AMERICAN UNIVERSITY OF BEIRUT

ON THE USABILITY OF DEEP LEARNING ALGOTIRTHMS IN DETECTING COVID-19 BASED ON X-RAYS

by
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ABSTRACT

OF THE PROJECT OF

Hassane Mohamad Ezzeddine for Master of Science
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Title: On the Usability of Deep Learning Algorithms in Detecting COVID-19 Based On X-Rays

SARS-COV-2 is a new strain of virus that was first detected in China. It quickly spread across the world affecting millions of people. The WHO declared the new disease as a global pandemic on Jan 30, 2020. The virus is very contagious with an estimated R0 (R-naught or R-Zero) average of 3.28, meaning that each infected person will infect on the average 3.28 persons. For this reason, early detection of the virus is mandatory in order to limit the spread of the virus. Real-time reverse transcription polymerase chain reaction (RT-PCR) and the antibody test are the main tests used to detect the virus. Chest X-rays (CXRs) and computerized tomography (CT) scans are also used to detect the virus although the American college of Radiology does not recommend using medical imaging as a diagnostic tool. Like other medical imaging, convolutional neural networks are used to classify the images. We believe that developing a model to detect COVID-19 has no clinical value regardless of the accuracy achieved since 58% of CXRs seem to be normal. During literature review, several papers with suspicious accuracy of 90% and higher were found. We believe that the dataset used to train and validate the network is not appropriate for deep learning as any model we train using the same dataset has achieved high accuracy. Our experiments on Cohen's Covid dataset, augmented with Wang dataset, shows that any model trained on Cohen dataset can easily achieve high accuracy while two experienced radiologists who participated in this study were only able to classify 60% as being Covid. Our study highlight the importance of developing more robust ML models based on well curated data.

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CHAPTER I

INTRODUCTION

Coronavirus disease 2019, also known as Covid-19, was originally discovered in Wuhan, China, on December 2019 and has spread ever since throughout the world. The sickness is caused by a virus from the coronavirus family. This family of viruses includes those that have produced outbreaks in the last 20 years, such as severe acute respiratory syndrome (SARS) and Middle East respiratory disease (MERS). The World Health Organization (WHO) proclaimed the current outbreak a worldwide pandemic on January 30, 2020, after findings of human-to-human transmission outside of China. This outbreak, according to the WHO, is a Public Health Emergency of International Concern (PHEIC). The WHO also awarded the coronavirus disease its official name, COVID-19, on February 11, 2020.

Fever, a dry cough, and exhaustion are all signs of COVID-19. Body soreness, nasal congestion, headache, sore throat, and loss of taste or smell are some of the less prevalent symptoms. It is expected that 80 percent of infected patients will not require hospitalization, but the other 20 percent may become critically ill. People over the age of 65 and those with a medical condition are at a higher risk. The mortality rate is anticipated to be around 3 to 4 percent. We had approximately 8 million verified cases and an average of 430.000 deaths on June 15, 2020.

COVID-19 must be detected as soon as possible in order to prevent the virus from spreading. The real-time reverse transcription-polymerase chain reaction (RT-PCR) and the antibody test are currently the most widely utilized detection methods. The virus can be detected by RT-PCR even before symptoms appear, whereas the antibody test can only detect the virus in the middle and late stages of the disease. The antibody test is beneficial for identifying the spread of the illness among the population. Chest imaging can also be used to detect the virus early. Fang et al. found out that computed tomography’ sensitivity (CT's sensitivity) can bypass the sensitivity of the RT-PCR by a wide margin (98% vs. 71%). His findings support the use of CT for patients with suspected coronavirus symptoms when RT-PCR result is negative.

COVID-19 can be detected via chest x-rays (CXRs). However, CXRs, on the other hand, are not as effective as CT in detecting the disease. Weinstock et al. looked at 636 CXRs from patients who had been diagnosed with the virus and discovered that 58 percent of them had a normal chest x-ray and 89 percent had a somewhat abnormal chest x-ray. The CXR has a sensitivity of 69 percent compared to 91 percent for the RT-PCR, according to Wong et al. His study, however, was limited to 64 patients and 255 CXRs.

