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Helping Healthcare Providers to Differentiate COVID-19 Pneumonia by Analyzing Digital Chest X-Rays: Role of Artificial Intelligence in Healthcare Practice

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Abstract

Background: Detecting COVID-19 pneumonia and differentiating it from community acquired pneumonia (CAP) has been a challenging task for healthcare providers since the pandemic began. We therefore aim to develop and evaluate a simple, non-invasive tool to accurately detect COVID-19 by using digital chest X-ray (CXR).

Methods and Results: We performed a retrospective, multi-center study in which deep learning frameworks were used to develop the system architecture of the diagnostic tool. The tool was trained and validated by using data from the GitHub database and two hospitals in Bangladesh. Python programming was used to calculate all statistical estimates. Our study revealed that the artificial intelligence (AI)-based diagnostic tool was able to detect COVID-19 accurately by examining chest X-ray (CXR). During the testing phase, the tool could interpret CXR with precision of 0.98, recall/sensitivity of 0.97 and F1 score of 0.97 for COVID-19. The evaluation results showed high sensitivity (90%) and specificity (92%) in detecting COVID-19. The AUC values for COVID-19 and pneumonia were 0.91 and 0.87, respectively.

Conclusion: The developed AI-based diagnostic tool can offer the healthcare providers an effective means of detecting and differentiating COVID-19 from other types of pneumonia, thus contributing to reducing the long-term impact of this deadly disease.(**International Journal of Biomedicine. 2022;12(3):459-465.**)

Key Points

- The major strength of this study is that it has led to the development of a technology-based tool that can precisely detect COVID-19 at an early stage and immediately isolate infected patients from the healthy population.
- This next generation test can be accessed by healthcare providers remotely and therefore provide an added convenience.
- The main limitation is with this tool COVID-19 pneumonia may be confused with other types of pneumonia if the quality of the chest image is too low. Moreover, it focuses only on detecting whether or not the disease is COVID-19, but not its severity.

Keywords: COVID-19 • chest X-Ray • artificial intelligence • Bangladesh

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Abbreviations

AI, artificial intelligence; **AUC**, area under the curve; **CAP**, community acquired pneumonia; **CT**, computed tomography; **CNN**, convolutional neural network; **CXR**, chest X-ray; **CL**, convolutional layer; DCNN, deep convolutional neural networks; **PAV**, postero-anterior view; **ROC** curve, receiver operating characteristic curve; **ReLU**, rectified linear unit; **VGG**, Visual Geometry Group.

Introduction

The novel coronavirus, known as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is responsible for COVID-19, which primarily causes respiratory illnesses of varying severity, ranging from the common cold to fatal pneumonia.[1-3] The virus is highly transmissible and has ravaged the world since it was first identified in late 2019. So far, it has affected millions of people, causing a global pandemic and incapacitating healthcare systems.[2-5] Although the SARS-CoV-2 potentially affects multiple organs of the human body, it mainly infiltrates the lower respiratory system, triggering inflammatory changes in the lung tissue. Most of these infected patients commonly present with mild fever and dry cough; however, about one-fifth of all infected patients progress to severe pneumonia or even death.[1,4-6]

Detecting COVID-19 throughout the pandemic has been a challenging and daunting task because of the shortage of diagnostic tools in many countries. The detection was mostly dependent on a molecular technique called Polymerase Chain Reaction (PCR), which has been the most preferred testing procedure since the beginning of this pandemic. However, as the transmission of COVID-19 escalated, the health systems of most countries struggled to provide the testing services to their entire population due to diverse technical, financial, and logistical barriers.[6-8] Moreover, due to the similarities between clinical presentations of COVID-19 and other types of pneumonia, establishing a correct diagnosis poses greater challenges to healthcare providers. Accordingly, major medical societies in multiple countries have recommended using chest radiography to diagnose COVID-19 pneumonia and also to differentiate it from other community acquired pneumonia (CAP).[6] In some cases, a CT scan has also been successfully used to detect COVID-19, even in patients with a negative PCR test or without symptoms.

