



COVID-19 CASES DETECTION BASED ON CHEST X-RAYS

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Abstract-The COVID-19 pandemic has a significant negative effect on people's health, as well as on the world's economy. Corona Virus Disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. In this paper, an automated COVID cases detection system is proposed using Deep Learning (DL). This system contains a network which is designed using ResNet-18, softmax and trained by chest X-rays (CXR) of all three classes (COVID, Pneumonia, normal). Data set is taken from Kaggle and entire design is coded in python. Further, the performance of the system is compared in terms of the accuracy, validation loss and F1 score and also calculated recall and precision. Volume of data and data preprocessing techniques also play a major role to improve the accuracy of proposed system.

Keywords- COVID-19, Pneumonia, CXR, DL, softmax.

1. INTRODUCTION

Around the world, COVID-19 causes severe damage to people's lives and healthcare systems. It is a new virus strain, discovered in 2019, that has never been seen by humans. The first COVID-19 positive case was discovered in Wuhan, China, in December 2019, and it quickly spread to a number of other Chinese cities as well as several other countries around the world [1, 2]. According to preliminary data, COVID-19 causes minor symptoms in about 99% of cases, while the remainder of cases are serious or critical. The number of people dying from Pneumonia caused by the COVID-19 virus is rising every day [3]. The rapid global spread of COVID-19 puts healthcare systems under tremendous pressure; this spread could significantly become slow if a reliable screening method for patients (COVID-19 infected people) is established. Doctors and researchers found themselves facing a daunting challenge to find ways to diagnose the disease quickly [4]. A COVID-19 infection can cause serious problems such as acute kidney failure, septic shock, heart attack, and pulmonary edema [5]. The early detection and isolation of patients with infection is critical in combating and addressing the COVID-19 pestilence [6,7]. The most common COVID-19 detection technique is real time Reverse Transcription–Polymerase Chain Reaction (real time RT–PCR). It has a high percentage of false-negative findings and may take up to two days to receive results, while having a sensitivity range of 70 to 90; it may also produce quite high number of false-negative results. In some countries, it may take up to five days or more due to the overwhelming number of samples that need to be analyzed.

Additionally, COVID-19 is detected and diagnosed using radiological screening tests such as CXR and Computed Tomography (CT)[8,9]. It has been noticed that CXR is one of the most effective methods for diagnosing Pneumonia around the world because it is a rapid, inexpensive, and popular clinical method that exposes the patient to less radiation than CTs [10,11]. However, radiologists are needed to look for the radiological signs that show COVID-19 symptoms on a CXR. To save time and effort, it is important to automate the CXR analysis [12].

As a result, fully automated and real-time radiography image analysis is required to assist physicians in accurately detecting COVID-19 infection. Physicians may use computer-aided diagnosis (CAD) systems based on DL methods to help them to perceive and understand the information in CXR images as well as to overcome the limitations of the image acquisition technique used. DL methods are becoming more common in medical imaging because of their ability to deal with massive datasets that surpass human capabilities. As shown in Figure 1, combining CAD techniques with radiologist medical diagnostics decreases stress on physician as well as improves the accuracy and statistical analysis [11].

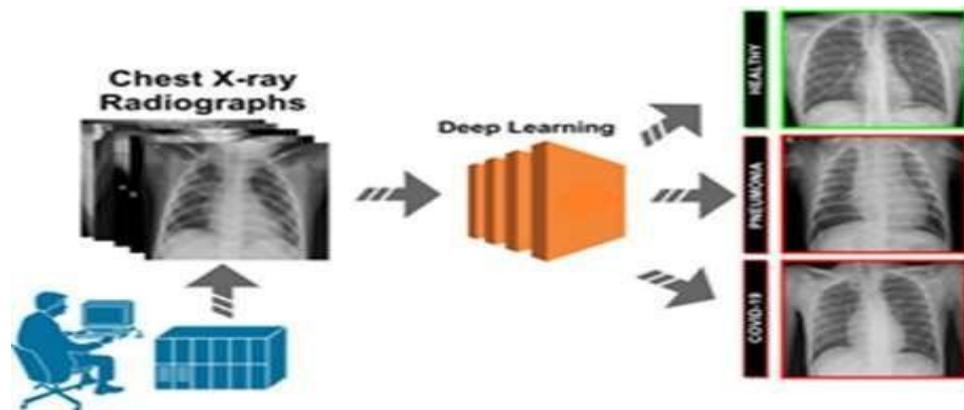


Figure 1: Model representation of CAD system.