To the best of our knowledge, Shih-Chung et al. were the first to employ a convolutional neural network (CNN) to diagnose lung nodules in 1993. These procedures did not become popular until computing power and medical imaging became more widely available. Indeed, deep learning models for mammograms, histopathological pictures, MRI, CT, ultrasound, and X-rays are currently accessible. Convolutional neural networks (CNN) were among the most successful image analysis models. CNNs require a large number of images for training in order to produce good results. Unfortunately, medical imaging is limited and difficult to obtain. To address this issue, the concept of "transfer learning" which is the use of a previously trained network as a feature extractor to overcome the scarcity of medical pictures, must be applied.

We believe that many published models that were developed to detect COVID-19 have no clinical value regardless of the accuracy achieved. We believe that the dataset used to train and validate the network is not appropriate for deep learning. We trained few models using the same dataset and achieved high accuracy. More specifically, our experiments on Cohen’s Covid dataset, augmented with Wang dataset, demonstrated that any model trained on Cohen dataset can easily achieve high accuracy in contrast with the opinion of two expert radiologists.

This project includes a radiologists’ feedback, which supports the credibility of the project. In addition, experiments have been conducted in order to test the best method for COVID-19 detection and that with the highest accuracy. A discussion that summarizes all our experiment-based findings followed.

The remaining of this report is organized as follows: Chapter II surveys existing solutions related to Covid-19 detection and classification in the literature. In this chapter, we focus on the different models available and the dataset used for Covid-19. In chapter III, we present our own hypothesis regarding the high accuracy found in the literature. In chapter IV, we go over the Covid-19 dataset used with two fellow radiologists from AUBMC. Chapter V presents our evaluation process and experiments of the dataset compared to other work. Finally, chapter VI concludes this project and presents recommendations for future work.

CHAPTER II

RELATED WORK

Whether CXRs are efficient in detecting COVID-19 or not is still debatable, and this debate puts doubt on the utility of deep learning models. This article, however, will concentrate on the usage of CXRs to identify COVID-19. The machine learning community was mobilized to develop solutions when the COVID-19 sickness first appeared. The most significant impediment found was obtaining relevant and trustworthy data. The American College of Radiology (ACR), however, does not advocate using CXR or CT for suspected COVID-19 infection because CXR results are not specific to COVID-19 and may overlap with other viruses such H1N1, SARS, and MERS.

Table.1 below summarizes most of the research and models used to detect Covid-19.

All of the models used have been pre-trained on ImageNet, a database of over 15 million photos and over 22000 categories. Training is often performed on a subset of ImageNet that includes 1.2 million copies for training, 50,000 photos for validation, and 150,000 images for testing

Author	COVID-19	None COVID	Model used	Accuracy
J Zhang et al. [2020]	Cohen Dataset-100 images	Wang et al. 1008 pneumonia images	18 layers ResNet	95%
A Narin et al. [2021]	Cohen Dataset -50 images	Kaggle pneumonia dataset-50 images	ResNet50 InceptionV3 InceptionResnetV2	98% 97% 87%
A Abbas et al. [2021]	Cohen Dataset - 105 images	80 normal CXR	DeTraC	95%

Hemdan et al. [2020]	Cohen Dataset -25 images	Cohen Dataset -25 normal images	VGG19 DenseNet201 ResnetV2 InceptionV3 InceptionResNetV2 Xception MobileNetV2	90% 90% 70% 50% 80% 80% 60%
Wang et al. [2020]	Cohen Dataset ActualMed COVID-19	RSNA Pneumonia Detection Challenge dataset	VGG19 ResNet50 Covid-Net	83% 90.6% 93.3%
Ozturk et al. [2020]	Cohen Dataset-127 images	Wang et al. 500 pneumonia images, 500 no finding	DarkCovidNet	87% (3 classes) 98% (2 classes)
Ismail et al.[2021]	Cohen Dataset - 180 images	200 healthy X-rays, source not mentioned	VGG16 ResNet18 ResNet50 ResNet101 VGG19	85.26% 88.42% 92.63% 87.37% 89.47%
Jain et al.[2021]	Cohen Dataset-490 imGES	Kaggle Pneumonia dtaset:1345 healthy, 3632 pneumonia	ResNeXt Inception V3 Xception	90% 95%
Luz et al.[2021]	Cohen dataset 183 images	Wang et al. dataset	EfficientNet B3-X	93.9%
Shankar et al.[2021]	Cohen dataset 220 images	Cohen dataset 27 images	Custom model FM-HCF-DLF	94.08%
Karakanis et al.[2021]	Cohen dataset 50 images	Kaggle pneumonia dataset	ResNet8	98%
Hussain et al.[2021]	Cohen dataset 500 *multiple datasets from same source	Kaggle pneumonia dataset	Custom model CoroDet	2 classes: 99.1% 3 classes: 94.2% 4 classes: 91.2%
Gupta et al.	Cohen dataset 250 *multiple datasets from same source	Kaggle pneumonia dataset	Custom model InstaCovNet-19	2 classes: 99.53% 3 classes: 99.08%

Table. 1. Current Work on Covid-19 and deep learning.