In almost all healthcare practices, clinicians use chest X-ray (CXR) images to diagnose pneumonia and other lung diseases. Nowadays, digital imaging machines–both static and mobile–are available in all hospitals and diagnostic centers; thus, digital X-rays are widely used for diagnostic purposes. However, the main challenge with the interpretation of CXR is that it requires a radiologist or a specialist doctor to do the analysis, and thereby can be time-consuming and logistically inconvenient.[6,7] Moreover, it can become burdensome to the already stretched health system as more and more people are getting sick due to new COVID-19 variants.

The use of artificial intelligence (AI) in the medical field is not new. In particular, the deep learning method is being widely used in many healthcare settings due to its unique advantages in precisely detecting some complex health conditions, such as tuberculosis and lung cancer.[6-9] Therefore, we hypothesized that an AI-based tool could be developed and trained to detect COVID-19 pneumonia accurately and to differentiate it from other types of CAP by using CXRs. In this paper, we present the system architecture of an innovative AI-based tool and the results of its validation and performance in differentiating the COVID-19 pneumonia from other types of pneumonia.

Materials and Methods

Development and Validation Data Sets

We trained our tool to distinguish CXRs of COVID-19 cases from other CAP. We also instructed the tool to isolate the chest radiology with no apparent abnormalities. A total of 299 digital CXR images were utilized for training this AI-based tool. Of them, 89 CXR were COVID-19 positive cases, 100 were diagnosed as pneumonia cases, and 110 CXRs of "normal" patients, i.e., CXR with no chest or lung diseases (Figure 1). The validation was carried out to evaluate the predicting power of the tool by using a sample of 24 CXRs of confirmed COVID-19 patients, 234 images of CAP, and 390 images of "normal" patients.

Strict selection criteria were applied to select the desired quality of CXRs. Only digital, postero-anterior view (PAV) of the images were used. For developing the tool, we used CXRs of confirmed COVID-19 cases and CAP; and CXRs of non-pneumonia or 'normal' cases. The CXRs of CAP and "normal" cases were selected randomly, fulfilling the inclusion criteria. Only confirmed SARS-CoV-2 cases were considered, which were anonymous but had a complete record, ranging from the identification (ID) number, clinical history, and the final outcomes of treatment. Chest images from any unauthorized sources or of low resolution were discarded.

We used CXRs from two hospitals (Rangpur Medical College Hospital, Rangpur; Cardio Care Hospital, Dhaka) in Bangladesh and the COVID-19 CXR images from the GitHub database.[10] Special attention was given to selecting CXR images of those patients who had a complete trail of demographic and diagnostic history in the dataset. Although we used CXR images of hospital patients, we had no direct contact with patients. All data were stored in a secure, encrypted database with strict security and privacy protocols in place.

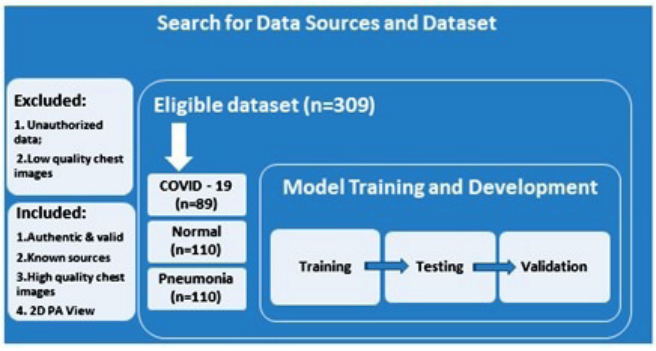

Fig. 1. *Data used to train the model.*

Although we used the chest images from a known dataset, we did not directly involve patients or any other human participants. The study protocol was reviewed and approved by the university ethics committee, and written permission was obtained from participating hospitals. Moreover, the data used were encrypted and anonymous.

