The Role of Artificial Intelligence in Accurate Disease Detection from Chest X-rays

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ABSTARCT

COVID-19 (also known as SARS-COV-2) pandemic has spread in the entire world. It is a contagious disease that easily spreads from one person in direct contact to another, classified by experts in five categories: asymptomatic, mild, moderate, severe, and critical. Already more than 66 million people got infected worldwide with more than 22 million active patients as of 5 December 2020 and the rate is accelerating. More than 1.5 million patients (approximately 2.5% of total reported cases) across the world lost their life. In many places, the COVID-19 detection takes place through reverse transcription polymerase chain reaction (RT-PCR) tests which may take longer than 48 hours. This is one major reason of its severity and rapid spread. We propose in this paper a two-phase X-ray image classification called DeepCovidNet for early COVID-19 detection using convolutional neural Networks model. DeepCovidNet detects COVID-19 infections in chest X-ray patient images in two phases. The first phase pre-processes a dataset of 392 chest X-ray images of which half are COVID-19 positive and half are negative. Finally, the simulations revealed that the proposed DeepCovidNet resulted in superior performance as compared to existing models.

Keywords: COVID-19, DeepCovidNet, Convolutional neural network, accuracy,

1. INTRODUCTION

The coronavirus (COVID-19) pandemic has affected billions of people since the time of its emergence from Wuhan, China in December 2019.[1] The virus led to an outbreak at a very fast rate. A lot of research was conducted to identify the type of virus that caused COVID-19 disease and it was concluded that it belonged to a huge family of respiratory viruses that can cause diseases such as Middle East Respiratory Syndrome (MERS-CoV) and severe acute respiratory syndrome (SARS-CoV). The new SARS-CoV-2 virus can develop viral pneumonia. The population has witnessed a very high mortality rate in some states. The death toll around the world is increasing day by day. Therefore, it is necessary to develop an accurate, fast and cost-effective tool for diagnosis of viral pneumonia. This will serve as the initial step for taking further preventive measures like isolation, contact tracing and treatment for stopping the outbreak. One popular method to detect the virus is viral nucleic acid detection using real-time polymerase chain reaction, also known as RT-PCR test.[2] This test is very sensitive and has several limitations. For example, it cannot detect coronavirus developed before taking DNA sequence samples. Moreover, it takes 2-3 days to produce the result and requires many arrangements, public space. Many countries are not able to provide these conditions for testing of thousands of patients. Hence, continuing this method might slow down the process of controlling the pandemic.[3] In this scenario, medical imaging can prove to be a vital technique for diagnosis. Chest radiography plays an important role in the early diagnosis of pneumonia. It is commonly used because of its fast-imaging speed and low cost.[4]

However accurate and fast diagnosis of a X-Ray image is only possible with the help of expert knowledge.[5][6] The common diagnosis is done based on pneumonia symptoms (fever, chills, dry

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cough) but due to many asymptomatic patients being tested positive, it is necessary to improve the screening process by taking the help of X-ray images and testing more people as soon as possible. Due to increasing cases and a smaller number of specialists available to make diagnosis, the screening process becomes a tough task. Hence, doctors must depend on machine learning models for a fast and accurate diagnosis. Several machine learning approaches have already been used for analysing the X-ray images.[7]

Traditional methods like support vector methods (SVMs) have several disadvantages. Over the years, their performance has degraded and is not considered at par with practical standards. Moreover, their development is very time-consuming. Deep learning approaches have led to major advancements in the field of medical image classification and has become an effective tool for doctors to analyse the images and diagnose the problem. The breakthroughs have made them capable of carrying out many existing medical image analysis tasks like detection, staging and description of pathological abnormalities. Convolutional Neural Network (CNN) is one popular approach for analysing images, and it has made remarkable achievements in the medical field.[8]

Deep Convolutional Networks (DCNNs) are being constructed to analyse chest images and diagnose common thorax diseases and differentiate between viral pneumonia and non-viral pneumonia.[9][10] While many common viruses like influenza A/B, chickenpox, coronaviruses, and measles can cause pneumonia, the ones with viral pneumonia cause substantial differences in X-Ray images. Which means that every case of viral pneumonia will contain variable visual appearances. Moreover, finding a dataset with positive samples poses another problem. Therefore, it is crucial to develop a model which can overcome these pathological abnormalities and detect the virus with high accuracy. These methods are being used in the medical field since 2012 and have shown significantly better performance than other methods. CheXNet, a CNN with 121 layers which was trained on ChestX-ray 14 dataset having 112,120 images of frontal-view chest X-rays performed better than the average performance of four radiologists [11] CNN has the ability to learn automatically from domain-specific images and hence differentiates itself from classical machine learning methods. Different strategies can be implemented to train CNN architecture to acquire the desired accuracy and results.