The models are enormous and require a lot of processing power to be trained. As an example, AlexNet has 60 million parameters, 650,000 neurons, and 5 convolutional layers. Figure (1) below shows a summary of CNNs while figure (2) shows a comparison between different models' size and their accuracy. The X-axis represents the model name along with the number of parameters in increasing order, while the Y-axis represents top-1 and top-5 accuracy. Top-1 accuracy denotes the correct answer as the projected output with the highest probability, whereas top-5 accuracy denotes the correct answer as being among the top five projected answers. Except EfficientNet, which achieved great accuracy with a relatively limited number of parameters, accuracy typically increases as the model grows larger and deeper.

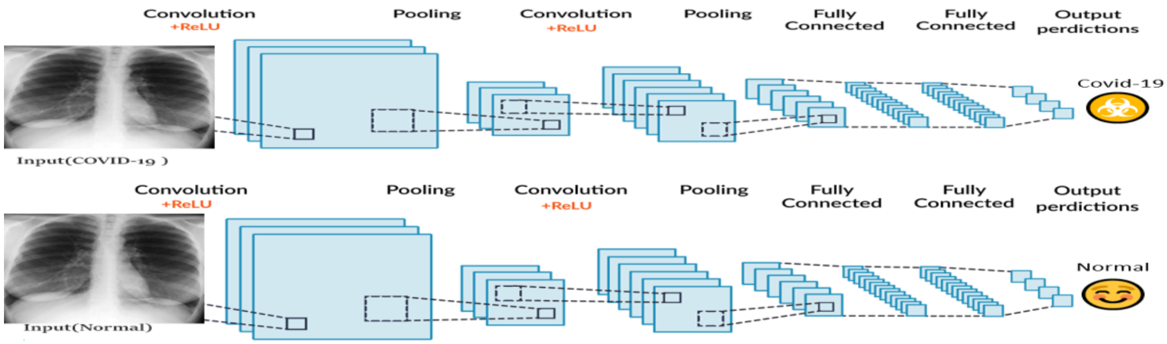


Fig. 1. Visual representation for a convolution neural network workflow applied to Xray

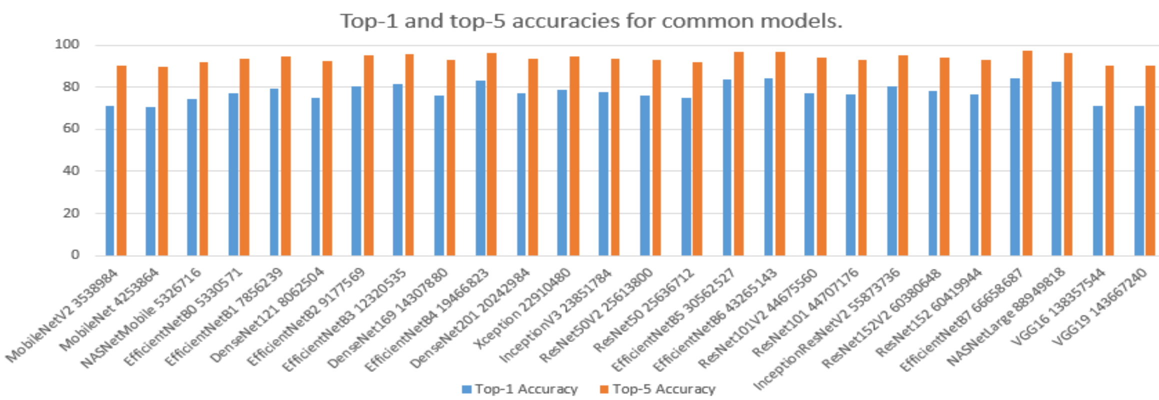


Fig.2. Top-1 and top-5 accuracy on ImageNet shown by increasing order of number of parameters.