Statistical analysis

In order to measure sensitivity and specificity, the AI-based tool was validated by randomly uploading data from the above-mentioned three data types. Rigorous statistical analysis was performed, and the outputs of each round of validations were observed and recorded. These outputs were then compared with the WHO dataset for accuracy and precision. The performance of the tool was analyzed and verified on the basis of standard measures, such as sensitivity, specificity, ROC curve and AUC. Python programming was used to calculate all statistical estimates. Furthermore, we drew an ROC curve, which is the plot of sensitivity versus 1-Specificity. The AUC was also used for an effective measure of accuracy.

Results

In the following section, we describe the system architecture of the AI-based tool and the results of the comparative performances of three deep learning image classifiers,[11-13] which we experimented with in this study.

Model architectures

For developing the system architecture, we examined different deep learning models that were derived from the field of artificial intelligence. These models are basically different architectures of CNN that has been a dominant method in computer vision tasks since the astonishing results were shared on the object recognition competition known as the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2012. CNN uses multiple perceptrons that analyze image inputs and are able to segregate the images from one another. Another advantage of using CNN is that it leverages the use of local spatial coherence in the input images, which allows them to have fewer weights as some parameters are shared. This process is found to be efficient in terms of memory and complexity.[14] The basic building blocks of CNN are as follows:

Convolution layer

In the convolutional layer (CL), a matrix named kernel is passed over the input matrix to create a feature map for the next layer. We performed a mathematical operation called convolution by sliding the kernel matrix over the input matrix. At every location, element-wise matrix multiplication was performed and the result summed onto the feature map. Convolution is a specialized kind of linear operation that can be applied over more than one axis. If we have a 2-Dimensional image input, I, and a 2-Dimensional kernel filter, K, the convoluted image is calculated as follows:

$$S(i,j) = \sum_m \sum_n I(m,n)k(i-m, j-n)$$

Non-linear activation functions

The activation function is a node that comes after CL, and the activation function is the nonlinear transformation that we do over the input signal.

Different activation functions are:

a. ReLU: Rectified linear unit activation function (ReLU) is a piecewise linear function that will output the input if it is positive; otherwise, it will output zero.

$$f(x)=max(0,x)$$

b. Leaky ReLU is a variant of ReLU. Instead of being 0 when z<0, a leaky ReLU allows a small, non-zero, constant gradient α (Normally, α=0.01)

$$R(z) = \{z \text{ when } z > 0, z \text{ when } z <= 0\}$$

c. Sigmoid takes a real value as input and outputs another value between 0 and 1. It is easy to work with and has all the nice properties of activation functions: it is non-linear, continuously differentiable, and it is used in the output layer when the classifier is binary.

$$S(Z) = \frac{1}{1+e-z}$$

Pooling layer

A pooling layer is a new layer added after the CL, specifically, after a nonlinearity (e.g., ReLU) has been applied to the feature map output by a CL. The drawback of the feature map output of a CL is that it records the precise position of features in the input. This means that cropping, rotation, or any other minor changes to the input image will result in a completely different feature map. To counter this problem, we applied down sampling of CLs. Down sampling was achieved by applying a pooling layer after the nonlinearity layer. Pooling helped to make the representation become approximately invariant to small translations of the input. Invariance to translation means that if we translate the input by a small amount, the values of most of the pooled outputs do not change (Figure 2).

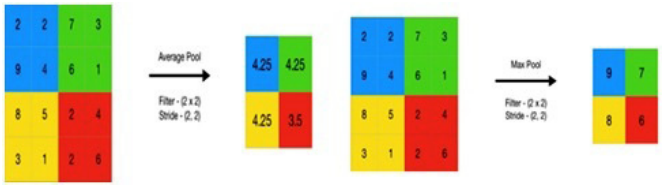

Fig. 2. *Types of pooling*

Fully connected layer

At the end of a CNN, the output of the last pooling layer acts as input to the fully connected layer. There can be one or more of these layers. Fully connected means that every node in the first layer is connected to every node in the second layer.

