Covid-19 Detection Using Chest X-Ray

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Abstract-COVID-19 continues to have a devastating impact on the lives of people all around the world. It is vital to screen the affected patients in a timely and cost-effective manner in order to combat this disease. Radiological examination is one of the most plausible steps in achieving this goal, with chest X-Ray being the most readily available and least priced option. We present a Deep Convolutional Neural Network-based approach to detect COVID-19 +ve patients using chest X-Ray pictures in this research. The implementation of a semi-quantitative CXR assessment has resulted from the addition of useful assistance to clinicians and the stratification of disease risk. Both severity scores and CXR results diagnosed early stage COVID-19 disease in this study. CXRs abnormalities were detected in 278 of 350 patients (78%) at certain points of the disease course. The DarkNet model was used in our study as a classifier for the you only look once (YOLO) real time object detection system. We implemented 17 convolutional layers and introduced different filtering on each layer. We have created a graphical user interface (GUI) application for public use. This application can be used by any medical personnel on any computer to detect COVID +ve patients using Chest X-Ray images in a matter of seconds.

Keywords: COVID-19, Coronavirus infections, Deep learning, Pneumonia, X-ray.

INTRODUCTION

On March 11, 2020, the World Health Organization declared the COVID-19 virus as an international pandemic [10]. The virus spreads among people via physical contact and respiratory droplets produced by coughing or sneezing. The current gold standard for diagnosis of COVID-19 pneumonia is real-time reverse transcription-polymerase chain reaction (RT-PCR). The test itself takes about 4 hours, however, the process before and after running the test, such as transporting the sample and sending the results, requires a significant amount of time [1,9]. Pertaining to PCR testing is not a panacea, as the sensitivities range from 70 to 98% depending on when the test is performed during the course of the disease and the quality of the sample. The clinical presentation of COVID-19 pneumonia is very diverse, ranging from mild to critical disease manifestations. Early detection becomes pivotal in managing the disease and limiting its spread [2]. In 20% of the affected patient population, the infection may lead to severe hypoxia, organ failure, and death [3,13]. In order to meet this need, high-resolution computed tomography (HRCT) and chest radiography (CR, known as chest X-ray imaging) are commonly available worldwide.

Coronavirus related respiratory illness usually manifests clinically as pneumonia with predominant imaging findings of an atypical or organizing pneumonia [14]. Plain radiography is very helpful for COVID-19 disease assessment and follow-up. It gives an accurate insight into the disease course. Chest radiography is a critical tool in the early detection, management planning, and follow-up evaluation of COVID-19 pneumonia; however, in smaller clinics around the world, there is a shortage of radiologists to analyze large number of examinations especially performed during a pandemic [5,6]. Limited availability of high-resolution computed tomography and real-time polymerase chain reaction in developing countries and regions of high patient turnover also emphasizes the importance of chest radiography as both a screening and diagnostic tool. However, despite the widespread availability of X-ray imaging, there is unfortunately a shortage of radiologists in most low-resource clinics and developing countries to analyze and interpret these images [7]. For this reason, artificial intelligence and computerized deep learning that can automate the process of image analysis have begun to attract great interest . X-ray is a cost effective and readily available option. Moreover, the X-ray machine is portable, making it versatile to be utilized in all areas of the hospital even in the Intensive Care Unit. Since the initial outbreak of the COVID-19, a few attempts have been made to apply deep learning to radiological manifestations of

COVID-19 pneumonia [4,12]. We aimed to determine the COVID-19 disease course and severity using chest X-ray (CXR) scoring system.