The Cohen dataset utilized for positive COVID-19 patients and the great accuracy in almost all of the models are the connecting threads throughout the many studies. This should allow us to question either the training data or the outcomes. Dr. Cohen attempted to construct a dataset for COVID-19 CXRs using existing literature and websites. The image resolution varies between 255X237 to 4298X4300, with an average resolution of 1370X1254. Before feeding the photos to the model, they were all normalized. JPG, PNG, and JPEG are some of the picture extensions.

CHAPTER III

PROPOSED HYPOTHESIS

As mentioned in the previous chapter, the photos were not acquired directly from the DICOM files, the quality of the photos most likely decreased throughout the copying process. We suspect that using photos from this dataset is causing problems. We can observe that regardless of the network chosen, it produces good results. We suspect that the model is recognizing photos from this dataset rather than the other dataset and not identifying COVID-19 CXR characteristics. Another possible explanation for the high accuracy is that the symptoms of COVID-19 in those CXRs are clearly distinguishable because all of these images are publicized to assist radiologists in appropriately diagnosing CXRs. For this, we requested from two fellow radiologists to provide feedback on Cohen Dataset. We also asked them to go over each image in the dataset to see if the CXR alone is enough to diagnose COVID-19. We also highlighted that Narin et al. used the pediatric pneumonia dataset, which means that the model is already biased because we are training COVID-19 adult patients with juvenile pneumonia patients. It should be noted that Ozturk et al. trained a model from scratch using only 1000 photos and achieved good accuracy. Several researchers attempted to detect pneumonia using CXR, and ChexNet received the highest AUROC score of 0.7680, to the best of our knowledge.

As a result, we propose to test for the following hypothesis:

H0: *The model utilized can detect Covid-19 with great precision, making it useful for clinical applications. The model is recognizing Covid-19 characteristics.*

H1:*The model employed to detect Covid-19 achieves great precision regardless of the network employed, and hence has little utility in identifying Covid-19. The model is unable to recognize Covid-19 characteristics.*

To put our theory into test, we use the Cohen dataset to train a model that has never been tested previously in any research. Regardless of the model, we aim to attain great accuracy. Finally, we run a reference test to see how it compares to the others. We anticipate that the reference test will be inaccurate. In the reference test, we will attempt to identify Pneumonia using photos from the Wang Dataset with a ‘no finding.'

Radiologists’ comments and inputs mentioned previously are furtherly discussed in chapter IV.

CHAPTER IV

RADIOLOGISTS’ COMMENTS

For reviewing the Cohen dataset, two fellow radiologists from the American University of Beirut medical center with more than five years of experience. The clinical assessment for the first radiologist consisted of a binary categorization of Covid-19 as clear or not clear. The clinical evaluation performed by the second radiologist included three granulations: normal CXR, aberrant CXR but cannot establish the presence of Covid-19, and Covid-19 clear in CXR. Both radiologists' findings support the H1 hypothesis.

The first radiologist found that, of the 241 verified COVID-19 CXRs already in the Cohen dataset, only 146 (or 60%) could be identified as COVID-19, while the remaining CXRs require more testing to confirm or reject the virus's existence. The findings of the second radiologists support our H1 hypothesis as well:

1. Normal CXR: 58.

2. Abnormal CXR but more tests are needed to confirm COVID-19: 141.

3. COVID-19 clear without further testing: 44.

These findings raise the question of how CNN models Covid-19 cases with 98 percent accuracy, whereas only about 60 percent of cases may be classified as Covid-19 without further testing based on the radiologists' clinical interpretation of the dataset.

Table 2 shows examples of CXRs diagnosed as Covid-19 that were taken from the dataset. However, without additional testing, the radiologists were unable to diagnose it as Covid-19.

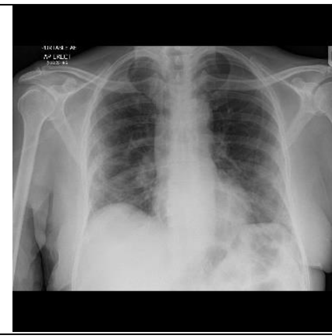
CXR image		
Filename	Covid-19-pneumonia-53.jpg	Covid-19-pneumonia-49-day4.jpg
Cohen label	Covid-19	Covid-19
Radiologists label	Normal	Abnormal but further testing needed to confirm Covid-19

Table 2. Comparison between Cohen label and our radiologist label

The radiologists' responses to our queries are summarized in Table 3.

