images collected from various providers. These images are indeed normalized to decrease model confusion.

## III. PROPOSED FRAMEWORK

*This project is to classify whether the given image belongs to the positive or negative class, Convolutional Neural Network with Tensorflow Keras is the main method that we applied.*

1. **Model:**

According to Lecun, Bottou, Bengio and Haffner ( 1998), Convolutional neural network is a class of deep learning, this learning algorithm builds a model with multi-layer neural networks which can learn major and relevant feature for images to deal diversity piece of works such as, detection, segmentation and classification.

In general, after receiving data from the post-processing step, these data will be passed through 4 layers of the CNN machine learning model with the first layer of data compression and the next 3 layers of convolution and this model used activation fuctions as “relu”. Finally the result is a possibility that could be close to the positive or negative class.

Diagram

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***Figure 2.1 Convolutional neural network model for Covid-19 prediction***

Figures 2.2 below shows the process in detail. All of image crossing through Rescalling layer will be converted to image with 256 pixels.

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***Figure 2.2 Model convolutional layer of chest X-ray images.***

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***Figure 2.3. Max-pooling layer***

*Maxpooling layer bases on the feature map to calculate the largest, maximum or value in each patch of each feature map.*

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***Figure 2.4. Rectified Linear Unit (ReLU)***

*Finally, “relu” the activation function is a non-linear function will calculate on the Maxpooling layer’s results whether it is positive or negative.*

## EXPERIMENTS & RESULTS

We have approached in 2 ways and we have trained each approach for 10 epochs. We apply all images into neural network with their size down sampled to 180x180.

* 1. **Data Split on dataset A**

In this approach, we have chosen only dataset A for training and testing. Figure 3.1 shows the first approach which splits 80% dataset for training data and the 20% for test with validation\_split by 0.2. This figure also indicates the results of model following the data split.

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***Figure 3.1. 80-20 Split and results of 10 epochs***

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***Figure 3.2. Training and Validation Accuracy/Loss***

The left graph of figure 3.2 illustrates that the model is not overfitting. However, it also shows Train and Validation accuracy are doubted high, targeting to 100%, which is thing we are very suspected. We have recognised that because we stored all dataset in one folder, then split it through the code which leads to the risk that model has gone through and memorized all of pictures in the dataset after it ran about 10 epochs.

* 1. **Applying both dataset A and dataset B into the model**

Another approach was chosen to avoid the issue addressed above. We set Train dataset on dataset A and Test dataset on dataset B.

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***Figure 3.2. New model with 2 separated datasets***

Figure 3.2 details new approach in our model without data split 80-20, instead of that, we feed the model with the train and test data separately from two folders. Eventually, we plot the results (Figure 3.3) below:

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***Figure 3.3. Training and Validation Accuracy/Loss***

Figure 3.3 indicates that model is overfitting as there is a significant gap between Training Accuracy and Validation Accuracy.

* 1. **Data augmentation :**

Recognizing the overfitting showed above, data augmentation was applied which rotated the image with different directions but same class with the original. The purpose of this step is making a larger of dataset and avoid the possibility that the model could learn too well in the training dataset but performed poorly in validation dataset.

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***Figure 3.4. Sample of data augmentation.***

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***Figure 3.5. Training and Validation Accuracy/Loss***

Figure 3.5 unexpectedly shows that the model is still strongly overfitting and there is no improvement on validation accuracy.

## CONCLUSION

We demonstrated a machine learning model for COVID-19 detection from Chest X-ray images, by Convolutional Neural Network (CNN) on training set. Over 2,000 images were collected from 2 datasets and prepared as main dataset in this project. Then, we experimented a detail analysis to evaluate the performance of learning model by different approaches. Based on the results, the models achieved a specificity rate of around 55% on average. It can be seen that the model has low capability of COVID-19 detection from radiography.