The exponential increase in COVID-19 patients is overwhelming healthcare systems across the world. With limited testing kits, it is impossible for every patient with respiratory illness to be tested using conventional techniques (RT-PCR). The tests also have long turn-around time, and limited sensitivity. Detecting possible COVID-19 infections on Chest X-Ray may help quarantine high risk patients while test results are awaited. X-Ray machines are already available in most healthcare systems, and with most modern X-Ray systems already digitized, there is no transportation time involved for the samples either. In this work we propose the use of chest X-Ray to prioritize the selection of patients for further RT-PCR testing. This may be useful in an inpatient setting where the present systems are struggling to decide whether to keep the patient in the ward along with other patients or isolate them in COVID-19 areas. It would also help in identifying patients with high likelihood of COVID with a false negative RT-PCR who would need repeat testing.

While RTPCR [7] is by far the most efective way of COVID-19 detection. this method is very time consuming (taking hours to even days) and requires special kits that may not be available in remote regions of a country due to geological, social and economic barriers. On the contrary, the rapid antigen test looks for the presence of antigens of the virus from a nasal swab but sufers from higher rate of false negatives. The serological test looks for the antibodies produced by the immune system against the virus from the blood sample of the patient. However, it only checks the IgM and IgG antibodies during or after recovery and does not help in early virus detection. CT scan and X-ray scans, both use invisible ranges of electro-magnetic spectrum to detect any kind of anomaly, used for early detects and have high clinical relevance. In this paper, we found out that the chest X-ray tests are economically afordable and the results are relatively easy to use. Chest X-ray tests are easily available, have portable versions, and a low risk of radiation. On the other hand, CT scans have high risk of radiation, are expensive, need clinical expertise to handle and are non-portable. This makes the use of X-ray scans more convenient than CT scans.

2. LITERATURE SURVEY

On 11th March 2020, The World Health Organization (WHO) declared the virus COVID-19 outbreak as pandemic and since then the virus has spread rapidly in various countries around the world, fatal in many.[12] Symptoms of COVID-19 are typically associated with the symptoms of pneumonia, which can be detected from radiography and imaging tests. Among these two, COVID-19 detection uses image testing in a fast and efficient way when it comes to commercial and wide-scale usage and can therefore be used to control the spread of the virus. Chest X-ray (CXR) and Computed Tomography (CT) are the imaging techniques that play an important role in the diagnosis of COVID-19 disease. With the technological advancement in the processing of radiography images and image testing (Chest Xray), more and more machine learning algorithms based on deep learning [13] are being proposed giving promising results in terms of accuracy in detecting COVID-19 from radiography imaging among infected patients. The primary focus is on the CT imaging [14][15][16][17] Even with the initial release of the proposed open-sourced COVID-Net, many research scholars and institutions face difficulty in accessing public research literature and are unavailable to gather a deeper understanding and extension of these algorithms and models.

However, significant efforts are being made worldwide recently for open access and open source of machine learning models for COVID-19 positive detection from the radiography-driven dataset.[18][19][20] with an exemplary effort being the open-source COVID-19 Image Data Collection, an effort by Cohen et al.16 to build a dataset consisting of COVID-19 cases including severe acute respiratory syndrome (SARS) and the Middle East respiratory syndrome (MERS) cases) with annotated CXR and CT images so that the research community and citizen data scientists can leverage the dataset to explore and build machine algorithms for COVID-19 detection. A number of research experiments have been conducted in the past 6 months in the area of SARSCOVID19 detection using chest X-ray images following the public release of the proposed COVIDx and COVID-Net dataset. A detailed study of these proposed research models states that the solution focuses primarily on the in-depth exploration of deep neural networks, specifically deep convolutional neural networks, with results varying depending on the cleanliness of the input data and parameters described in the model for performing the given computer vision task.