Our Inquiry	Radiologists feedback
What do you think of the overall dataset quality? Is the images' quality adequate to make a diagnosis?	On a scale of 0 to 10, I rate the image quality of the dataset at seven. We always prefer large images in Dicom format (allowing us to manipulate and window properly) and displayed on a high-resolution diagnostic radiology workstation.
From a radiologist point of view, knowing that COVID CXR findings overlap with other finding such as SARS, or H1N1, why some images are clear as COVID while others are not?	Features of peripheral ground-glass opacities predominant at the lung bases are typical of COVID. When we deviate from these findings, we are stuck knowing that these typical features are seen in advanced cases where the virus has already affected both lungs. Other processes such as influenza pneumonia and organizing pneumonia (as

	can be seen with drug toxicity and connective tissue disease) can cause a similar imaging pattern. Therefore, even the typical features can sometimes lead us to the wrong diagnosis if we do not consider the patient as a whole. There is always a bias in real life while approaching cases with regards to seasonal epidemics, patient history, and demographics. On another note, if we talk about early detection (since we all know that disease has to start somewhere, for example from a single lobe), we can neither be sensitive nor specific on x-ray imaging even on CT imaging!
Overall, would it be advisable to use CXR as a diagnosis tool for COVID?	No
Do you think CXR should have any role in diagnosing COVID?	Not in diagnosing COVID, but during follow-up, mainly for ICU patients. A negative x-ray will not exclude COVID. I can only see a potential benefit (in the diagnosis setting) to triage a patient to a lower care unit when the x-ray is negative and PCR is positive.

Table 3. Radiologists' feedback

We now move to chapter V, which revolves around experimentally validating Cohen Dataset.

CHAPTER V

EXPERIMENTS

A .Dataset

We used the Wang et al. dataset, which contains over 100.000 high-quality CXRs extracted straight from DICOM files, in addition to the Cohen Covid-19 dataset. For training and validation, all models were trained using the same data. The number of photos taken from the Wang dataset is comparable to the previous studies. The information has been organized as follows:

i) Pneumonia pictures: 322 photos were used, with 262 serving as training images and 60 serving as validation images.

ii) No Findings: 364 training photos and 90 validation photos were used to create 454 images.

iii) COVID-19: There are 241 total images, with 192 training images and 49 validation photos.

We measured also each set's average brightness and saturation. The Cohen dataset yielded a score of 0.52/0.065, while the Wang dataset yielded a score of 0.485/0.0.

B. Models

To test our theory, we chose two new models that have never been examined before by any of the researchers mentioned above. All models were trained with the same hyper-parameters on Google Colab Pro. The photographs were compared to each other, and no three class's classification was done**.** The following models were chosen: DenseNet121, ResNet152, and Dark-CovidNet, which is tested by Ozturk et al. and is available on GitHub.

C. Experiment one: Pneumonia vs. COVID-19

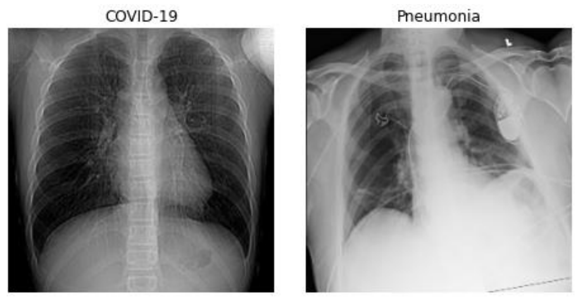


Fig. 3. Sample image for Covid-19 and Pneumonia.

This experiment is based on the comparison between two different CXRs, one showing pneumonia infection and another showing COVID-19 infection. The results are summarized in the tables below.