Development of system architecture

In this study, we applied three different architectures of CNN: i) Visual Geometry Group Network 16 (VGG16), ii) Residual Networks 50 (ResNet50), and iii) Depthwise CNN, to assess their comparative performances in detecting COVID-19 (Figure 3). The results of each of these tests were recorded.

Firstly, we studied the performance of VGG16 in distinguishing COVID-19 and other types of pneumonia. VGG16 is a CNN architecture. It was initially developed by the Oxford Robotics Institute's Karen Simonian and Andrew Zisserman and was first submitted to the ImageNet Large Scale Visual Recognition Challenge 2014(ILSVRC2014), where it performed very well and achieved 92.7% top-5 accuracy.[15] The first and second CLs consist of 64 feature kernel filters, and the size of the filter is 3×3. As the input image (RGB image with depth 3) passes into the first and second CL, dimensions change to 224×224×64. Then the resulting output is passed to the max-pooling layer with a stride of 2. The third and fourth CLs are of 124 feature kernel filters, and the size of the filter is 3×3. These two layers are followed by a max-pooling layer with stride 2, and the resulting output will be reduced to 56×56×128. The fifth, sixth and seventh layers are CLs with a kernel size of 3×3. All three use 256 feature maps. These layers are followed by a max-pooling layer with stride 2. The eighth to thirteenth layers are two sets of CLs with kernel size 3×3. All these sets of CLs have 512 kernel filters. These layers are followed by a max-pooling layer with a stride of 1. Layers fourteen and fifteen are fully connected hidden layers of 4096 units, followed by a softmax output layer (sixteenth layer) of 1000 units.

Secondly, we deployed ResNet-50, which is also a CNN[14] that is 50 layers deep:

•At first, there is a convolution with a kernel size of 7 * 7 and 64 different kernels, all with a stride of size 2, giving us one layer.

•Next, we got max pooling with also a stride size of 2.

•In the next convolution, there was a 1 * 1.64 kernel, after that a 3 * 3.64 kernel, and at last 1 * 1.256 kernels; these three layers were repeated in total 3 times so, giving us 9 layers in this step.

•Next, we saw the 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 times so, giving us 12 layers in this step.

•After that, there was 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 did an average pool and ended it with a fully connected layer containing 1000 nodes and, in the end, a softmax function, so this gives us one layer.

•So, totaling this it gave us a 1 + 9 + 12 + 18 + 9 + 1 = 50 layers DCNN.

This network allowed us to load a pre-trained version of the network trained on more than a million images from the ImageNet database. As a result, the network has learned great feature representations for a wide range of images.

Thirdly, we examined the performance of Depthwise CNN, which is another deep learning AI function that mimics the functioning of the human brain in processing data and creating models for use in decision-making. The Depthwise convolution model is a 2D convolution that helps to reduce overfitting when the number of parameters is high. It deals not just with spatial dimension but with depth dimension as well as the number of channels. What we did here is apply a 2D depth filter at each depth level of the input tensor in our dataset so that we had 3*4095*4095 (input channels, max-width, max-height). The filter we used to extract the feature was 3*3*3. So the Depthwise convolution breaks the image and filter into three different channels and then convolves the corresponding channel and then stacks them back. After that, we used a 1*1 filter to cover the dimension. Here the amount of parameters is reduced by the number of input channels. The feature from the Depthwise spatial convolutional model is sent to fully connected layers, where the output layer consists of three nodes (COVID-19, CAP, and Normal) (Figure 3).

