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Automatic COVID-19 lung images classification system based on convolution neural network

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ABSTRACT

Coronavirus disease (COVID-19) still has disastrous effects on human life around the world. For fight that disease. Examination on the patients who have been sucked in quick and cheap way is necessary. Radiography is most effective step closer to this target. Chest X-ray is readily obtainable and cheap option. Also, because COVID-19 is a virus, distinguish COVID-19 from common viral pneumonia from common viral pneumonia is difficult. In this study, X-ray images of 500, 500, 500, and 500 patients for healthy controls, typical viral pneumonia, bacterial pneumonia and COVID-19, were collected respectively. To our knowledge, this was the first quaternary classification study that also included classical viral pneumonia. To efficiently capture nuances in X-ray images, a new model was created by applying convolution neural network for accurate image classification. Our model outperformed to achieve an overall accuracy, sensitivity, specificity, F1-score, and area under curve (AUC) of 0.98, 0.97, 0.98, 0.97, and 0.99 respectively.

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1. INTRODUCTION

Chest computed tomography (CT) performs essential part in patients evaluation with coronavirus disease (COVID-19). So far, deep learning (DL)-based chest CT analysis has mainly focused on diagnosing or classifying COVID-19 in order to distinguish between positive COVID-19 patients and patients with normal pneumonia. The widespread implementation of reverse transcription polymerase chain reaction (RTPCR) testing reduces the need to use screening radiographs. However, radiographic imaging is still important to detect lung intrusion in COVID-19 patients. In particular, it has been proposed to use CT scans of lesions as surrogate imaging of disease burden and to identify critically ill patients requiring hospitalization.

As assured by world health organization [1], coronavirus recorded the first formal cases in Wuhan, China. To date, millions of people have been killed, and there are millions of confirmed cases worldwide. Epidemics in the form of pandemics have a devastating impact on health of people all over world [2]. This infectious infection, expands quicker than other common flus. RTPCR used to distinguish COVID-19 [3]. This examination seems to be accurate. Even if the patient's sample contains only a small amount of the virus. However, polymerase chain reaction (PCR) examinations are complex, take long time and expensive. Therefore, not all health care institutions are able to do this. With these limitations in mind, a standalone approach to disease detection is to analyze chest radiographs to detect the presence or absence.

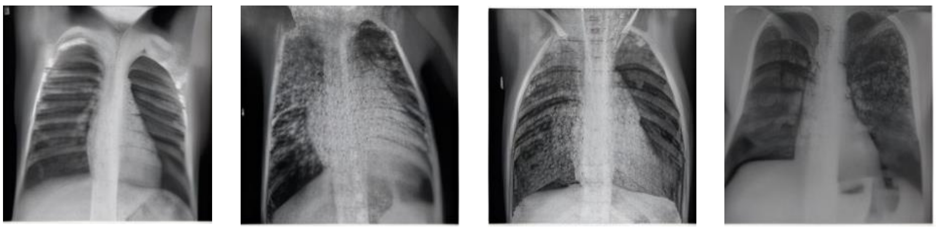
The main problem with radiographic-based diagnosis of COVID-19 patients is the lack of trained and well-available physicians. Furthermore, the radiation symptoms associated with COVID-19 are unknown, as many specialized have no expertise with COVID-19 infected patients. Recently, many methods have emerged that use artificial intelligence to distribute pneumonia and COVID-19 from CT or X-rays. There are basically two types: COVID-19 to non-COVID-19 and COVID-19 to other pneumonia. Xu *et al.* [4] introduced a distinguish system for classifying COVID-19, influenza, and healthy individuals with 86.7% accuracy. Li *et al.* [5] ResNet50 was used to distinguish COVID-19 from non-pneumonia with 90% sensitivity. Chen *et al.* [6], Ouyang. [7], Apostolopoulos *et al.* [8]. However, because COVID-19 is also a variant of the virus, all this work ignores the typical viral pneumonia that infects the most difficult and typical virus.

In this study, X-ray images of 500, 500, 500, and 500 patients for healthy controls, typical viral pneumonia, bacterial pneumonia and COVID-19, were collected respectively. According to our knowledge, this was the first quaternary classification study that also included classical viral pneumonia. To efficiently capture nuances in X-ray images, a new model was created by a recently developed convolution neural network for accurate image analysis. Our model outperformed the commonly used reference model, achieving an overall accuracy, sensitivity, specificity, F1-score, and AUC of 0.98, 0.97, 0.98, 0.97, and 0.99 respectively.