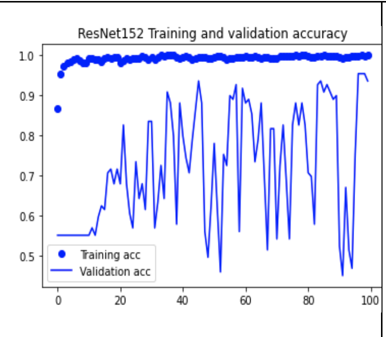
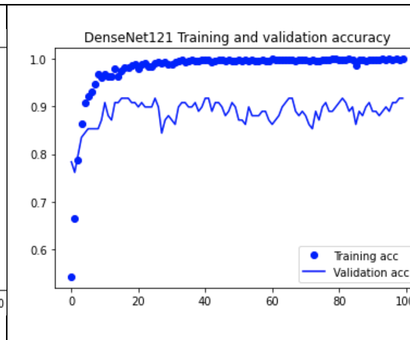
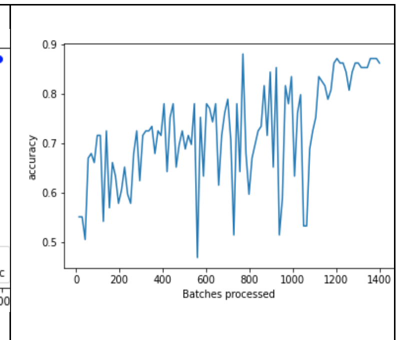
		

Fig.3-a. ResNet152 Accuracy per epoch	Fig. 3-b. DenseNet121 accuracy per epoch	Fig. 3-c. Dar kCovidNet accuracy per batch

	Class	Precision	Recall	F1-score	Accuracy
ResNet152	COVID-19	0.90	0.92	0.91	0.92
	Pneumonia	0.93	0.92	0.92	
DenseNet121	COVID-19	0.87	0.94	0.90	0.91
	Pneumonia	0.95	0.88	0.91	
DarkCovidNet	COVID-19	0.95	0.71	0.81	0.85
	Pneumonia	0.81	0.97	0.88	

Table. 4. Summary of experiment one*:* Pneumonia vs. COVID-19

The findings of the first experiment may be seen in Figures 3, 3a-b-c and Table 4. The following outcomes match our expectations. In terms of COVID detection, all three models are quite accurate and precise. ResNet152 and DarkCovidNet both have varying degrees of accuracy. The average accuracy, though, remains high. DenseNet121's accuracy varies between 85 and 90 percent. When compared to the other two models, ResNet152 had the superior precision and recall. True positives divided by true positives and false positives equals' precision, while true positives divided by true positives and false negatives equals recall.

D. Experiment two: No finding Vs. COVID-19

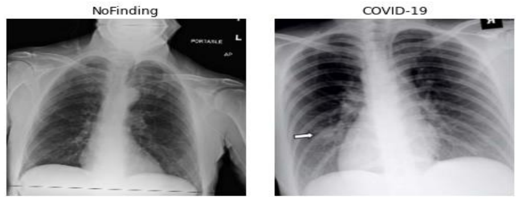


Figure 4. Sample images for Covid-19 and No finding

This experiment is based on the comparison between two different CXRs, one showing no critical finding and another showing COVID-19 infection. The results are summarized in the tables below.

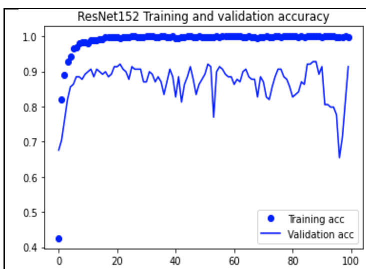
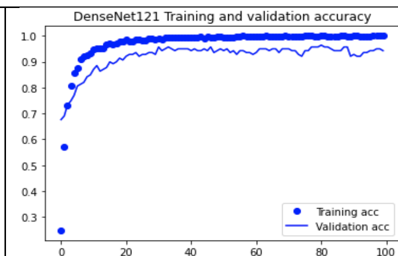
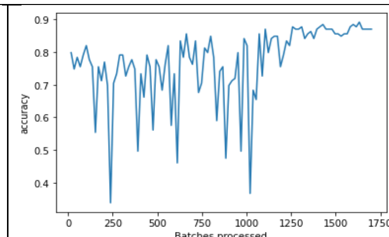
		

Fig. 4-a ResNet152 acc. per epoch	Fig. 4-b. DenseNet121 acc. per epoch	Fig. 4-c. DarkCovidNet acc. per batch

Table. 5. Summary of experiment two*:* No finding Vs. COVID-19

The findings of the second experiment are shown in Figures 4a-b-c. These outcomes are consistent with our expectations. In identifying COVID, all three models achieve great accuracy and precision. The best results are achieved by ResNet152 and DenseNet121.

