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COVID-19 Detection from Chest X-Rays

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***Abstract*: The outbreak of COVID-19 in different parts of the world is a major concern for all the administrative units of respective countries. COVID-19 has infected 223 countries and caused 45.5 lakh deaths worldwide. India is also facing this very tough task for controlling the virus outbreak and has managed its growth rate through some strict measures. Early diagnosis of COVID patients is a critical challenge for medical practitioners, governments, organizations, and countries to overcome the rapid spread of the deadly virus in any geographical area.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. Given recent developments in the application of machine learning models to medical imaging problems, there is fantastic promise for applying machine learning methods to COVID-19 radiological imaging for improving the accuracy of diagnosis, compared with the gold-standard RT–PCR, while also providing valuable insight for prognostication of patient outcomes. This study is aimed at evaluating the effectiveness of the state-of-the-art pre trained Convolutional Neural Networks (CNNs) on the automatic diagnosis of COVID-19 from chest X-rays (CXRs). The dataset used in the experiments consists of 1200 CXR images from individuals with COVID-19, 1345 CXR images from individuals with viral pneumonia, and 1341 CXR images from healthy individuals. In this paper, the effectiveness of artificial intelligence (AI) in the rapid and precise identification of COVID-19 from CXR images has been explored based on different pre trained deep learning algorithms and fine-tuned to maximize detection accuracy to identify the best algorithms.**

***Keywords*: Artificial Intelligence, Computer vision, COVID-19, COVID detection, Data science, Machine Learning.**

1. Introduction

COVID-19, or more popularly known as Novel Corona Virus, is associated with the respiratory disorder in humans which has been declared as a global epidemic and pandemic in the first quarter of the year 2020 by the World Health Organization.[1] As per the latest data (1st December 2021) by John Hopkins University [2] and other tracking websites, there are currently more than 263,532,223 people infected by the Novel Corona Virus all around the world and close to 5,224,797 deaths reported from different parts of the world.

While Reverse Transcription-Polymerase Chain Reaction (RT-PCR) is the current gold standard for disease diagnosis, molecular testing of respiratory tract specimens is also highly recommended, which allows for laboratory confirmation of infections. However, the dramatic proliferation of COVID-19 has resulted in an insufficient number of laboratory kits, creating a significant challenge. Thus, the use of radiological examinations in identifying infections has become increasingly attractive during the COVID-19 outbreak.

COVID-19 cases can be detected or diagnosed very easily through chest X-ray imaging analysis for abnormalities. Detecting Covid-19 from Chest X-Rays is a faster way and can act like a precursor to the RT-PCR test. In this way if the patient tests positive the treatment and medication can be started immediately after consultation from a doctor. Considering the present pandemic situation, there is an apparent need for faster detection of Covid-19 in patients in need.

In multiple works, deep learning-based techniques have been developed to identify pneumonia [3], [4], different classes of thoracic diseases [5], skin cancer [6], haemorrhage classification [7], etc. from medical images.

Unavailability of a large number of image data of COVID-19 +ve patients is a challenge faced by most researchers working in this area. Development of COVIDGAN for the generation of data artificially has been done in a work by Waheed et al., [8], which in turn will help in improved COVID-19 detection.

2. Proposed Architecture

A convolutional neural network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data. CNNs are powerful image processing, artificial intelligence (AI) that use deep learning to perform both generative and descriptive tasks, often using computer vision that includes image and video recognition. The combined expertise of the medical experts along with the help of the computer vision models would help in reaching a more reliable and trusted conclusion.

Computer Vision has been of prominence in the medical domain. It is useful in the medical diagnosis which require visual checks. Computer vision focuses on image and video understanding. It involves tasks such as object detection, image classification, and segmentation. Medical imaging can greatly benefit from recent advances in image classification and object detection. Several studies have demonstrated promising results in complex medical diagnostics tasks spanning dermatology, radiology, or pathology. Deep-learning systems could aid physicians by offering second opinions and flagging concerning areas in images.

