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APPLYING AI/ML AND DCNNS FOR PANDEMIC CONTROL: THE BATTLE BETWEEN ACCURACY AND PRECISION

Technology

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KEYWORDS

INTRODUCTION

Covid 19 is associated with multiple health risks along with increased risk of post-acute sequelae which can be categorized majorly as impacting pulmonary systems.

This virus constitutes an extended family of respiratory viruses which can cause mild to moderate diseases, from the common cold to respiratory syndromes such as Severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome(MERS) as explained by Holmes(2003). This virus has a crown like, or coronal appearance on its surface (Hoek et al.,2004).

Yang et al.,2019 mentions that the coronaviruses are so named because of their characteristic solar corona (crown-like) appearance when observed under an electron microscope. Most of animal species specially bats and camels carry these types of viruses. Very rarely these viruses can evolve and infect humans and then spread to the neighbouring populations to cause epidemics/ pandemics (Abroug et al., 2019).

The Coronavirus strain that was identified in 2019 was never seen in humans before and this specific strain entered the humans at end of 2019. First cases about the virus were received from the Huanan Seafood Market from the city of Wuhan in the province of Hubei, China. Since then, the virus spread to various parts of the world.

The World Health Organization (WHO) named the infectious disease caused by this kind of virus COVID-19 on Feb 11, 2020 (Sohrabi *et al., 2019*). According to Boyi et al., 2020 The current COVID-19 pandemic threatens human life, health, and productivity and it is also spreading worldwide according to Gionata et al. AI plays an essential role in COVID-19 case classification as we can apply machine learning models on COVID-19 case data to predict infectious cases and recovery rates using chest x-ray. Known symptoms of the disease include dry cough, chills, fever, and impact on lungs. Michal et al.,2020 specifies that the Covid- 19 Virus, like other family members, is sensitive to ultraviolet ray and heat.

If we can actually make a diagnosis from just imaging, it will be very useful. However, this is compounded with a lot of literature that has flawed evaluations. Testing and imaging can still play a role in triaging patients due to high polymerase chain reaction(PCR) turnaround times. The objective is prognostic predictions which is useful for triaging patients and answering questions such as:
a. Should this patient stay home, or will this patient need the ICU care in a few days?
b. Can this patient survive at all?
c. Will he respond to a specific treatment such as intubation or some drug?
d. Should the tube be removed?
e. Should the patient be taken off a ventilator now?

The first step to building any of these models is collecting data so that we have a large dataset. Out of the existing datasets of COVID-19 + Imaging AI Resources of Stanford University, GitHub, BIMCV or pyimagesearch it was important to carry out an evaluation on the choice of dataset.

Literature Review

There has been a boom of COVID-19-related imaging data and AI resources coming from both academic and industry settings. Take for instance the “COVID-19 + Imaging AI Resources" portal by the Center for Artificial Intelligence in Medicine Imaging at Stanford University that actually amalgamates many such resources. https://aimi.stanford.edu/resources/covid19

Lungs as a body organ are highly impacted due to covid 19 and in most clinical procedures lungs are the first to be seen by medical practitioners as clinical evidence of the disease.

As said by Rezaul et al.(2020) the definitive test for COVID-19 is the reverse transcriptase-polymerase chain reaction (RT-PCR) test, which has to be performed in specialized laboratories and is a labour-intensive process. COVID-19 patients, however, show several unique clinical and para-clinical features, e.g., presenting abnormalities in medical chest imaging with commonly bilateral involvement. The features were shown to be observable on chest X-ray (CXR) and CT images but are only moderately characteristic to the human eye and not easy to distinguish from pneumonia features.

Although RT-PCR(Reverse transcription polymerase chain reaction) is used as a main screening method for COVID- 19, total positive rate of RT-PCR for throat swab samples is reported to be 30 to 60%(Yang et al., 2020). Chest CT has a high sensitivity for diagnosis of COVID-19 (Ai et al., 2020) and X-ray images show visual indexes correlated with COVID-19 (Kanne et al., 2020). Chest radiography imaging (e.g., X-ray or computed tomography (CT) imaging) as a routine tool for pneumonia diagnosis is easy to perform with fast diagnosis.

