

Real-Time Diagnosis System of COVID-19 Using X-Ray Images and Deep Learning

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Abstract— The novel coronavirus named COVID-19 has quickly spread among humans worldwide, and the situation remains hazardous to the health system. The existence of this virus in the human body is identified through sputum or blood samples. Furthermore, computed tomography (CT) or X-ray has become a significant tool for quick diagnoses. Thus, it is essential to develop an online and real-time computer aided diagnosis (CAD) approach to support physicians and avoid further spreading of the disease. In this research, a convolutional neural network (CNN) -based Residual neural network (ResNet50) has been employed to detect COVID-19 through chest X-ray images and achieved 98% accuracy. The proposed CAD system will receive the X-ray images from the remote hospitals/healthcare centres and perform diagnostic processes. Furthermore, the proposed CAD system uses advanced load balancer and resilience features to achieve fault tolerance with zero delays and perceives more infected cases during this pandemic.

I.INTRODUCTION

COVID-19 was first perceived in Wuhan, China. This disease causes fever, cough, fatigue, and muscle pain during the initial phases.1 Usually, people with COVID-19 indicate fever and minor respiratory after 5–6 days. Mostly, the infected cases of COVID-19 are not extreme. The findings show that this virus spreads from individual to individual. Around 80% of affirmed cases have minor ailments and they are recuperating without special treatment. Infected individuals should be quarantined to avoid further spreading and must be treated within an isolation unit. Other complications like heart issues, respiratory problems, and lung infections are also possible. Infected individuals have observed serious respiratory issues in certain cases. However, the expanding numbers of recently suspected and infected cases have become disturbing because of the lack of resources and medications. The existence of COVID-19 in the individual is identified through sputum or blood samples test. However, an X-ray and computed tomography (CT) scan are also advised.

The X-ray procedure is mostly advised to scan the affected organ, for example, lung infections, tumours finding, bone dislocations, pneumonia, and bone fractures.

II.EXISTING SYSTEM

Butt et al. propose a deep learning model using a dataset of 618 CT images to detect coronavirus. Among them, 219 images with coronavirus, 224 cases with pneumonia, and 175 images of normal people. The proposed paradigm accomplished an AUC of 0.996, a specificity of 92.2%, and a sensitivity of 98.2%.

Shan et al proposed a deep learning framework and achieved a Dice similarity coefficient of 91.6%.

Wang et al. uses the inception migration-learning model and training is performed on 217 CT images and achieved with 82.9%, 80.5%, and 84% accuracy, specificity, and sensitivity, respectively.

Xuan yang et al employed machine learning classifiers to differentiate typical pneumonia and SARS using X-Ray images.

Sl. No.	Title	Methodology	Advantages
1	Deep learning in medical image analysis	CNN	About fundamentals of deep learning methods; review their successes to image registration, anatomical/cell structures detection, tissue segmentation, computer-aided disease diagnosis or prognosis, and so on.
2	Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network	CNN	To classify the lung patterns by using X-Ray.
3	CT Imaging of the 2019 Novel Coronavirus (2019-nCoV) Pneumonia	CNN	It's about various parameters to detect the COVID-19 in CT images.
4	Understanding of a convolutional neural network	ANN	CT images are used on various parameters to detect the COVID-19.

TABLE I: LITERATURE SUMMARY

III. PROPOSED SYSTEM

We propose transfer deep learning architecture through chest X-Ray images is applied. The main reason for choosing chest X-Ray images is their easy availability from any hospital without delay and difficulty. The experimental results illustrate that the ResNet50 model produced 98% accuracy. Chest X-Ray images have been acquired from the publicly available dataset. This dataset is already augmented and contains 1824 images in which 912 belong to coronavirus and 912 belong to non-COVID images. A deep CNN model known as ResNet50 is used to solve vanishing gradient problems by deploying skip functions and “Real-Time Diagnosis of COVID-19 using X-Ray Images and Deep Learning” Dept. of CSE, MSEC 2021-22 Page 6 boosting architecture performance. ResNet50 model, a network of 50-layers is employed to classify the chest X-Ray images into COVID-19 and non-COVID categories. The main advantage of employing the ResNet50 model is that it adds shortcuts among layers to provide a quick solution. It avoids the distortion that arises as the architecture becomes complex and deeper.