PROPOSED MODEL AND DATASETS

A typical CNN structure has a convolution layer that extracts features from the input with the filters it applies, a pooling layer to reduce the size for computational performance, and a fully connected layer, which is a neural network. By combining one or more such layers, a CNN model is created, and its internal parameters are adjusted to accomplish a particular task, such as classification or object recognition. Here, we used the Darknet-19 model as the base model of the research. Darknet-19 is the classifier model that forms the basis of a real-time object detection system named YOLO (You only look once). The Darknet-19 model consists of 19 convolution layers, with 5 pooling layers, using Maxpool. Each layer is having different filter numbers, sizes, and stride values. The proposed architecture consists of 17 convolutional layers. The architecture diagram is given in Figure 1. In each DN (DarkNet) layer has one convolution layer followed by Batch Norm and Leaky ReLU operations. The 3 x Conv layer has the same setup three times in successive form. The model is proposed for two types of classification. In the first classification where there are 2 classes, the model detects COVID-19. In the second classification, the model detects for 3 classes i.e. COVID-19, Pneumonia, and no-findings. The Dark Covid Net deep learning model consists of 1,164,434 parameters and used Adam optimizer for weight updates, cross-entropy loss function, and selected the learning rate as 3e-3. The dataset of this work has been collected from Kaggle repository, which contains Chest X-Ray scans of Covid-19 affected, normal and pneumonia. An X-ray image database with 125 chest X-ray images of diagnosed patients with COVID-19 are used [8]. In these images, 43 female and 82 male cases data are present. Also, the Chest X-ray 8 database provided was used for normal and pneumonia images. In order to avoid any unbalanced data problem, the authors have used 500 no-findings and 500 pneumonia chest X-ray images are added to the dataset.

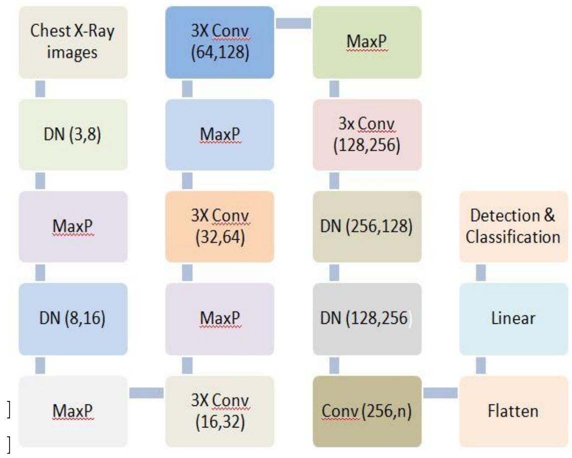

Figure 1. Dark Covid Net Proposed Architecture

RESULTS AND DISCUSSION

It can be noted from Figure 2 that there is a significant increase in loss values in the beginning of the training, which decrease substantially in the later stage of the training. The main reason for this sharp increase and decrease is attributed to the number of data in the COVID-19 class, which is far less than the other two (Pneumonia and No-Findings) classes. The proposed algorithm is sown below.

Algorithm 1: Proposed method

Initialization:
Calculate the best and worst generations:
$gbest = max(f_i : i = 1 \text{ to } N)$
$gworst = min(f_i : i = 1 \text{ to } N)$
Mutate:
$mutated_p$ = Randomly pick traits from both $gbest$ and $gworst$ to generate a new person of dimension $(1, D)$
if $fitness(mutated_p) >= fitness(gworst)$ **then**
 | Replace $gworst$ with $mutated_p$
end
else
 | Reject the mutation
end

However, when the deep model examines all X-ray images over and over again for each epoch during the training, these rapid ups and downs are slowly reduced in the later part of the training. The multi-class classification performance of the DarkCovidNet model has been evaluated for each fold, and the average classification performance of the model is calculated.

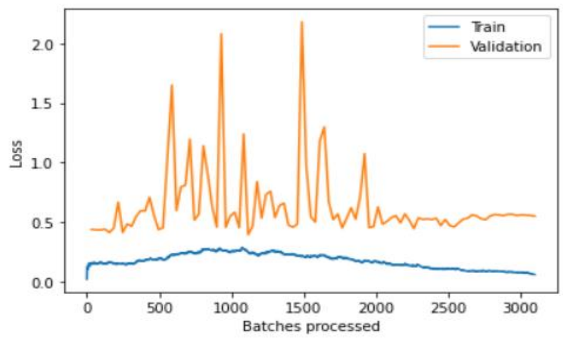

Figure 2. Validation and training loss obtained for proposed DarkCovidNet model

The overlapped confusion matrix (CM) is shown in Figure 3. The overlapped CM is created using the sum of CMs obtained in all folds. Thus, it is aimed to obtain an idea about the general perforations of the model. The DarkCovidNet model achieved an average classification accuracy of 87.01% to classify: no findings, COVID-19, and Pneumonia categories.

