Acta Scientific COMPUTER SCIENCES

Volume 4 Issue 4 April 2022

Research Article

DLCC: Deep Learning in Effective COVID-19 Classification

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Received: November 15, 2021

Published: March 17, 2022

Abstract

Recent history is not that generous and kind when it comes to viral infections from animal reservoirs to target humans. Re-emergence of mutating strains of such virus has only added more misery. In 2019, SARS-CoV2 had a daunting presence in and around the world, pausing grave threats to the perspective of global health, economy, livelihood and human race itself. Although numerous rigorous efforts are made to contain the contagious disease, there is a continuous steep rise in the number of clinically confirmed cases and fatalities. Medical facilities across the globe are in a crisis particularly when it comes to conducting adequate testing. RT-PCR (Reverse Transcription-Polymerase Chain Reaction) although reliable, consumes a lot of valuable time. Thus, an automated COVID-19 diagnosis strategy with efficient detection and minimum error is the need of the hour. Recently, Deep Learning techniques have become very popular for detecting COVID-19 using chest X-Ray images. In this paper, we propose a deep learning-based approach called DLCC to classify COVID-19 chest X-Rays with high accuracy. DLCC includes eight CNN architectures namely ResNet (18, 34, 50), AlexNet, VGG, and DenseNet (121, 161, 169) for best possible classification of diseased instances. All the models are fine-tuned using transfer learning. For the purpose of validation, a publicly available dataset containing four classes of chest radiograph, namely COVID-19, Lung opacity, Viral pneumonia and normal samples. From our study, it has been observed that DenseNet model gives the best performance in terms of accuracy (96.4%). This work might be used as a base to develop more effective CNN-based models for early detection of COVID-19.

Keywords: COVID-19; Pandemic; Virus; Genome; Strains; Coronavirus

Introduction

On December, 2019 the very first documented case of a previously unknown zoonosis transpired in the city of Wuhan, China. Patients reported with pneumonic symptoms attributed to unknown aetiology. Most of these reported cases are credited to a neighborhood involving a local seafood market. However, its role till date is still unclear to many. The cases indicated the cause to an infectious disease that might be a result of animal to human transmission. Gradually, there evolved other infected cases which had no record of visit to the seafood market but were in traceable direct contact with the previously confirmed cases. This suggests that the causative pathogen is capable of human to human transmission. Subsequently, in no time the transmissions resulted in the formation of clusters, cluster of patients infected by the pathogen. Clinical reports suggested the patients suffered from mild to severe pneumonia like symptoms of fever, dry cough and dyspnea [16]. Rigorous research led to the pathogen being recognized as a novel coronavirus, and hence named 2019-nCoV by the World Health Organisation and later abbreviated as COVID-19 (Coronavirus Disease 2019) on February 11, 2020.

Effective screening of infected patients, their isolation, immediate appropriate treatment and care is a very crucial step to defeat COVID-19. From the inception of the virus, PCR testing is used as a standard method to screen and identify infected individuals. PCR tests are reliable, however, the downside of such tests are many fold. They are expensive, involves a complicated manual procedure, requires ample amount of time to obtain an outcome as well as special kits. Screening through X-rays on the other hand, are quick in nature, relatively less expensive and required machines are also readily available. To this end, Deep Learning techniques can be utilized to analyze medical images for the detection of COVID-19 infection. This ensures that the process is automated, reliable and inexpensive.

Deep learning methods have shown much better performance than traditional machine learning methods in many application domains. Deep Learning methods are widely used in clinical methodology for various reasons like identification of anomaly, malignant tumour, fractures in radiographic images including, CT, MRI, and X-ray. Therefore, for automatic identification of whether a patient is suffering from COVID-19, Viral Pneumonia, or Lung opacity we employ Deep Learning techniques to the chest X-Ray images of the patient. The proposed method also helps to point out the Region of Interest (ROI) in the radio-graphic image where the method focuses more during the training phase so that it can distinguish two X-Ray images from two different classes as accurately as possible. During the training phase of the method, quality of the radio-graph image is checked for the presence of noise and adequate information in the image. The learning process in Deep Learning involves discovering inherent representations/patterns in the raw data for the task of classification of a problem at hand. In the context of medical imaging classification by deep learning, pixel information of the concerned image is used at the input level. This automatic procedure of learning the pixel patterns serves as an advantage because it leaves behind the errors resulting from traditional segmentation and/or feature extraction procedure.