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Computer vision solutions use various types of medical imaging e.g., Computed Tomography scan (CT scan), Magnetic resonance imaging (MRI), Positron Emission Tomography scan (PET scan), ultrasound and Chest X-Ray (CXR) images.

In this project, we decided to use the Resnet-18 architecture.

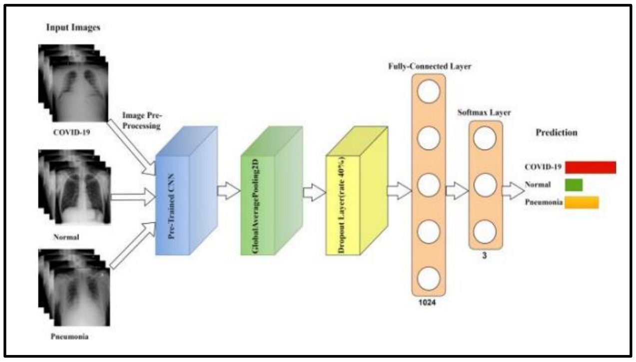

Fig 1. General architecture

RESNET: ResNet [9], is a contemporary convolutional network which addresses the vanishing or exploding gradient problems by the use of "residual blocks" in the architecture. In a residual network, multiple residual blocks stacked up one after another. Each residual block, shown in fig. 2, is formed of short-cut connections skipping one or more layers. Resnet uses the pre-activation of weight layers.

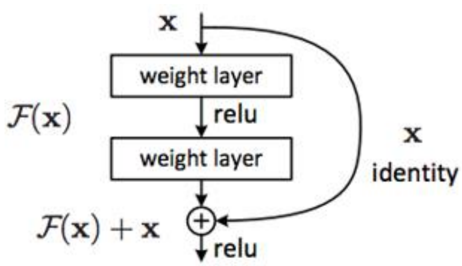

Fig. 2. Residual block

ResNet-18 is a convolutional neural network that is 18 layers deep. ResNet architecture, in Fig-3 and Fig-4 consists of one convolution and pooling step followed by 4 layers of similar behavior. Each of the layers follow the same pattern. They perform 3x3 convolution with a fixed feature map dimension - [64, 128, 256, 512] respectively, bypassing the input every 2 convolutions. Furthermore, the width and height dimensions remain constant during the entire layer.

The reduction between layers is achieved by an increase on the stride, from 1 to 2, at the first convolution of each layer; instead of by a pooling operation, which we are used to seeing as down samplers.

Every layer of a ResNet is composed of several blocks, Fig - 2. This is because when ResNets go deeper, they normally do it by increasing the number of operations within a block, but the number of total layers remains the same — 4. At the end there is an Average Pooling Layer followed by a Fully Connected Dense Layer of Neurons followed by the Softmax Layer to get the final predictions. There are a total of 11.174M parameters in the Resnet-18 model.

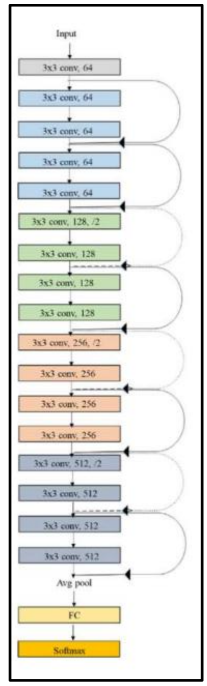

Fig. 3. Resnet-18 architecture

Layer Name	Output Size	ResNet-18
conv1	$112 \times 112 \times 64$	7×7, 64, stride 2
conv2_x	$56 \times 56 \times 64$	3×3 max pool, stride 2
		$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$
conv3_x	$28 \times 28 \times 128$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$
conv4_x	$14 \times 14 \times 256$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$
conv5_x	$7 \times 7 \times 512$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$
average pool	$1 \times 1 \times 512$	7×7 average pool
fully connected	1000	512×1000 fully connections
softmax	1000	

3. Methods and Materials

For this research work, we had collected the images from different open sources one being the COVID-19 Radiography Database available on Kaggle [10, 11, 12]. The datasheet contained 189 COVID-19 positive Xrays along with 1311 Normal, and 1315 Viral Pneumonia images. This data contains Chest X-ray images of different patients from which only the frontal images are considered and lateral images are discarded. This is because our region of interest is the lungs and lungs can be better examined with a frontal view than a lateral one. Shown below are the examples of each type of image in the dataset.