With the rapid global spread of COVID-19, researchers have begun using state-of-the-art deep learning techniques for the automated detection of COVID-19 within patients. The onerousness of obtaining COVID-19 data in its initial stages has forced researchers to create their own model using pretrained networks [9–22]. However, the bulk of these experiments used a limited dataset comprising just a few COVID-19 samples. This renders the stated results in these studies are difficult to generalize and does not ensure the reported output would be retained when these models are evaluated on a larger dataset. Therefore, the transfer learning approach for detecting COVID-19 X-ray images must be verified on a large dataset. In addition to the fact that the combination of healthy and pneumonia cases is considered inappropriate where the model would attempt to disregard the intraclass variation between these two classes, the accuracy obtained in this way is not an accurate measure [23]. Deep learning has been shown to play an important role in distinguishing between viral and bacterial pneumonia [24– 26] and diagnosing the most common thoracic diseases [27– 29]. Moreover, the challenge is to develop an algorithm capable of identifying a patient with COVID-19.

Nevertheless, this task remains challenging as COVID-19 can share similar radiographic features with other types of pneumonia. In [10], the authors mentioned the poor performance of MobileNet in distinguishing cases of COVID-19 from other pneumonia cases when the training dataset included only bacterial pneumonia cases. We thus attempt to distinguish COVID-19 from viral pneumonia (not bacterial pneumonia) by aiming to rapidly detect clusters of COVID-19 caused by a novel virus. Furthermore, the COVID-19 versus non-COVID classification is a severe imbalance problem regarding the number of COVID-19 versus non-COVID-19 samples due to the difficulty of obtaining an adequate number of positive COVID-19 samples. This paper is aimed at reducing both the false-positive and false-negative rate as much as possible. The number of frozen layers has been shown to affect the recognition capability of pretrained models [30]. However, no work has been carried out to investigate the performance of the popular pretrained models with different number of frozen layers, and previous works have not comprehensively considered comparative analysis of these models' performances in COVID-19 diagnosis. Therefore, it is sensible to tune the frozen layers to utilize the full potential of pretrained models in order to improve COVID-19 recognition capability. With this goal in mind, eight popular pretrained deep learning networks were compared in terms of various performance metrics, each with different numbers of frozen layers. This enabled the identification of the best framework in the extraction of COVID-19 manifestations. Thereby, our work differs from the prior proposals [10, 13, 21, 22] in that the proposed model is not only evaluation-based but also COVID-19-specific.

3. PROPOSED METHOD

Considering the advantages of X-ray tests, we propose a novel model called DeepCovidNet that uses a convolution of positive COVID+ and negative COVID− chest X-ray images to train a network and detect COVID-19 viruses in early infection stages. The developed a convolutional neural network (CNN) categorize the chest X-ray images of patients as positive COVID+ or negative COVID−. Our DeepCovidNet model uses a CNN with the Adam optimizer and a learning rate 0.001. It does not require any feature selection method and uses a handcrafted seed dataset for CNN local and global features with 196 of COVID+ patient chest X-ray images and 196 of COVID−images. The recorded X-ray images (positive and negative) belong to different domains and have multiple views of the same scan to minimize the bias towards a particular class. As the segmentation of pneumonia related images was very difficult in earlier approaches, the proposed DeepCovidNet model based on computerized automated detection can understand the features more efciently and detect COVID19 faster than other classical learning methods. Our trained CNN comprises three convolutional layers with the kernel size of 3 × 3 followed by a rectified linear unit (ReLU) activation function which takes input images of size 224 × 224 × 3. We trained, tested and validated the proposed DeepCovidNet system and achieved an accuracy of 98.44% in classifying chest X-ray images.