2. METHOD

2.1. Data set and model inputs

In current work, chest X-ray obtained from various open sources [9]–[15]. This data set contains 4,900 X-ray images, categorized into three sectors, namely natural, COVID-19 and pneumonia. The pneumonia category consists of bacterial pneumonia images and viruses pneumonia images. In Figure 1, the chest X-ray imaging dataset is rearranged into four types: normal, bacterial pneumonia, viral pneumonia, and COVID-19 as shown in Figures 1(a) to 1(d) respectively.



(a) (b) (c) (d)

Figure 1. Chest X-ray samples from the test datasets (a) normal, (b) bacteria, (c) virus and (d) COVID-19

2.2. Pre-processing operations

Since this data set consists of large and different lung images; and in order to handle reasonable computing time during the convolutional neural network (CNN) training experiment, all images are adjusted to a single dimension and rescaled to smaller images. 310×310 to adapt to the standard input of a custom structure. To standardize the input of CNN, the original image is preliminarily divided before the resizing step. Regarding the test, the trained model was tested on distinct dataset taken from IEEE DataPort [16].

2.3. Data augmentation

Data augmentation is method may drastically growth number of data times in dataset for training a model [17]. For the four categories image datasets (healthy controls, typical viral pneumonia, bacterial pneumonia and COVID-19, this method utilizes basal image procedures like flip, rotate, crop, and pad for enlargement. Next, the dataset will be expanded to include these converted images resulting from subsisting image set. This enlarges dataset size for training neural networks [18]–[24]. A data expansion method was used in this study to fix availability of few datasets problem that impacts proposed CNN performance. This technique has expanded the dataset. Moreover, extra learning countenances are available in knowledge model. In this study, image transformation procedures, mirroring, and rotation, were utilized for data expansion. In initial stage of data expansion, 100 X-ray images were mirrored to capture an additional 100 images. After using this operation, the resulting dataset was expanded to 180 images. In second stage, authentic 100 images are rotated another 90° to obtain another 100 images, after that, rotated 180 degrees to obtain another 100 images, and finally the original 100 images rotated the image of 270 degrees further and 100 more images were obtained. These operations created 500 datasets each for healthy controls, typical viral pneumonia, bacterial pneumonia, and COVID-19 X-rays. Table 1 introduces image transformation procedures applied on all image types and the related images generated number by operations. Figure 2 introduces impact of the extension technique performed to authentic image sample of dataset utilized in this work. Figure 2(a) is the ordinary image, Figure 2(b) is the rotated image with 90°, Figure 2(c) is the rotated image with 180°, Figure 2(d) is the rotated image with 270° and Figure 2(e) is the flipped image.

Table 1. Total image number after augmentation

Image augmentation operation	Number of healthy controls images	Number of typical viral pneumonia images	Number of bacterial pneumonia images	Number of COVID-19 images
Ordinary	100	100	100	100
Rotation of ordinary images by 90˚	100	100	100	100
Rotation of ordinary images by 180˚	100	100	100	100
Rotation of ordinary images by 270˚	100	100	100	100
Flipping of ordinary images	100	100	100	100
Total	500	500	500	500

(a) (b) (c) (d) (e)

Figure 2. X-ray image augmentation methods on an (a) ordinary, (b) 90° rotation, (c) 180° rotation, (d) 270° rotation, and (e) flipping

2.4. Convolutional neural networks (CNNs)

CNNs are invigorated through the human brain’s visual framework. So, the background of CNNs is to allow computers to see the world people see. Therefore, CNNs can be utilized in image analysis and classification [25]. CNN is type of deep neural network with convolution, max pool, and non-linear activation level. The convolutional layer, which can be viewed as the CNN kernel layer, applies process known as "convolution," which CNN is named after. The base of convolutional layer is performed to input layer. Convolutional layers outputs are decreased to feature maps. In this work, rectified linear unit (ReLU) was utilized for activation task with a convolutional layer that helps to expand nonlinearity of input image because image is nonlinear. Therefore, CNNs with ReLU are easier and faster in the current situation. Since ReLU characterized as in (1).

$$Z = Max(0, i) \tag{1}$$

Here the function assumes that the output z is zero for all negative values, and positive values keep i constant.

2.4.1. The proposed system

As appeared in Figure 3, the study starts with the series of essential dataset consists of four image categories: healthy controls, typical viral pneumonia, bacterial pneumonia, and COVID-19. The X-ray image was preprocessed concurring to the preprocessing above steps. Dataset expanded utilizing standard expansion methods to expand its size. Resulting dataset was utilized to train model in next stage. Then, model's disease detection performance was tested. The proposed CNN model tests were done utilizing primary dataset test and independent validation dataset. Table 2 details the dataset, including training sets, test sets, and number of X-ray images for the four prediction classes. Finally, aggregation image-level predictions for image of each case were done to provide the reasonable result.