Although the results did not meet the team’s expectation, it is reasonable firstly due to the lack of publicity available images that could be considered as a limitation. Secondly, the unbalanced input dataset which consisted of 400 COVID-19 images and 2,000 images of negative patients, would be another considerable limitation that could affect the quality of model. Importantly, even though there are significant abnormalities been recognized by radiologist in Covid-19 Positive X-ray images such as ground-glass, mixed attenuation, asymmetric patchy or diffuse airspace opacities, however, it’s apparently still at early stage of saying it happens in all positive cases from medical point of view. In saying this, we are not sure that all actual 400 positive Xray images that we used to feed the model contain these abnormalities to expect the good learning performance of the model.

In conclusion, due to the limited number of COVID-19 images publicly available so far, and due to the simple applied framework, further experiments are needed on a larger set of cleanly labelled COVID-19 images and more advanced machine learning model need to be applied for a more reliable estimation of the accuracy.

## REFERENCES

Bhosle, V., Supriya, S., Sowmya, M., Subramani, V., & Shruthi, G. (2018). Face Recognition with 2D-Convolutional Neural Network. *International Journal of Advanced Research in Computer Science, 9*(Special Issue 3), 373-377. <https://doi.org/10.26483/ijarcs.v9i0.6271>

Feng, Z.-M., Zhuang, Z.-J., He, W.-B., Ding, J.-P., Yang, W.-J., & Chen, X.-Y. (2016). Lung Cancer with Diffuse Ground-glass Shadow in Two Lungs and Respiratory Failure. *Chinese Medical Journal, 129*(15). <https://doi.org/10.4103/0366-6999.186632>

Department of Heath of Australia Government. (2020). *What you need to know about coronavirus (COVID-19)*. <https://www.health.gov.au/news/health-alerts/novel-coronavirus-2019-ncov-health-alert/what-you-need-to-know-about-coronavirus-covid-19>

Kanne, J. P., Little, B. P., Chung, J. H., Elicker, B. M., & Ketai, L. H. (2020). Essentials for Radiologists on COVID-19: An Update- Scientific Expert Panel. *Radiology, 296*(2), E113. <https://doi.org/10.1148/radiol.2020200527>

Li, C., Guo, J., Porikli, F., & Pang, Y. (2018). LightenNet: A Convolutional Neural Network for weakly illuminated image enhancement. *Pattern recognition letters, 104*, 15-22. <https://doi.org/10.1016/j.patrec.2018.01.010>

Li, H., Jiang, G., Zhang, J., Wang, R., Wang, Z., Zheng, W.-S., & Menze, B. (2018). Fully convolutional network ensembles for white matter hyperintensities segmentation in MR images. *NeuroImage (Orlando, Fla.), 183*, 650-665. <https://doi.org/10.1016/j.neuroimage.2018.07.005>

Minaee, S., Kafieh, R., Sonka, M., Yazdani, S., & Jamalipour Soufi, G. (2020). Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning. *Medical image analysis, 65*. <https://doi.org/10.1016/j.media.2020.101794>

Rodrigues, J. C. L., Hare, S. S., Edey, A., Devaraj, A., Jacob, J., Johnstone, A., McStay, R., Nair, A., & Robinson, G. (2020). An update on COVID-19 for the radiologist - A British society of Thoracic Imaging statement. *Clinical radiology, 75*(5), 323-325. <https://doi.org/10.1016/j.crad.2020.03.003>

Wang, L., & Wong, A. (2020). COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images. *arXiv.org*.

Wang, W., Xu, Y., Gao, R., Lu, R., Han, K., Wu, G., & Tan, W. (2020). Detection of SARS-CoV-2 in Different Types of Clinical Specimens. *JAMA : the journal of the American Medical Association, 323*(18), 1843-1844. <https://doi.org/10.1001/jama.2020.3786>

WHO. (2020). *Coronavirus disease (COVID-19) pandemic*. <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>

## APPENDIX

CODE CAPTURES:

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=> This code was used to separate Positive and Negative images from raw dataset.

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