Model training to predetermined images (having seed data as well), afects the bias, variance trade-of and results in under-fitting and over-ftting of the model. To reduce these drawbacks, we tuned the DeepCovidNet model on four sets with diferent training and testing data ratios, with the F1 score ranging from 89.26 to 97.94%, unlike other state-of-the-art works (see Table 5 in Sect. 4). We further tuned DeepCovidNet model in three diferent ways, unlike earlier approaches: 1. We trained the entire architecture; 2. We trained some layers and froze the others; 3. We froze the entire architecture. While existing studies focused on deep learning, they do not pay much attention to model tuning. The advantage of the proposed DeepCovidNet model is the proper use of structural deep network, improved parameter value selection and refned succinct boundary conditions. This section describes DeepCovidNet method consisting of two phases, illustrated in Fig. 1: (i) data engineering and (ii) model training and validation.

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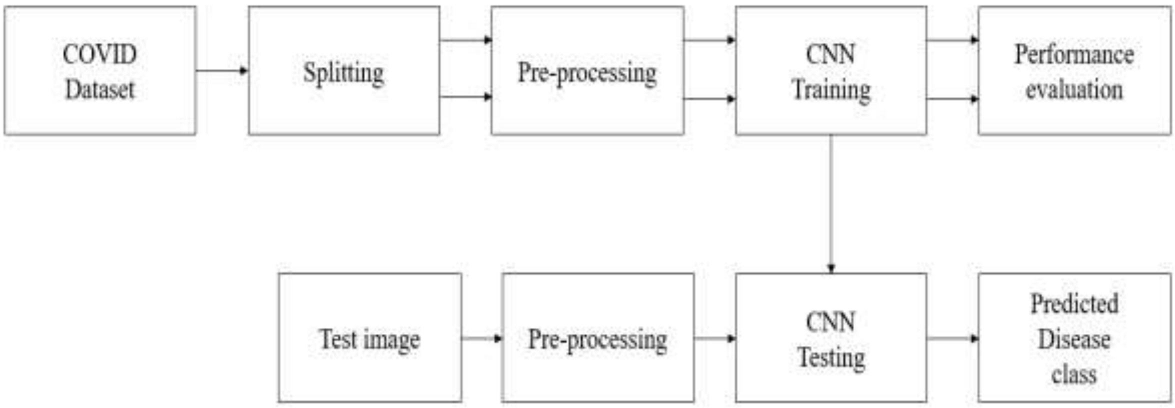

Fig. 1. Proposed DeepCovidNet model phases

Dataset: We use two chest X-ray image datasets in our method, summarized in Table 2. Dataset-1 [36] contains total of 950 X-ray images3 labeled with more than ffteen types of disease fndings such as: pneumocystis, streptococcus, klebsiella, legionella, SARS, lipoid, varicella, mycoplasma, infuenza, herpes, aspergillosis, nocardia, COVID-19, tuberculosis and others. This image dataset contains anteroposterior (front to back), front postero-anterior (back to front) and lateral (side) X-ray image views. Front postero-anterior images give clear lung representations, therefore we selected 196 COVID+ pre-processed chest X-ray images labelled with front view for our experiments and removed the rest. Table 1 shows the sample dataset.

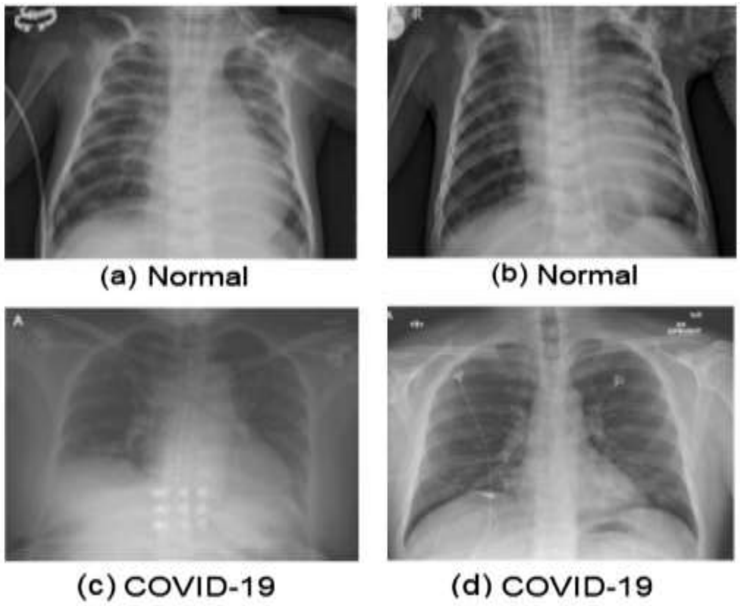

Fig. 2. X-ray image samples of COVID-19-infected and healthy (i.e., normal) patients