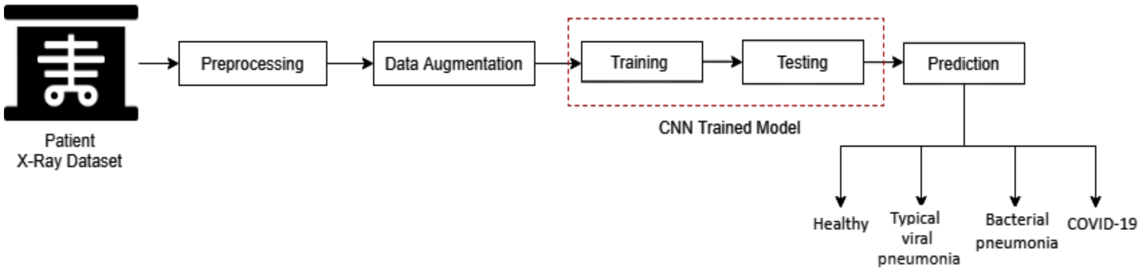


Figure 3. System workflow

Table 2. Images number for training and testing

Dataset	Healthy Controls	Typical Viral Pneumonia	Bacterial Pneumonia	COVID-19	Total
Images number	500	500	500	500	2,000
Training	400	400	400	400	1,600
Testing	100	100	100	100	400

3. RESULTS AND DISCUSSION

The proposed classification system for COVID-19 diagnostics was implemented on a processor with the programming language Python 3.8 and Intel R Core i58300H CPU @ 2.30GHz x 8 and 8 GB RAM, Windows 10, RADEON AMD 1050, and 4 GB graphics. Google Collab GPU, Python 3.7 and Tensor Flow 2.2.0. The Tensor Flow 2.2.0 deep learning library is used to implement CNN, and training and testing steps are performed on the Google Collab platform.

In this model, CNN used to effectively classify COVID-19. Proposed technique is trained on four public datasets and outperforms itself in all classes. CNN is used for the final classification with accuracy, sensitivity, specificity, F1 score and AUC giving the best results of 0.98, 0.97, 0.98, 0.97, and 0.99 respectively as in Table 3. So that, this approach using X-ray imaging and computational diagnostics can be used as a large, faster, and cheaper screening method. It also reduces the required testing time. Training with larger datasets and field testing with larger cohorts can be very helpful in making clinically effective predictions of COVID-19.

Table 3. Model overall performance primarily based totally on unbiased validation data

Evaluation parameters	Degree
Accuracy	0.98
Sensitivity	0.97
Specificity	0.98
F-1 score	0.97
ROC AUC	0.99

Receiver operating characteristic area under curve (ROC AUC)

To examine the overall performance, classification accuracy, sensitivity, specificity and F1-score, measured:

$$\text{Accuracy}=\frac{\text{TPR + TNR}}{\text{TPR + FPR + TNR + FNR}} \tag{2}$$

$$\text{Sensitivity}=\frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

$$\text{Specificity}=\frac{\text{TN}}{\text{TN+FP}} \tag{4}$$

$$\text{F1-score}=\frac{2\text{*TP}}{2\text{*TP+FP+FN}} \tag{5}$$

where TP stands for true positive, TN for true negative, FP for false positive, FN for false negative and FP for false positive TN for true negative. Figure 4 shows train and test losses of the proposed CNN model. As can be seen in Figure 4, proposed CNN does not take much time to converge. Figure 5 shows a graph of training and test accuracy done by the proposed CNN model. Figures 6 and 7 shows the characteristic curve of the receiver operating characteristics at AUC=0.99 and the sensitivity-specificity curves for the various case types respectively.