IV. SYSTEM IMPLEMENTATION

List of Modules:

1. Image Collection
2. Data Pre-processing
3. Building Model
4. Covid-19 Detection

1. Image Collection: Total image dataset includes 1,878 X-Ray images out of which 570 pneumonic and 630 non-pneumonic X-Ray images were procured from open image database from 2018 and 369 COVID-19 positive images were procured from open image database available at Societ`a Italiana di Radiologia Medicae Interventistica (SIRM) and radiopaedia.org which included X-Ray reports of patients aged 25-67 years old as shown in the figure 1. Additionally, 309 COVID-19 negative X-Ray images were also procured from the open database of European Society of Radiology (ESR).

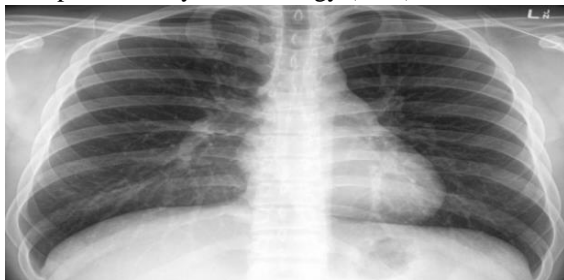


Figure 1: Normal Chest X-Ray

2. Data Pre-processing: Appropriate pre-processing of the training data was done for eviction of heavily degraded images that would cost the accuracy of the trained model. The data was augmented which includes rotation ($\pm 10\%$), left and right shift ($\pm 10\%$), height shift ($\pm 10\%$), zoom in (20%). The X-Ray image was normalized by 1/225. The training dataset obtained after data augmentation resulted in a total number of 15,024 X-Ray images from a limited dataset.

3. Building Model: In this module a RESNET50 model is use for tensor flow. The proposed architecture based on keras framework using Tensor flow backend is inspired by 3 state-of-threat architectures - Inception, DenseNet, Xception, and are combined by selecting appropriate features from all, smooth gradient flow and fast convolution respectively. The model is implemented using 2D convolutions as it is easy to train it with more training samples which results in higher accuracy. ResNet50 is a variant of ResNet50 model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8×10^9 Floating points operations. It is a widely used ResNet50 model and we have explored ResNet50 architecture in depth.

4. COVID-19 Detection: We are applying the ResNet50 model to detect the pneumonia and COVID-19. We will pass X-Ray images as input to our system; our system will efficiently detect the pneumonia and COVID-19 using ResNet50 model as shown in the figure 2.

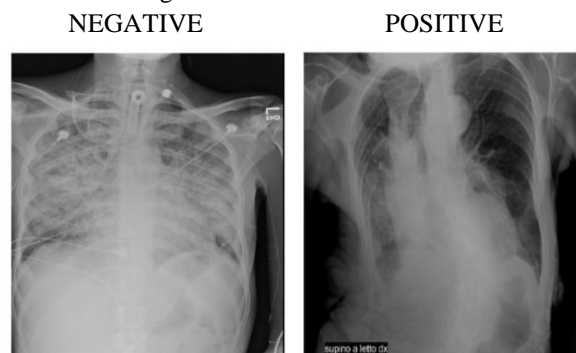


Figure 2: COVID-19 Detection

For the prediction, multiple supervised learning algorithms are trained using the training set, after which using the testing set performance evaluation occurs. These algorithms are:

V. SYSTEM ARCHITECTURE

The system “design” is defined as the process of applying various requirements and permits it physical realization. Various design features are followed to develop the system the design specification describes

the features of the system, the opponent or elements of the system and their appearance to the end-users. The dataset contains pre-processed Chest X-Ray images of COVID-19 affected, normal and pneumonia patients as per above figure 3. This collected dataset from kaggle.com is given as input to the deep learning model RESNET50. These modules extract the image features, trained and predicted the COVID-19 symptoms from the normal and show the performance evaluation based on X-Ray images.