Dataset-2 contains total 5856 chest X-ray images labeled in three categories: normal, viral pneumonia, and bacterial pneumonia. All X-ray images have a front posteroanterior view. We randomly selected 196 X-ray images of normal category and labelled them as COVID− image type. The reason for this selection was to keep the data unbiased and balanced by keeping COVID+ and COVID− data size equal. We performed four image pre-processing steps to reduce the noise: (i) rescaling, (ii) shearing, (iii) zooming, and (iv) horizontal fip. Finally, we reduced the pre-processed image size to 224 × 224 × 3 and made them uniform before applying model training (Fig. 2)

ISSN: 0975-3583, 0976-2833 VOL 13, ISSUE 7, 2022

Table 1. Dataset description

X-ray image type	X-ray front posteroanterior view	Dataset-1 image count [36]	Dataset-2 image count [37]
COVID-19 positive	✓	196	–
	×	388	–
COVID-19 negative	✓	–	1583
	×	–	–
Other disease	–	366	4273

DeepCovidNet CNN architecture

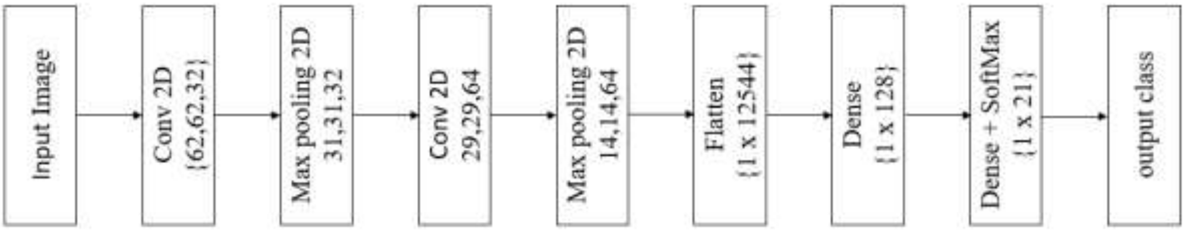

Fig. 3. DeepCovidNet CNN architecture

We used a layered sequential model architecture for X-ray image classification with four convolutional layers displayed in Fig. 3. The first convolutional layer has 32 filters, the second layer has 64 filters, the third layer has 64 filters, and the last layer has 128 filters. The number of filters corresponds to number of features the network can extract at each layer. We gradually increased the number of filters in the proposed network because the lower layers detect features in a very small part of the image and learn a hidden pattern during the network training. The receptive feld of the CNN layer architecture increases with its depth in the network. This means that by increasing the number of layers, the network extracts the features from the larger part of the original picture, as the deeper layers in the network will detect higher level features. We fixed the default kernel size to 3 × 3 at the convolutional layer and applied a non-linear ReLU activation function.

Figure 4 clearly shows that the ReLU curve is half rectified, unlike the linear activation function. This means that ReLU returns zero as output value for all negative input values and represented. If the value of y is less than 0 then value of f(y) will be zero otherwise output will be y. Similarly, we used three max-pooling layers and kernel window of size 2 × 2 with the increased number of filters in each layer to contain the more complex image patterns in training network. Table 2 summarizes the proposed CNN model parameters, used to classify the chest X-ray dataset. We implemented proposed CNN model on the selected datasets with 196 positive and 196 negative COVID-19 images. We trained the model and tuned it using different learning parameters and training and testing dataset distributions. We experimented with three CNN architectures: 1. CNN model-1 with a maximum pool size of 2 × 2 and one stride; 2. CNN model-2 with a maximum pool size of 2 × 2 and two strides; 3. CNN model-3 with a maximum pool size of 3 × 3 and three strides.