E. **Experiment three: Pneumonia Vs. No finding**

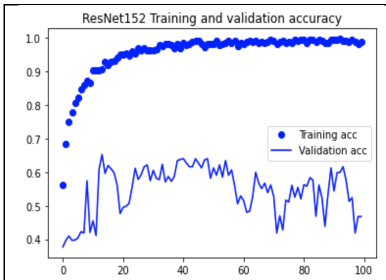
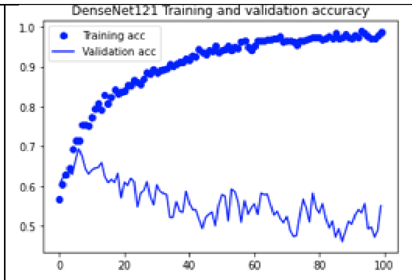
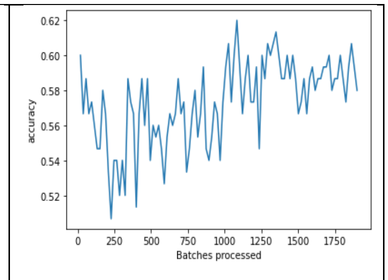
		

Fig 5-a. ResNet152 accuracy per epoch	Fig.5-b DenseNet121 accuracy per epoch	Fig.5-c. DarkCovidNet accuracy per batch

Table. 6. Summary of the data of experiment three*:* Pneumonia Vs. No finding

This test serves as a reference test with regards to other tests since all images are from a single dataset. The findings of the third experiment are shown in Figures 5, a-b-c. The results of this test back up our suspicions, as all of the models produce poor results. When we combine photos from a single dataset, the findings appear to be doubtful. The models, on the other hand, perform flawlessly when the photos come from two independent sources.

Finally, we discuss our findings and results in chapter VI.

CHAPTER VI

CONCLUSION

In this thesis, we tried to explain the high accuracy in detecting covid-19 using X-rays. Our approach consisted of training new models with images from different dataset and compared it to the same model performance when image source is the same dataset. It seems that when we train and validate the model with two different datasets, it achieves good accuracy. The model appears to be learning additional minor features rather than COVID-19 CXR characteristics. When we compare the reference test, we can see that the models have poor accuracy when the source is a single dataset.

The comments of the radiologist back up our idea, since only 60% of the samples were certified as COVID-19.

We believe that a model to detect COVID-19 using X-rays has no clinical utility, regardless of the rationale for the high accuracy. As a result, the AI community should seek to assist in various ways.

Dr. Cohen's efforts to collect those CXRs in a single spot are greatly appreciated. However, in order to develop early COVID detection using machine learning, health facilities must be more willing to share anonymized high-resolution images data as well as physiological and clinical information.

REFERENCES

Abbas, Asmaa, Mohammed M. Abdelsamea, and Mohamed Medhat Gaber. "Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network." *Applied Intelligence* 51.2 (2021): 854-864.

ACR Recommendations for the use of Chest Radiography and Computed Tomography (CT) for Suspected COVID-19 Infection https://www.acr.org/Advocacy-and-Economics/ACR-Position-Statements/Recommendations-for-Chest-Radiography-and-CT-for-Suspected-COVID19-Infection

Akkus, Zeynettin, et al. "Deep learning for brain MRI segmentation: state of the art and future directions." *Journal of digital imaging* 30.4 (2017): 449-459.

Carneiro, Gustavo, Jacinto C. Nascimento, and António Freitas. "The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods." *IEEE Transactions on Image Processing* 21.3 (2011): 968-982.

Cheng, Jie-Zhi, et al. "Computer-aided diagnosis with deep learning architecture: applications to breast lesions in US images and pulmonary nodules in CT scans." *Scientific reports* 6.1 (2016): 1-13.

Chest X-Ray Images (Pneumonia) https://www.kaggle.com/paultimothymooney/chestxray-pneumonia

Cohen, Joseph Paul, et al. "Covid-19 image data collection: Prospective predictions are the future." *arXiv preprint arXiv:2006.11988* (2020).

Coronavirus disease (COVID-19) Pandemic https://www.who.int/emergencies/diseases/novel-coronavirus-2019

Coudray, Nicolas, et al. "Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning." *Nature medicine* 24.10 (2018): 1559-1567.