This paper proposes a DL system which uses Resnet-18 and softmax approaches to accurately detect COVID-19 symptoms from CXR images. The proposed system has two significant phases: pre-processing and classification. The pre-processing phase is used to improve the overall contrast of the image in order to reduce inconsistencies between images obtained from various X-ray devices. The image is also resized and normalized to suit the size of the training model throughout that process.

The rest of the paper is organized as follows. Section 2 describes the literature survey of various machine and deep learning techniques in the COVID-19 detection while section 3 presents the methodology of proposed system. Section 4 presents the experimental setup and results. Finally, the conclusion is given in section 5.

2. LITERATURE SURVEY

Several researchers have worked on machine learning and deep learning models. Convolutional neural networks (CNNs), which are one of the most effective DL models, have successfully proved their mastery over conventional methods in several disciplines, including image classification and pattern recognition [13,14]. Currently, it has indeed been successfully implemented in the field of medicine with impressive outcomes and outstanding performance in different challenging settings. Various medical imaging systems using DL techniques have also been developed to assist physicians and specialists in effective COVID-19 diagnosis, care, and follow-up examination [15]. On the other hand, Wang et al. [16] have suggested using CXR images to automatically establish a new deep architecture called COVID-Net to detect COVID-19 instances. Using a database containing 13,975 CXR images, the key strength of this approach is that the conceptual composition could create a balance between different goals such as accuracy and computational costs through architectural design choices. Hemdan et al. [17] introduced COVIDXNet, a DL frame work for detecting COVID-19 infections in CXR images. A small dataset of 50 images was used to compare seven DL techniques such as MobileNetV2, ResNetV2, VGG19, DenseNet201, InceptionV3, Inception, and Xception. Further, a supervised transfer-learning method for COVID-19 infection detection using an extreme version of the Xception model was developed in [12]. Further many studies [18-20] introduced the system for COVID-19 identification using CXR for automatic detection. It was created to provide consistent and reliable diagnostics for multi-class classifications (COVID- 19, mild, and Pneumonia) and binary classifications (COVID vs. non-COVID). Using the DarkNet model, they were able to achieve a classification performance of 98.08% for binary classification and 87.02% for the classification

of multi-class. Many studies have tried to find COVID-19 infections in CXR images by using different DL methods [21–23]. As the investigation of COVID-19 identification and diagnostic systems that rely on CXR images indicated that there are still a number of vulnerabilities that need additional investigation. For starters, the majority of current systems have been validated with limited CXR datasets as well as a small presence of positive COVID-19 cases. The size of the datasets is insufficient to indicate the true output of the proposed systems. And also most of the systems concentrated on binary classification. This proposed method is a multi-classification, large amount of data is fed to DL network and the training time also very less compared to existing methods with the high percentage of accuracy.

3. PROPOSED SYSTEM

3.1 Architecture

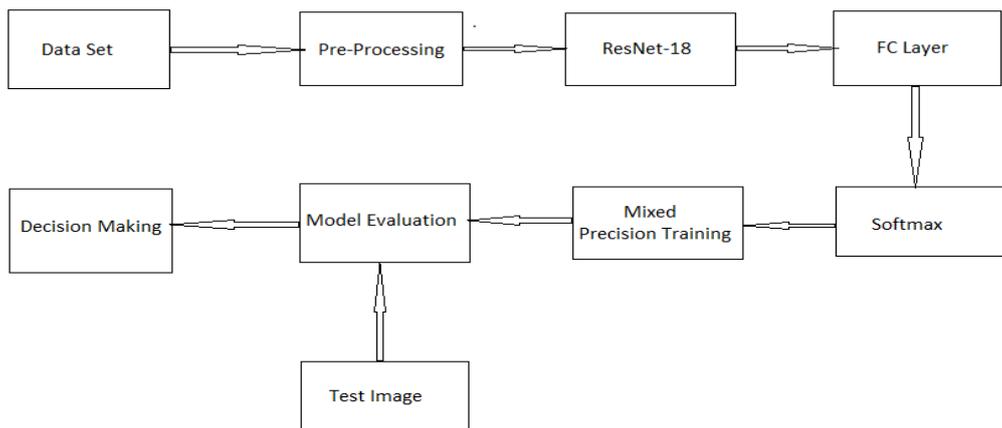


Figure 2: Block diagram representation for CAD

The proposed approach shown in Figure 2 aims to set up an arrangement that detects COVID-19 among the numerous chest x-ray images. The individual detection from images will be tedious and time-consuming.