As stated by Fang et al.(2020) and Ai et al.(2020), a possible better diagnosis of COVID-19 is through radiological imaging. For this reason, in this paper, we use X- Ray images directly from selected dataset to evaluate the possibility of detecting COVID-19. In this paper supervised machine learning is exploited to build a model from a set of patients who are COVID-19 positive and patients with no COVID-19.

X-ray images cannot easily distinguish soft tissue with a poor contrast to limit the exposure dose to the patients [Kroft et al., and Karar et al.]. To overcome these limitations, Computer-Aided Diagnosis (CAD) systems have been developed to assist physicians to automatically detect and quantify suspected diseases of vital organs in X-ray images [Merk *et al.* and Messerli *et al.*]. The CAD systems are mainly relying on the rapid development of computer technology such as graphical processing units (GPUs) to run the medical image processing algorithms, including image enhancement, organ and/or tumor segmentation, and interventional navigation tasks [Tian et al., He et al. and Hannan et al.]. Now, artificial intelligence techniques such as machine learning and deep learning become the core of advanced CAD systems in many medical applications; for example, pulmonary diseases [Liang et al. and Hussein et al.], cardiology [Karar et al.], and brain surgery [Ghassemi et al., Rathore et al.].

Deep learning techniques have shown promising results in the last few years to accomplish radiological tasks by automatic analyzing multimodal medical images [Chen et al., Gao et al. and Kim et al.]. Deep convolutional neural networks (DCNNs) are one of the powerful deep learning architectures and have been widely applied in many practical applications such as pattern recognition and image classification in an intuitive way as mentioned by Zhou. DCNNs as mentioned by Ho et al are able to handle four manners:
1) Training the neural network weights on very large available datasets.
2) Fine-tuning the network weights of a pre-trained DCNN based on small datasets.
3) Applying unsupervised pre-training to initialize the network weights before putting DCNN models in an application.
4) Using pre-trained DCNN, also called an off-the-shelf CNN, as a feature extractor.

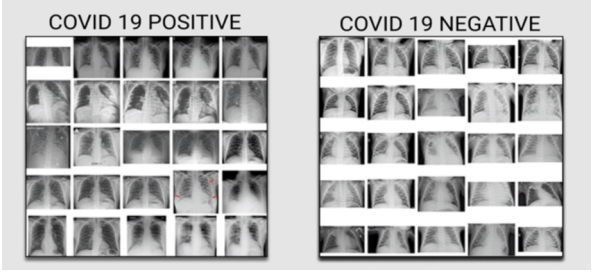
In previous studies, DCNNs have been exploited in X-ray image

classification to successfully diagnose common chest diseases such as Tuberculosis screening by Pasa et al. and mediastinal lymph nodes in CT images by Miki *et al*. However, the application of deep learning techniques to identify and detect novel COVID-19 in X-ray is still very limited so far.

While both Hemdan et al.,2020 and Karim et al.,2020 have acknowledged that VGG-19 and DenseNet-201 are the most accurate neural networks for the detection of covid 19 in chest radiographs in this scenario, no study has yet been carried out to give a clear comparison between both methods. The comparative analysis of VGG-19 and DenseNet-201 is the objective of this research paper.

Methodology

This is a detailed exploratory study where several facts and findings have been explored with the help of supportive information. Medical sciences related cases are usually explored with the help of either descriptive research design or causal research design. To get dataset from various parts of the world we contacted different medical authorities. Hospitals in India had overflow of data during upsurge of COVID-19 and the data was overwritten and inconsistent. We added 3 X-rays of confirmed COVID-19 +ve death cases and 3 confirmed cases of covid -ve recovered cases from family members of deceased and recovered patients in the neighbourhood of Gurgaon, Haryana, India. The rest of the data were taken from countries like Vietnam, Taiwan, China, Canada, USA, Hong Kong, South Korea, Sweden, Italy, Australia, Israel, UK, Saudi Arabia, Egypt, Jordan, Spain, Belgium, Portugal, Columbia, Qatar, turkey, Germany, Greece, Guatemala, Austria, Hungary, Pakistan, Malaysia, Ukraine, Malta, Russia, Japan, New Zealand, Philippines, Iran, Thailand, Denmark.