Fang, Yicheng, et al. "Sensitivity of chest CT for COVID-19: comparison to RT-PCR." *Radiology* 296.2 (2020): E115-E11.

Gupta, Anunay, Shreyansh Gupta, and Rahul Katarya. "InstaCovNet-19: A deep learning classification model for the detection of COVID-19 patients using Chest X-ray." *Applied Soft Computing* 99 (2021): 106859.

He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Hemdan, Ezz El-Din, Marwa A. Shouman, and Mohamed Esmail Karar. "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images." *arXiv preprint arXiv:2003.11055* (2020).

https://github.com/asmaa4may/DeTraC COVId19

Hussain, Emtiaz, et al. "CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images." *Chaos, Solitons & Fractals* 142 (2021): 110495.

Ismael, Aras M., and Abdulkadir Şengür. "Deep learning approaches for COVID-19 detection based on chest X-ray images." *Expert Systems with Applications* 164 (2021): 114054.

Jaeger, Stefan, et al. "Automatic tuberculosis screening using chest radiographs." *IEEE transactions on medical imaging* 33.2 (2013): 233-245.

Jain, Rachna, et al. "Deep learning based detection and analysis of COVID-19 on chest X-ray images." *Applied Intelligence* 51.3 (2021): 1690-1700.

Karakanis, Stefanos, and Georgios Leontidis. "Lightweight deep learning models for detecting COVID-19 from chest X-ray images." *Computers in biology and medicine* 130 (2021): 104181.

Lo, Shih-Chung Benedict, et al. "Computer-assisted diagnosis of lung nodule detection using artificial convoultion neural network." *Medical Imaging 1993: Image Processing*. Vol. 1898. International Society for Optics and Photonics, 1993.

Luz, Eduardo, et al. "Towards an effective and efficient deep learning model for COVID-19 patterns detection in X-ray images." *Research on Biomedical Engineering* (2021): 1-14.

Narin, Ali, Ceren Kaya, and Ziynet Pamuk. "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks." *Pattern Analysis and Applications* (2021): 1-14.

North America, R. S. RSNA pneumonia detection challenge. https://www.kaggle.com/c/rsna-pneumonia-detection-challenge/data(2019)

Ozturk, Tulin, et al. "Automated detection of COVID-19 cases using deep neural networks with X-ray images." *Computers in biology and medicine* 121 (2020): 103792.

Rajpurkar, Pranav, et al. "Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning." *arXiv preprint arXiv:1711.05225* (2017).

Ribli, Dezső, et al. "Detecting and classifying lesions in mammograms with deep learning." *Scientific reports* 8.1 (2018): 1-7.

Shankar, K., and Eswaran Perumal. "A novel hand-crafted with deep learning features based fusion model for COVID-19 diagnosis and classification using chest X-ray images." *Complex & Intelligent Systems* 7.3 (2021): 1277-1293.

Sze-To, Antonio, and Zihe Wang. "tchexnet: Detecting pneumothorax on chest x-ray images using deep transfer learning." *International Conference on Image Analysis and Recognition*. Springer, Cham, 2019.

Wang, Linda, Zhong Qiu Lin, and Alexander Wong. "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images." *Scientific Reports* 10.1 (2020): 1-12..

Wang, X., et al. "Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases." *IEEE CVPR*. 2017.

Weinstock, Michael B., et al. "Chest x-ray findings in 636 ambulatory patients with COVID-19 presenting to an urgent care center: a normal chest x-ray is no guarantee." *J Urgent Care Med* 14.7 (2020): 13-18.

WHO Timeline - COVID-19 https://www.who.int/news-room/detail/27-04-2020-who-timeline---covid-19

Wong, Ho Yuen Frank, et al. "Frequency and distribution of chest radiographic findings in patients positive for COVID-19." *Radiology* 296.2 (2020): E72-E78.

Xiang, Fei, et al. "Antibody detection and dynamic characteristics in patients with coronavirus disease 2019." *Clinical Infectious Diseases* 71.8 (2020): 1930-1934.

Zhang, Jianpeng, et al. "Covid-19 screening on chest x-ray images using deep learning based anomaly detection." *arXiv preprint arXiv:2003.12338* 27 (2020)..

Zhou, Peng, et al. "A pneumonia outbreak associated with a new coronavirus of probable bat origin." *nature* 579.7798 (2020): 270-273.