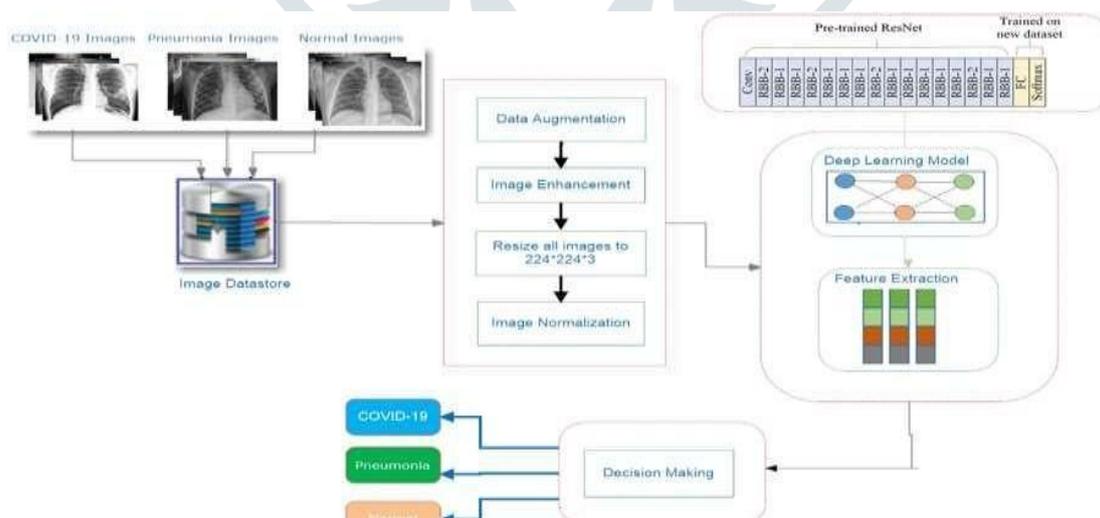


Figure 3: A schematic methodology for the COVID-19 detection system.

Figure 3 shows the schematic methodology for the COVID-19 detection system. It gives the clear picture of steps involved in the model.

ResNet 18

ResNet18 is 72-layer architecture with 18 deep layers. The architecture of this network aimed at enabling large amounts of convolutional layers to function efficiently. The network can classify images into 1000 object categories. Networks with large numbers (even thousands) of layers can be trained easily without increasing the training error percentage.

Fully Connected Layer

A fully connected layer (FC layer) multiplies the input by a weight matrix and then adds a bias vector. The convolutional and down-sampling layers are followed by one or more fully connected layers. As the name suggests, all neurons in a fully connected layer connect to all the neurons in the previous layer.

Softmax

Softmax assigns decimal probabilities to each class in a multi-class problem. Those decimal probabilities must add up to 1.0. Softmax is implemented through a neural network layer just before the output layer.

Mixing Precision Training

Mixed precision training is the use of lower-precision operations (float16 and bfloat16) in a model during training to make it run faster and use less memory. Using mixed precision, the performance can be improved by more than 3 times on modern GPUs and 60% on TPUs.

Algorithm

The Proposed algorithm has the following sequence of steps.

1. Downloading the Data set
2. Importing libraries
3. Creating Custom Dataset
4. Image Transformations
 - i. Resize (image)/224*24*3
 - ii. flipping: RandomHorizontalFlip ()
 - iii. Normalize
5. Prepare DataLoader
6. Creating the Model (resnet-18, FC layer, and softmax)
7. Training the model by Extracting features
8. Optimizing the Freeze layers, Learning rate, and batch size
9. Save the model
10. Inference on a Single Image

3.2 Dataset

A total of 15152 Chest X-Ray images were collected from public databases available on various kaggle repositories. Among these, 3616 were of COVID-19 positive patients, 1344 were of patients who had the virus Pneumonia, and 10214 were normal as shown in table 1. Figure 4 shows samples of images belonging to the classes COVID-19, Normal and ViralPneumonia.