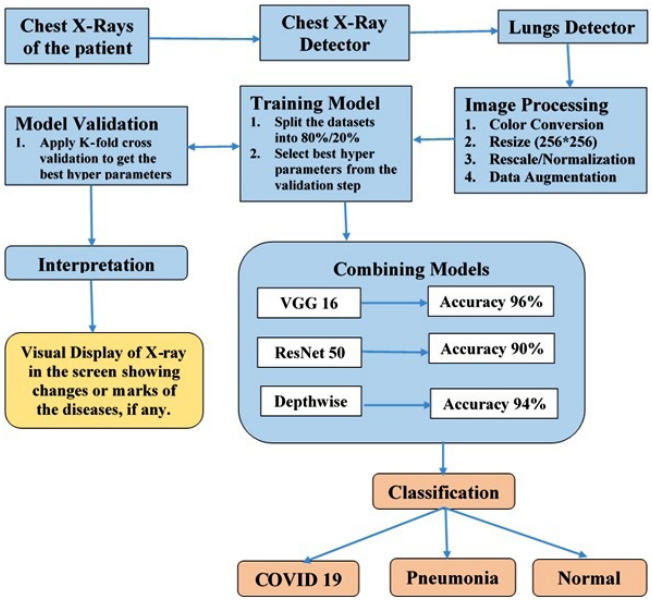

Fig. 3. *System architecture.*

Finalization of system architecture

The comparative analysis showed that among the three deep learning image classifiers used in this study (Figure 4), VGG16 produced the best results. We observed that the VGG16 was able to read COVID-19 images more accurately than ResNet50 and Depthwise CNN, with a precision of 0.98, recall/sensitivity of 0.97, and F1 score of 0.97 (Table 1). Once the tool was fully trained, the model was recalibrated and refined based on the outputs of the testing process. The whole process was random and was meticulously monitored and recorded. After several repetitions, the model was finally ready for validation (Figure 4).

Table 1.

Comparison of used deep learning models

Type of Data	Sensitivity, %	Specificity, %	AUC
VGG 16	97	99	98
ResNet50	95	98	97
Depthwise CNN	96	97	97

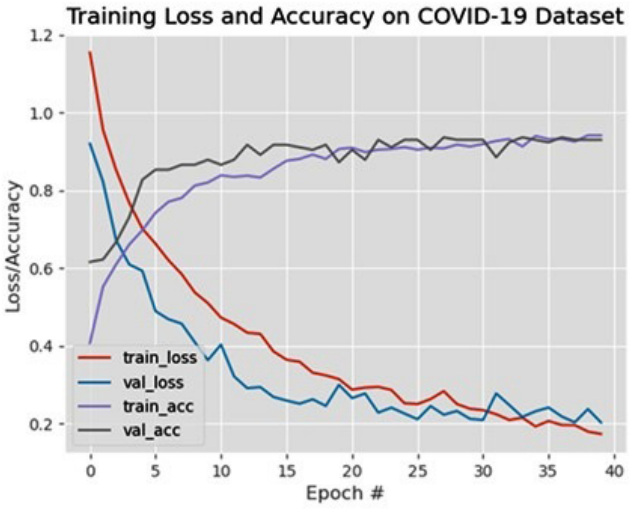

Fig. 4. *Power of VGG16 in detecting COVID-19 images accurately.*

<u>*Performance evaluation of the tool*</u>

The age group of the study population and patients from data sources was between 20 and 90 years.

The tool was found to be very quick in processing any given CXR image. On average, it took 5.7 seconds to complete while we ran the tests through our server. We also observed that the model was able to accurately detect COVID-19 as the tool/model detected 96% of cases as true positive. On the other hand, it exhibited a high power of rejecting non-COVID-19 cases, as specificity is approximately 98%. In addition, the results showed low false positives and false negatives, which gave us confidence about the accuracy of the model. Similarly, the model could also identify pneumonia and normal images fairly accurately (Table 2). It is important to note that the proposed model has achieved a low rate of false negatives, as a high rate of false-negative diagnoses may have moral, ethical, financial, and social implications.

Table 2.

Validation results of the Tool

Type of Data	Sensitivity, %	Specificity, %	AUC
COVID-19 (n=24)	90	92	91
Normal (n=234)	8	8	84
Pneumonia (n=390)	86	88	87

We evaluated our AI-based tool for detecting COVID-19 by using CXRs from confirmed Bangladeshi COVID-19 cases. The evaluation results showed high sensitivity (90%) and specificity (92%) in detecting COVID-19. The AUC values for COVID-19 and pneumonia were 0.91 and 0.87, respectively (Table 2).