Data has been also been taken from the following sources - Italian Society of Medical and Interventional Radiology (SIRM) for publicly providing the COVID-19 Chest X-Ray dataset [13], Valencia Region Image Bank (BIMCV) padchest dataset [14] and would like to thank J. P. Cohen for taking the initiative to gather images from articles and online resources

[15]. Finally, to the Chest X-Ray Images (pneumonia) database in Kaggle and Radiological Society of North America (RSNA) Kaggle database for making a wonderful X-ray database for normal, lung opacity, viral, and bacterial pneumonia images [16], [17]. Also, a big thanks to our collaborators!

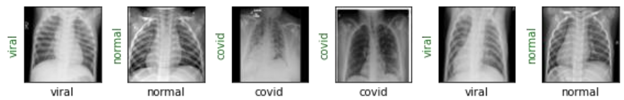

Fig. 4. Data samples

The images were resized to 224 x 224 pixels and were then normalized. Data augmentation such as Random Horizontal Flips were used to increase the number of samples available.

The images were then shuffled and split into two sets - Training and Test sets. The training set had 2815 samples - 1311 normal samples, 1315 viral samples and 189 covid samples, whereas the Test set had 90 samples - 30 normal samples, 30 viral samples and 30 covid samples.

If there are two or more images of the same patient, it is ensured that those images are either marked as training data or as test data—but not in both.

A. Tools Used

We have used Google Colab GPU (Tesla K80 12GB GDDR5 VRAM), Python 3.8 and PyTorch 1.10.0. For the implementation of the ResNet model, we have used PyTorch along with Torch vision which is a computer vision library. The training and testing procedures were done in Google Colab.

4. Experiments and Results

All the models have been trained for 20 epochs with Early Stopping callbacks when Accuracy goes above 95%. Adam optimizers used for faster convergence with the parameters as learning rate α=0. 005.The same optimizer is used for all three sets. It can be observed that the number of correctly classified COVID +ve images is consistently high for the proposed algorithm.

Table 1

S. No.	Number of steps	Validation Loss	Accuracy
1	0	1.2770	0.2667
2	20	0.9506	0.6556
3	40	0.5448	0.8556
4	60	0.3072	0.9222
5	80	0.2432	0.9444
6	100	0.2101	0.9556

5. Conclusion

A few characteristic findings in the lungs of patients with COVID-19 can be identified by chest X-rays. In this study, the ResNet-18 model is suggested for diagnosis and detection of the COVID-19 disease based on chest X-rays. The number of cases continues to rise exponentially as COVID-19 spreads across the world. To prevent crippling of the healthcare system, the use of a tool that can help diagnose the disease in people by using an inexpensive and fast process is necessary. Within this context, the literature suggests that the diagnosis may be assisted by the use of data mining methods to classify COVID-19 in chest X-rays.

6. Further Studies and Applications

In the future work, the proposed method will be expanded to be abdicable for different types of COVID-19 datasets such as SARS-CoV-2 CT-scan, COVID-CT and statistical datasets. However, the quality of predication method in COVID-19 disease will be combined with optimization techniques using classification and regression algorithms. Further, we can use deeper neural networks and ensemble techniques such as Stacking to further improve the accuracy of the model.

With the world facing a new challenge with respect to the new mutant Omicron which is reported to spread 5 times faster than any of the strains discovered till date, using AI and Deep learning methods to combat this challenge can prove to be instrumental in our war against COVID-19.

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