Figure 4: Examples of COVID-19 infected, normal, and Pneumonia infected chest X-Ray images.

Table 1: Details regarding dataset

S.No.	Class	No. of images
1	COVID-19	3616
2	VIRAL PNEUMONIA	1344
3	NORMAL	10214

4. RESULTS AND DISCUSSIONS

The architecture is implemented using ResNet18, FC layer, softmax layer, as well as Pytorch framework with TensorFlow as the backend. Pytorch provides pre-trained weights from the ImageNet database. Though the images in the ImageNet dataset on which these models are trained may not be similar to images collected for study but may help by transferring knowledge learned to make the intended task more efficient. Also, pre-trained weights reduce the requirement of a large volume of data for training. Online Google colab is a cloud-based service which is used to execute the Python code. The Tesla T4 GPU was used for faster processing which is provided by Collaboratory. For training, the batch size was set to 6 and learning rate is 0.0003 and the number of steps was set in such a way until accuracy ≥ 0.98 .

Table 2: Validation results for different runs

Execution	Accuracy	Validation loss
Run-1	0.98	0.256
Run-2	0.98	0.189
Run-3	0.98	0.092

The code is written in Python3 and evaluated on a Windows 10 machine with a Core i5 and 8GB RAM. All tests were carried out using an 80 percent random array of CXR images as a training collection for the proposed DL systems, according to the proposed training scheme during the learning process, twenty percent of the training data were chosen at random.

The system gets trained until accuracy becomes more than or equal to 0.98. Table 2 shows the validation results of the proposed system. The execution will complete when accuracy becomes greater than or equal to 0.98. Validation loss is also very less at this point, which is 0.0928 as shown in Figure 5.

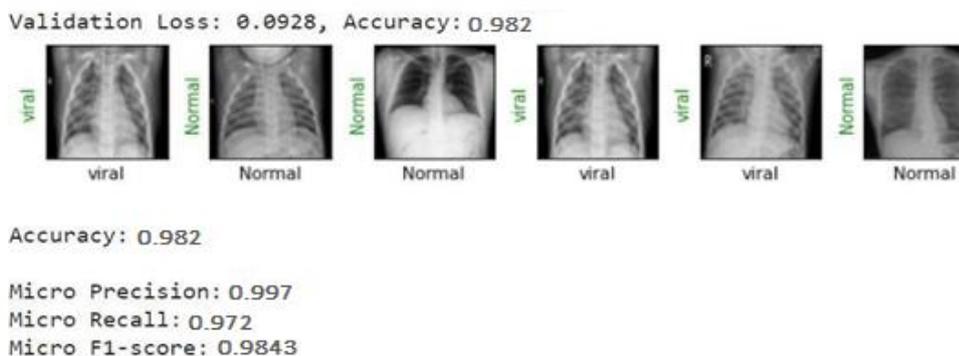


Figure 5: Proposed system validation results after training the system

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Probabilities: [1.2296219e-02 5.5911602e-04 9.8714465e-01]
Predicted class index: 2
Predicted class name: COVID
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Figure 6: Classification based on probabilities.

Class index: 0 -Normal Class index: 1 -Viral Pneumonia Class index: 2 -COVID

Figure 6 shows sample testing result for a sample image. Here a COVID patient chest X-ray image given to the trained system, it classified as Covid class and provide the class index.

Table3: Performance comparison of proposed and existing methods

Parameter	Existing Method	Proposed method
Accuracy	0.952	0.982
Validation Loss	0.26	0.0928
F1 score	0.92	0.9843

Table 3 shows the comparison results between existing method and proposed method. Result shows that proposed method gave better accuracy and gives accurate results.

5. CONCLUSION

In this paper, a deep CNN architecture was investigated on images of chest X-Rays for diagnosis recommendation of COVID-19 patients. Resnet-18 with the combination of FC layer and softmax model gives good results. The results suggested that proposed CNN based architecture have the potential for the correct diagnosis of COVID-19 disease. A new architecture will be developed, as future work, based on CNN for the detection of the percentage of the severity of COVID-19 on a patient's health, which means early or medium stage or completely affected.

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