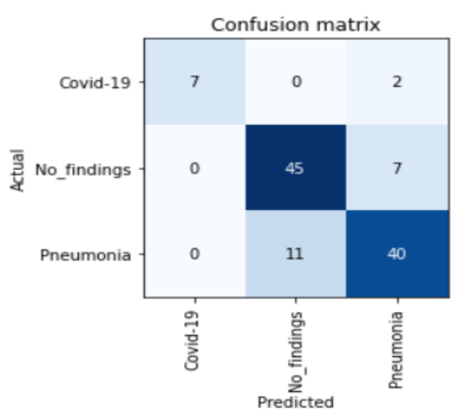

Figure 3. Confusion matrix of proposed model

Sensitivity, specificity, precision, F1-score, and accuracy values are shown in Table 1 for the detail analysis of the model for the 3-class problem. It can be noted from the overlapped confusion matrix of the multi-class classification task that the deep learning model classified COVID- 19 better than the classes of pneumonia and no findings. The obtained sensitivity, specificity, and F1-score values are 85.36%, 92.19%, and 87.38%, respectively.

The model may be more useful evaluate the efficacy of treatment based on the heatmap. It can also assist experts in terms of diagnosis, follow-up, treatment, and isolation of patients. Figure 3 shows the difference between a few COVID and pneumonia case images. The following primary findings are frequently observed in the chest X-rays of COVID-19 patients. Ground-glass opacities (GGO) (bilateral, multifocal, subpleural, peripheral, posterior, medial and basal), a crazy paving appearance (GGOs and inter-/intra-lobular septal thickening), air space consolidation, bronchovascular thickening (in the lesion) and traction bronchiectasis. Similarly, chest X-ray findings of pneumonia patients are observed as follows. Ground-glass opacities (GGO) central distribution, unilateral, reticular opacity, vascular thickening, distribution more along the bronchovascular bundle and bronchial wall thickening. In COVID-19, isolated lobar or segmental consolidation without GGO, multiple tiny pulmonary nodules, tree-in-bud, pneumothorax, cavitation, and hilar lymphadenopathy smoother interlobular septal thickening with pleural effusion are rare, while these findings can often be seen in pneumonia.

Table 1. Sensitivity, specificity, precision, F1-score, and accuracy values obtained for each fold of the proposed model.

Folds	Sensitivity	Specificity	Precision	F1-Score	Accuracy
Fold-1	88.18	93.65	90.96	89.45	89.32
Fold-2	88.56	90.62	89.38	86.62	84.89
Fold-3	84.12	90.13	89.89	86.55	85.78
Fold-4	83.17	92.30	90.62	86.41	87.12
Fold-5	85.84	92.76	89.72	87.58	88.01
Average	85.36	92.19	89.97	87.38	87.01

In the COVID-19 epidemic, radiological imaging plays an important role in addition to the diagnostic tests performed for the early diagnosis, treatment, and isolation stages of the disease. Chest radiography can detect a few characteristic findings in the lung associated with COVID- 19. Deep learning models are sensitive in detecting COVID-19 lung involvement and hence the diagnostic accuracy rate is high. During the evaluation of the model, X-ray radiographs of COVID-19 patients confirmed positive by the PCR Test are used [11]. The model can easily detect GGO, consolidation areas, and nodular opacities, which are the pathognomic findings of patients for COVID-19 on X-ray radiography. In COVID-19, bilateral, lower lobe, and peripheral involvement is observed, and the proposed model can detect localization of the lesion. These models are particularly important in identifying early stages of COVID-19 patients.