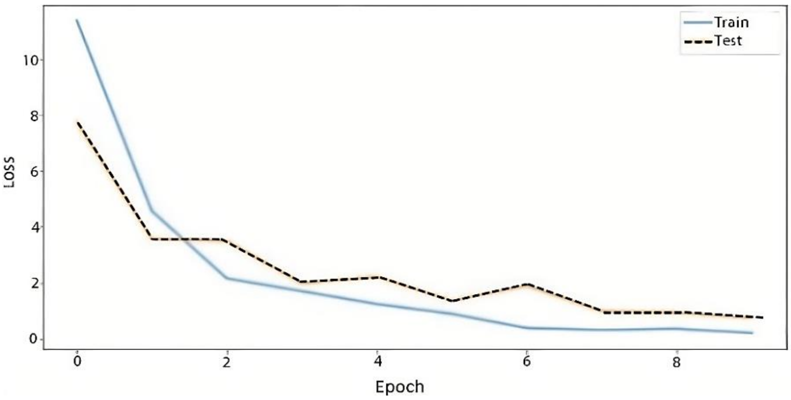


Figure 4. Train and test loss plot by using CNN

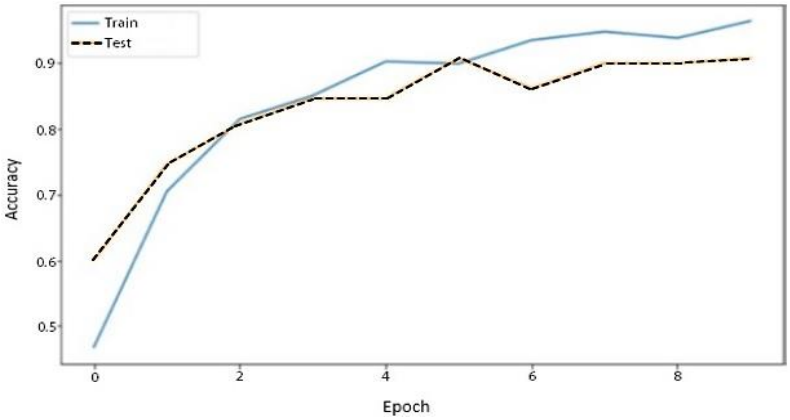


Figure 5. Train and test accuracy plot by using CNN

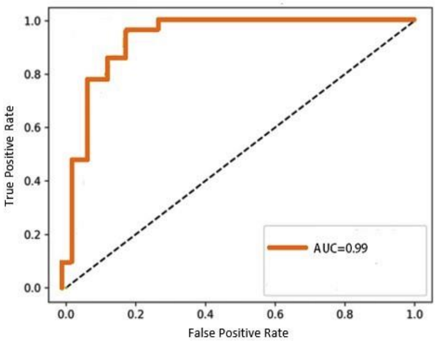


Figure 6. ROC curve of classification

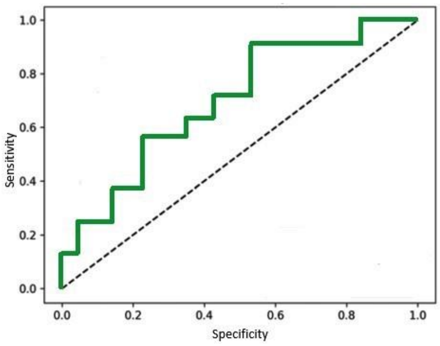
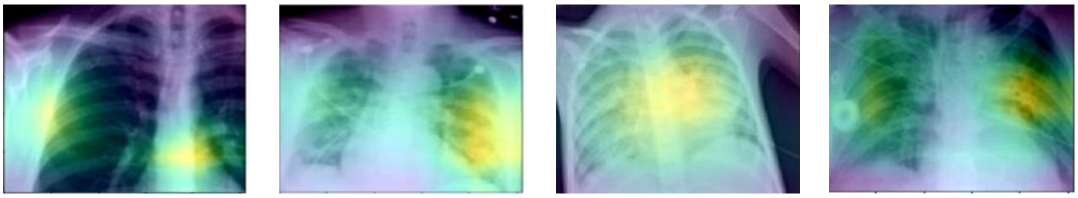


Figure 7. Sensitivity and specificity curve of classification

As evidence of introduced CNN system in classification importance for detecting COVID-19 from X-ray images, trained model was examined on distinct dataset from IEEE DataPort. The distinct test dataset consists of 100 COVID-19 X-rays. 100 regular images were added to dataset for testing. In addition, a feature map of four different X-RAY images types excerption by the classification model and examined overall learning feature then renders possibility of network. As in Figure 8, area that the lesion is existed shows a superior level of response, indicating that the model was eligible to learn underlying properties from radiography of three different patients' cases. Figure 8(a) shows healthy X-Ray image, Figure 8(b) shows COVID-19 X-Ray image, Figure 8(c) shows viral pneumonia image and Figure 8(d) shows bacterial pneumonia image.



(a) (b) (c) (d)

Figure 8. The X-Ray images feature maps four types of people extracted by proposed classification model (a) healthy X-Ray image, (b) COVID-19 X-Ray image, (c) viral pneumonia image, and (d) bacterial pneumonia image

4. CONCLUSION

By applying CNN, X-ray deep learning diagnostic system for rapid COVID-19 diagnosis was created. This model can individually detect COVID-19 X-rays from healthy individuals, X-rays from patients with bacterial pneumonia, and X-rays from patients with typical viral pneumonia. This model able to differentiate so various different kinds of pneumonia at once. Results have shown that introduced model fulfill high accuracy, specificity, sensitivity, AUC ROC and F1 score that shows the reliability of the model.

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