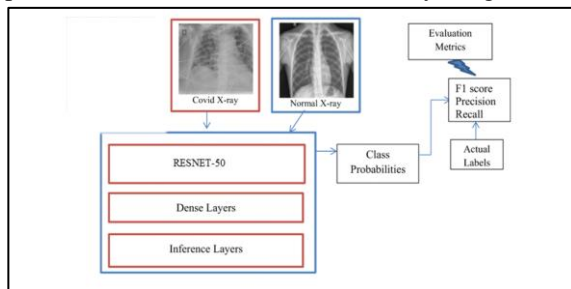


Figure 3: Proposed System Architecture

ResNet50

The proposed architecture developed on Keras framework using Tensorflow backend is inspired by 3 state-of-threat architectures - Inception, DenseNet, Xception, and are combined by selecting appropriate features from all, smooth gradient flow and fast convolution respectively. The model is implemented using 2D convolutions as it is easy to train it with more training samples which results in higher accuracy.

ResNet50 is a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8×10^9 Floating points operations. It is a widely used ResNet model and we have explored ResNet50 architecture in depth.

TABLE II: RESNET-50 LAYERS

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112x112	7x7, 64, stride 2				
conv2.x	56x56	3x3 max pool, stride 2				
		$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3.x	28x28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$
		$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$
conv3.x	14x14	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
		1x1 average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

So as we can see in the table II the ResNet50 architecture contains the following element:

A Convolution with a kernel size of $7 * 7$ and 64 different kernels all with a stride of size 2 giving us 1 layer.

Next we see max pooling with also a stride size of 2. In the next convolution there is a $1 * 1$, 64 kernel following this $3 * 3$, 64 kernel and at last a $1 * 1$, 256 kernel, these three layers are repeated in total 3 time so giving us 9 layers in this step.

Next we see kernel of $1 * 1$, 128 after that a kernel of $3 * 3$, 128 and at last a kernel of $1 * 1$, 512 this step was repeated 4 time so giving us 12 layers in this step. After that there is a kernel of $1 * 1$, 256 and two more kernels with $3 * 3$, 256 and $1 * 1$, 1024 and this is repeated 6 times giving us a total of 18 layers.

And then again a $1 * 1$, 512 kernel with two more of $3 * 3$, 512 and $1 * 1$, 2048 and this was repeated 3 times giving us a total of 9 layers.

After that we do a average pool and end it with a fully connected layer containing 1000 nodes and at the end a softmax function so this gives us 1 layer.

We do not actually count the activation functions and the max/ average pooling layers. So totaling this it gives us a $1 + 9 + 12 + 18 + 9 + 1 = 50$ layers Deep Convolutional network.

ResNet50 Algorithm:

- Step 1: Read input image from user
- Step 2: Pre-process the image
- Step 3: Load pre trained model
- Step 4: pass the image to pre-train model
- Step 5: Predict COVID or normal
- Step 6: Display result

VI. RESULTS AND DISCUSSION

The system was created using Windows 10 as well as a 64-bit processor with 8 GB of RAM. The model implemented with the help of Python v3.7.8. The performance of the classification techniques are studied with different evaluation measures, namely, accuracy (AC), Precision, Recall and F-1 Score.

$$Precision = \frac{True_Positive}{True_Positive + False_Positive} \tag{1}$$

$$Recall = \frac{True_Positive}{True_Positive + False_Negative} \tag{2}$$

$$F - Measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

$$Accuracy = \frac{True_Positive + True_Negative}{True_Positive + True_Negative + False_Positive + False_Negative} \tag{4}$$

Screenshot 1

The below figure 4 show the interface of the software. The interface contains the selecting dataset and the buttons to train and predict the result.

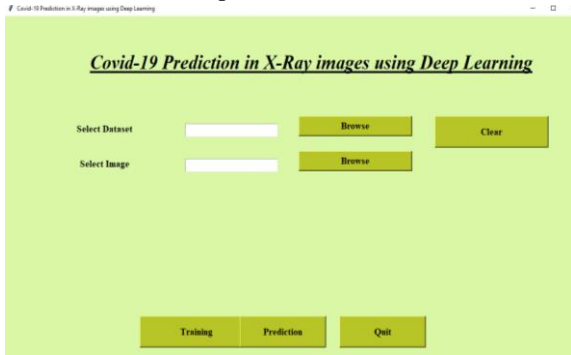


Figure 4: Interface of Software

Screenshot 2

The model can predict the COVID-19 patient as shown in figure 5. The image can be browse from the dataset and then click on the prediction button to predict the COVID-19 in patients.