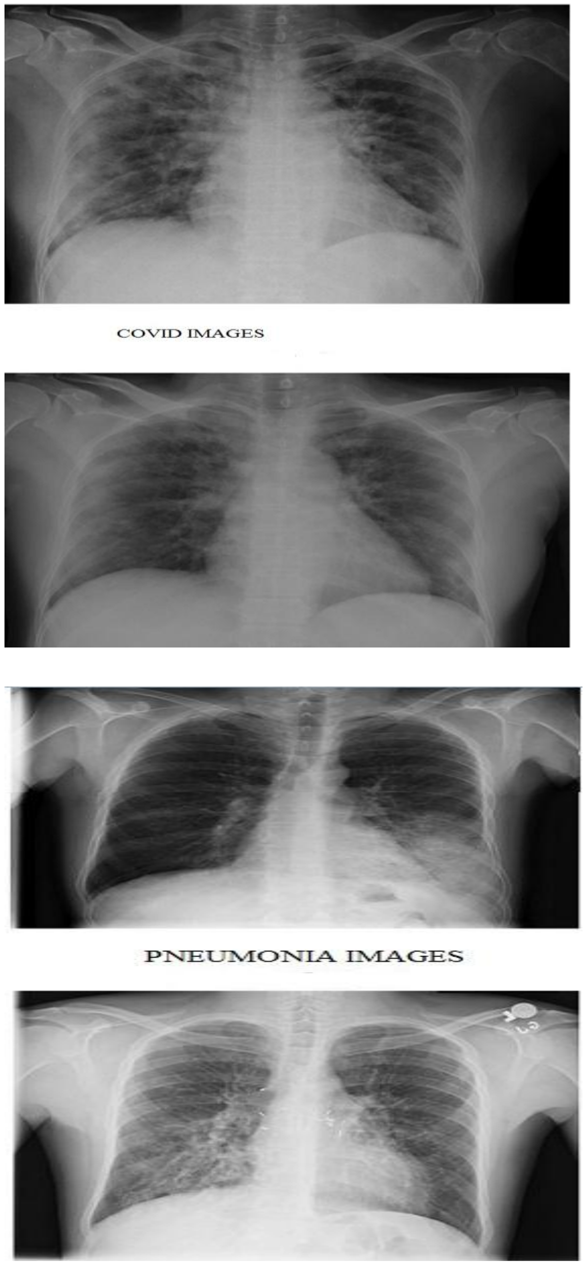

Figure 3. Differences observed in some COVID and pneumonia case images

Early diagnosis of the disease is important to provide immediate treatment and to prevent disease transmission. The models can also play an indispensable role in patients lacking early symptoms. There is a margin of error in patients with diffuse late lung parenchyma and in patients with significantly reduced lung ventilation due to poor quality X-ray images. X-rays that are not of optimal quality are difficult to evaluate by radiologists. The clinical and radiological images of later-stage patients are well established and it is easier to detect the findings by experts. The role of deep learning models is more prominent in screening and diagnosis when the infection is at its early stages. The models can be readily used in healthcare centers. There is no need to wait long hours for the radiologists to screen the images. Thus, healthcare workers and patient relatives can focus on isolation of suspicious cases so that treatment can begin. Hence, the spread of the disease can be significantly reduced. The patients can seek a second opinion if they are diagnosed as positive by our system. Hence, waiting time can be significantly reduced, and it will alleviate clinician workload.

CONCLUSION

In this study, we have proposed a deep learning based model to detect and classify COVID-19 cases from X-ray images. The proposed model can be used for the diagnosis of COVID-19 using X-ray radiographs. X-ray radiographs are preferred because they are readily accessible for disease diagnosis. They are widely used in health centers worldwide during the pandemic. The model has the ability to diagnose COVID-19 within seconds. In the future, we intend to validate our model by incorporating more images. A limitation of the study is the use of a limited number of COVID- 19 X-ray images. This developed model can be placed in a cloud to provide diagnosis instantly and to help rehabilitate affected patients immediately.

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