Both ROC and AUC curves played a central role in evaluating the diagnostic ability of tests to show the true state of the disease condition, finding the optimal cut-off values (close to sensitivity of 100%), and AUC was close to 1. Figure 5 reveals that ROC and AUC as alternative diagnostic tasks performed well in this case.

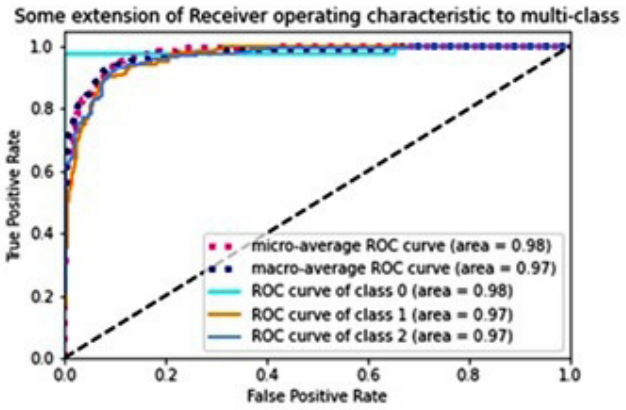

Fig. 5. *ROC and AUC curves for the diagnostic tests.*
(Note: Class 0 is covid-19, class 1 is Normal and class 2 is Pneumonia)

While evaluating the model, we observed that there is a strong relationship between pneumonia and COVID-19 (Figure 6). This may partly be explained by the fact that COVID-19 causes serious pneumonia.

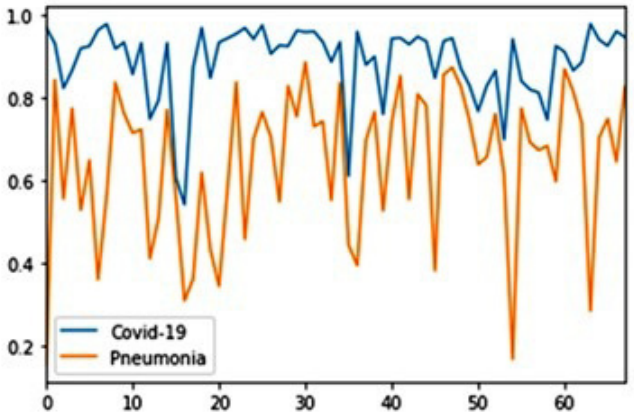

Fig. 6. *Relationship between Covid-19 and Pneumonia.*

<u>*Operationalizing the tool*</u>

We developed a website to operationalize the AI-based tool (www.helpus.ai). The website can be accessed and used by health facilities or medical professionals both domestically and internationally, provided they have computer access. New users will need to register and have their account verified before they will be granted a login ID to access the website. A webmaster will monitor and manage the system in order to protect it from unscrupulous use. A short online training program is included to enable new users to use the detection tool. The system is user-friendly and consists of a minimum interface. Authorized users can upload a digital CXR image to be tested on the website. The program will detect if a valid CXR image (PAV) has been uploaded; otherwise, it will reject it. If a valid image has been submitted, the results of the test will be displayed instantly. Our system is tuned to display "positive"

or "negative" results along with a percentile probability of that image, whether it is COVID-19, pneumonia, or normal. The entire process can take from a few seconds to a couple of minutes, depending on the computer and connection speed of the user. The data provided by the users can be stored in our cloud-based server while maintaining security and privacy protocols. The data can be retrieved by users and are accessible by the research team for future analysis.