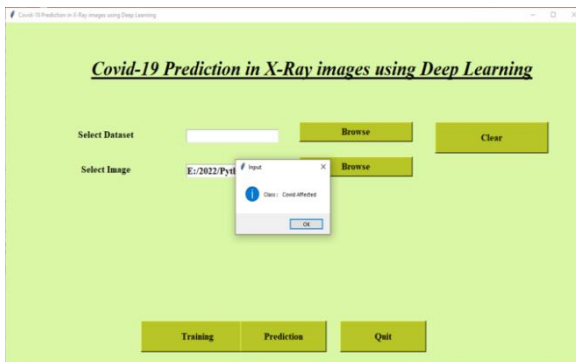


Figure 5: Detecting the COVID-19 in patient

Performance Analysis:

The performance of the model can be shown using the below figure 6. It is the performance analysis graph of Loss/Accuracy with the Epoch. The training loss and value loss of model is decreasing as number of epoch is increasing as shown in graph. The training accuracy and value accuracy is increasing as the number of epoch increases.

The training accuracy of model goes on increasing as the number of epoch increases and be at constant at their maximum and goes on decreasing. The value accuracy fluctuates at beginning and get constant as the number of epoch used to train the model.

The training loss can be reducing to around 35% and the value loss can be reduced to about 20% of the proposed model.

The training accuracy will increased to 95% during the training of the model and value accuracy can also move around 95% of the proposed model.

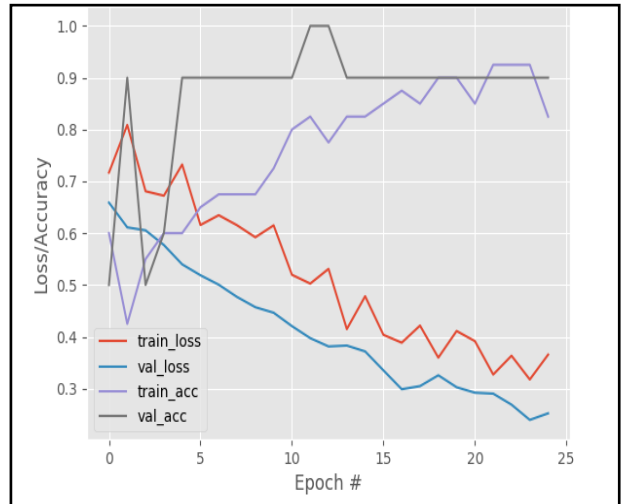


Figure 6: Performance Analysis Graph

CONCLUSION

In the work, transfer deep learning architecture through chest X-Ray images is applied. The main reason for choosing chest X-Ray images is their easy availability from any hospital without delay and difficulty. The experimental results illustrate that the ResNet50 model produced 98% accuracy. Chest X-Ray images have been acquired from the publicly available dataset. The dataset is already augmented and contains 1824 images in which 912 belong to coronavirus and 912 belong to non-COVID images. A deep CNN model known as ResNet50 is used to solve vanishing gradient problems by deploying skip functions and boosting architecture performance. The Proposed algorithm ResNet-50 to detect the COVID-19 patients using X-Ray images, ResNet50 model, a network of 50 layers, is employed to classify the chest X-Ray images into COVID-19 and non-COVID categories. The main advantage of employing the ResNet50 model is that it adds shortcuts among layers to provide a quick solution. It avoids the distortion that arises as the architecture becomes complex and deeper.

FUTURE SCOPE

The research work required a large number of X-ray images that are employed for the diagnosis of

COVID-19. Future work may extend by adding more data and different models.

A more interesting approach for future research would focus on distinguishing patients showing mild symptoms, rather than pneumonia symptoms, while these symptoms may not be accurately visualized on X-rays or may not be visualized at all.

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