Positive and negative COVID-19 cases taken from public dataset of X-ray images used in this study for classifying provided belong to Dr. Joseph Cohen (https://github.com/ieee8023/covid-chestxray-dataset) and Dr. Adrian Rosebrock (https://www.pyimagesearch.com/category/ medical/). Two categories, 25 normal cases and 25 positive COVID-19 images of the dataset were taken from 5 countries Malayasia, Thailand, Pakistan, China, & Vietnam which has geographical proximity with India in addition to the data from India. The dataset includes 50 X-ray images, as shown in fig above, and shows a sample of normal and COVID-19 images extracted from the dataset. COVID-19 disease X-rays show a pattern of haziness as in opaque ground-glass with occasional consolidation in the patchy, peripheral, and bilateral areas as said by Ng *et al*. The original size of tested images is ranging from 1112 x 624 to 2170 x 1953 pixels. For the experimental setup, all images were scaled to the size of 224 × 224 pixels.

This paper is researched on a framework which includes deep learning classifiers, VGG-19 and Densenet-201, which have been implemented using Python and the Keras package with TensorFlow2.

The experiments were executed using a MacBook Pro with 16 GB memory running mac OS Monterey having a M1 SOC(System on a chip) Processor.

The two methods we will be comparing are illustrated below :
a) ***VGG-19*:** Visual Geometry Group Network (VGG) was developed based on the convolutional neural network architecture by Oxford Robotics Institute's Karen Simonyan and Andrew Zisserman. It was addressed at the 2014 Large Scale Visual Recognition Challenge (ILSVRC2014). The VGGNet performed very well on the ImageNet dataset. In order to have improved image extraction functionality, the VGGNet used smaller filters of 3×3, compared to AlexNet 11×11 filter. There are two versions of this deep network architecture; namely VGG-16 and VGG-19 have different depths and layers. VGG-19 is deeper than VGG-16. The number of parameters for VGG-19, however, is larger and thus more expensive than VGG-16 to train the network.

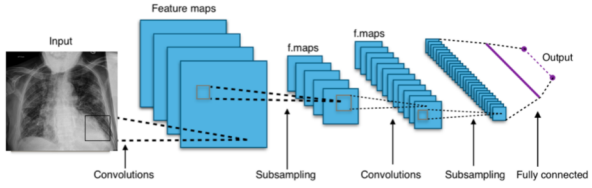
b) ***DenseNet-201:*** The Dense Convolutional Network (DenseNet) has several compelling benefits: they lighten the vanishing-gradient problem, reinforce feature propagation, encourage feature reuse, and the number of parameters reduce substantially [Huang et al.]. DenseNet-201 is a Dense Net model which generated with 201 layers, the model was loaded with pre-trained weights.

Steps Followed

Step#1: Preprocessing
Before we do hot encoding as proposed by Harris et al., all X-ray images are collected in one dataset for scaling at a fixed size of 224 X 224 pixels to be suitable for further processing within the deep learning pipeline. We also apply data labels on image data to indicate the case of COVID-19 positive or COVID-19 negative for each image in the dataset.

Step#2: Steps to Training and Validate Model
Further, before we start the training phase of the selected convolutional neural networks, we split the data set which has been preprocessed in an 80-20 ratio in accordance with the well-known Pareto principle. This implies that for this research paper 20% data will be used in the testing phase. Again , we splitted 80% data to construct validation and training sets of equal ratio. We then randomly subsample parts of training data for the Classifier and then we apply evaluation metrics. Following this we can record the performance on the validation set.