Discussion

The pace of transmission of different variants of COVID-19 is so exponential that many health systems are facing an uphill battle to cope with the testing of COVID-19 and detection of COVID-19-induced pneumonia.[1,6] Traditionally, CXR is part of the routine check-up for patients with respiratory symptoms, and digital imaging is widely accessible, even in resource-poor healthcare settings. Therefore, integrating the proposed AI-based tool will help healthcare providers to analyze a combination of chest radiography in their existing general practice. Our results provide evidence that this AI-based tool has the potential to improve the quality and accuracy of the radiologic interpretation of COVID-19 pneumonia. We also believe that it can be acceptable to both healthcare workers and patients and can become relatively inexpensive, compared to other diagnostic methods. Intensive efforts have been made in recent years to generate evidence suggesting that the examination of radiologic images is an effective method for diagnosing COVID-19. Others have demonstrated that AI technology is able to read CXR and CT scans to detect different lung diseases, especially pneumonia, lung cancers, and tuberculosis. However, the main challenges are either getting a radiologist to interpret the chest radiographs or even the inability to differentiate COVID-19 pneumonia from other CAP if the radiologist is not trained in reading the COVID-19 radiographs. In our study, we demonstrated that a fully developed AI-based tool could read any chest radiographs with high precision. We have also operationalized the tool via user-friendly software, which instantly displays the correct result once the CXR is scanned. The software can be operated by any service provider having basic IT knowledge. During the evaluation, our AI-based tool showed excellent performance with high sensitivity (90%) and specificity (92%) in detecting COVID-19 pneumonia. The AUC values for COVID-19 and pneumonia were 0.91 and 0.87, respectively. Our result corroborates the outcomes of other similar efforts where machine learning models were trained to diagnose COVID-19. However, most of those studies were limited in their scope and dataset. Only a couple of studies had relatively larger datasets with varying degrees of precision. Some studies also trained the machine learning tools to detect COVID-19 by analyzing CT scans.

In Bangladesh, digital imaging is available almost everywhere, both in rural and urban clinics. Due to technological advancements, good-quality digital imaging machines are also in good supply. There are even mobile imaging units in the most remote areas of the country, which allows the clinicians to get the chest imaging done as and when they need it. In our study, we systematically validated the tool by using real-life data from two hospitals in Bangladesh. We also included a good number of CXRs of random patients with no known chest symptoms to train and test our tool to differentiate the non-pneumonia or "normal" cases from the pneumonia ones.

During the testing and validation, our AI-based tool performed very well in identifying COVID-19 by analyzing the 2D chest radiology PAV. We further evaluated the AI tool by using CXRs of COVID-19 patients from two Bangladeshi hospitals. We demonstrated that our tool had high sensitivity and specificity, which conforms to previous studies.[6-9,16-18] However, the uniqueness of our model is that it is simple and is able to differentiate three scenarios – COVID-19 pneumonia, CAP, and those with no obvious abnormalities – by analyzing readily available digital CXR instead of CT scans which, in turn, could easily be integrated into the regular medical practice.

Although our AI-based tool was able to detect COVID-19 accurately, this research has some limitations. As COVID-19 is caused by a type of coronavirus, it may produce changes in the chest imaging similar to CAP. This tool may sometimes give incorrect results only if the image quality is too poor. However, during our validation process, it consistently produced highly accurate results for randomly selected CXR images. Another limitation is that due to the limited availability of data, we were unable to evaluate the tool with real-time Bangladeshi data extensively. Lastly, the tool focuses only on detecting the existence of COVID-19, not the severity of the disease.

Conclusion

In this study, we developed a simple, non-invasive, AI-based tool to diagnose COVID-19 pneumonia by using traditional CXR, which can assist the government and the private healthcare workers who are attempting to triage both symptomatic and asymptomatic COVID-19 patients. We demonstrated that our AI-based tool is effective in detecting COVID-19 and can differentiate COVID-19 from other CAP by analyzing CXRs. Therefore, it gives a glimpse of hope to the policy-makers and service providers who are striving for an alternative diagnostic tool to screen, detect and triage the mass population for COVID-19. However, further validation of this tool may be needed with larger datasets before operationalizing it nationwide.

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Competing Interests

The authors declare that they have no competing interests.

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