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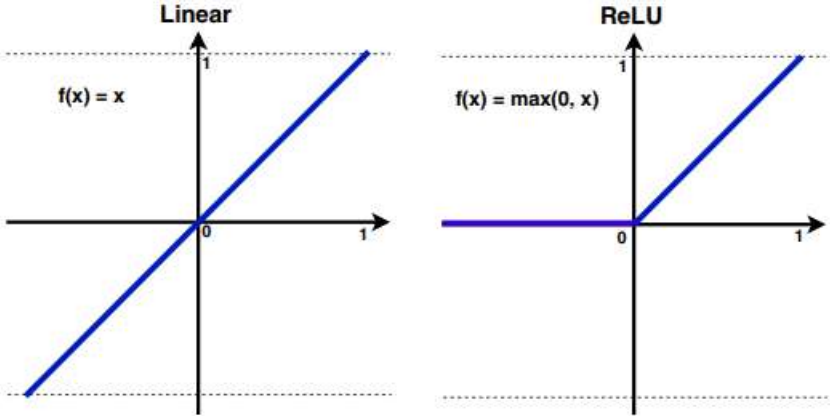

Fig. 4. Linear and ReLU activation function

Table 2. CNN model parameters for chest X-ray image dataset

Layer Name	No. of filters	Feature size	parameters
Conv 2D	32	62 x 62	896
Max pooling 2D	32	31 x 31	0
Conv 2D	64	29 x 29	18496
Max pooling 2D	64	14 x 14	0
Flatten	-	1 x 12544	0
Dense	-	1 x 128	1605760
Dense	-	1 x 21	2709

4. RESULTS

This section gives the detailed analysis of simulation results implemented using "python environment". Further, the performance of proposed method is compared with existing methods using same dataset. Figure 5 and Figure 6 shows the predicted outcomes using proposed method. Table 1 compares the performance of proposed method with existing methods. Here, Proposed DeepCovidNet resulted in superior Accuracy, Precision, Recall, and F1-SCORE as compared to existing CNN. The graphical representation of table 1 is presented in figure 7.

ISSN: 0975-3583, 0976-2833 VOL 13, ISSUE 7, 2022

Fig. 5. Disease predicted as: pneumonia viral COVID-19.

Fig. 6. Disease predicted as: Pneumonia.

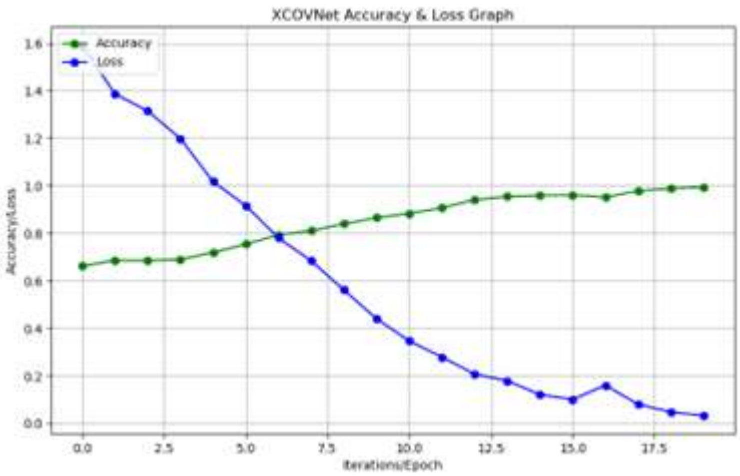

Fig. 7. Accuracy and loss graph.

Table. 1. Performance comparison.

Method	NB	RF	SVM	Proposed
Accuracy (%)	67.37	77.48	78.37	99.5

5. CONCLUSION

We developed in this work a model to detect the COVID-19 infection using chest X-ray images. For this purpose, we used a publicly available dataset of 392 positive COVID+ and negative COVID− X-ray patient images. We fixed each input image size to 224 × 224 × 3 and performed CNN training for a accurate classification. We implemented three convolutional layer-based models with a kernel size of 3 × 3. we still face a serious need to find out the severity level of the infection too. In the future, we intend to perform experiments on chest CT scan image data for COVID-19 detection and combine both the models to identify the severity level. Voice recognition based early COVID19 infection detection using intelligent methods is also part of our future plans.

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