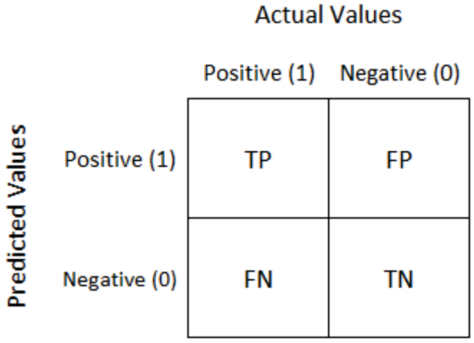
Step#3: Sorting
The respective deep learning classifier is used to categorize all the image patches into one of two cases: confirmed positive COVID-19 or normal case (negative COVID-19). After this we analyze the overall performance of the deep learning classifier at the end of the workflow and evaluate it. We have also described metrics in the next section.



Data Analysis

For machine learning classification problems, Confusion matrix is a performance measurement where output can be two or more classes. It is a table with 4 different combinations of actual and predicted values .It is extremely useful for measuring Recall, Precision, Specificity and Accuracy.

(https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62)



Confusion Matrix

TP - True Positive
FP - False Positive
FN - False Negative
TN - True Negative

Using the confusion matrix, this research calculates the following metrics,

1) Accuracy
accuracy is the ratio of correct predictions to total predictions made.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2)Recall- Out of the total positive, what percentage are predicted positive

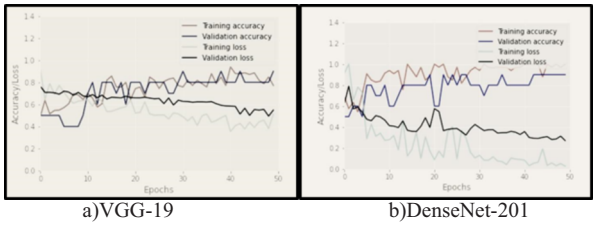
$$Recall = \frac{TP}{TP + FN}$$

3)Precision
Out of all the positive predicted, what percentage is truly positive.

$$Precision = \frac{TP}{TP + FP}$$

4) F1 Score
It is the harmonic mean of precision and recall. It takes both false positive and false negatives into account. Therefore, it performs well on an imbalanced dataset.

$$F1\ score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$$



a)VGG-19 b)DenseNet-201

Fig: Training Loss And Accuracy Evaluation Of Densenet-201 & VGG-19

	Classifier			
	DenseNet 201		VGG-19	
	COVID-19	Normal	COVID-19	Normal
Precision	0.86	0.99	0.88	0.98
Recall	0.98	0.82	0.91	0.80
F1-Score	0.91	0.89	0.89	0.88

CONCLUSION

It was truly stated by Curtis Langlotz that "AI won't replace radiologists, but radiologists who use AI will replace radiologists who don't". Through this research paper we attempted to further compare the Convolutional Neural Networks (VGG-19 and DenseNet-201) which may be used to increase accuracy and precision for the detection of Covid 19 using radiographic images of the lungs. Our findings show that DenseNet-201 has a slight edge over VGG-19 in this application case, with F1 scores in case of Covid 19 as 0.91 and 0.89 respectively.

Lastly, we want to outline potential areas of improvements: first, since only a limited amount of CXR images for COVID-19 infection cases were at hand, it would be unfair to claim that we can rule out overfitting for our models. More unseen data from similar distributions is necessary for further evaluation to avoid possible out-of-distribution issues. Secondly, due to external conditions, we were yet not been able to verify the diagnoses and localization accuracies with the radiologists. Thirdly, accurate predictions do not only depend on single imaging modalities but could also build upon additional modalities like CT and other decisive factors such as patients demographic and symptomatic assessment report.

Human judgement can in no way be replaced by AI when a patient's life is at stake. It is hoped that the findings of this research paper will be a useful tool in fighting Covid 19 and its variants and towards increasing acceptance and adoption of AI assisted applications in clinical practice.

The Future

To improve accuracy of data and to distinguish COVID-19 from multiple other pathologies, a desirable step in the future would be larger data sets, automation of steps to pre-process information and better image refining methodologies. The models must also root themselves in strong ethical foundations (patient data privacy, model bias eradication etc.). Such systems, if deployed off-the-shelf in clinical and medical settings, will hopefully automate the diagnosis of COVID via a simple X-ray in the majority of cases, hence enhancing the reach of diagnosis. For complex diagnoses, human judgement in no way will however be replaced and will always be most important.

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