Contribution

This work focuses on the accurate and reliable screening of COVID-19 from chest X-ray images. For this, a total of eight CNN deep learning models namely, ResNet18, ResNet34, ResNet50, DenseNet121, DenseNet162, DenseNet169, VGG, and AlexNet are used. For establishing the effectiveness of the proposed method, we compare the models in terms of validation accuracy, sensitivity, and specificity. Additionally, the hyper parameters such as learning rate, batch size, and number of epochs are studied along with their impact on the model performance. The main challenge pertaining to the problem however is the limited availability and inadequacy of public datasets. Privacy among others being the main reason behind it. To overcome these limitation, several data augmentation techniques are used so as to obtain several variations of a single image without losing the original meaning and at the same time maintaining the original quality of the image. Furthermore, these techniques help in handling the model overfitting problem.

Organisation of the paper

The remainder of the paper is divided into the following sections. In Section 2, we discuss a few definitions, data sources, data preprocessing techniques along with the proposed method. Section 3 presents the results of our work in addition to comparison with other works. We wind up in Section 4 and Section 5 with discussion and conclusion.

Materials and Methods

In the following sub-sections, we discuss the datasets in detail and the methodology employed.

Proposed method

Our proposed model illustrated in Figure 1, intends to perform automated diagnosis of COVID-19 cases. The model aims to classify a given chest X-ray image into four categories, covid, lung opacity, viral pneumonia, and normal with minimum false alarm.

Problem statement

For a given radio-graphic image R_i, the problem is to categorize R_i into any one of the four classes.

Below we discuss few definitions useful to describe our work.

Definition 2.1 (Prediction model)

A model is said to be a prediction model if it can learn or gather knowledge from past experiences and predict the outcome of a given task in the future. (It is validated against additional data).

Definition 2.2 (Transfer learning)

A technique where knowledge gathered/learned from a particular domain say D_s with learning task T_s is used to learn another task T_t from a different target domain say D_t.

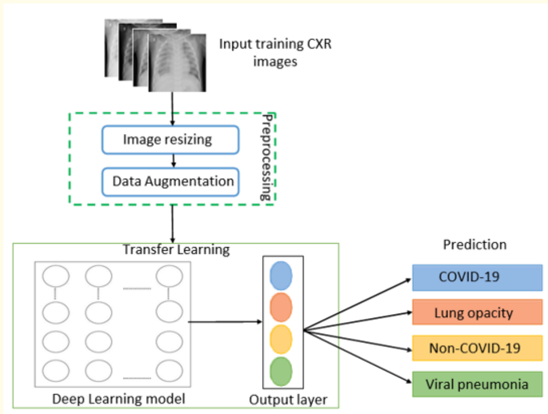

Figure 1: Overview of the proposed method.

Definition 2.3 (Data augmentation)

These are techniques by which new data can be obtained by modifying existing data in order to better the performance of the learning model.

Definition 2.4 (Normal class instance)

An instance is considered to be a normal class instance if it belongs to the normal class category.

Definition 2.5 (Disease class instance)

An instance is considered to be a disease class instance if it belongs to either COVID19, pneumonia, or lung opacity classes.

Definition 2.6 (Misclassified instance)

An instance is said to be misclassified if it actually belongs to class say C_i but the predictive model incorrectly classifies it to be in class C_j.

Convolutional Neural Networks (CNN) require relatively large datasets which may consume huge amount of computational resources in addition to being time consuming. This is the reason why, such networks are generally not trained from scratch. So, we utilize the benefits of transfer learning, where a learning model formerly trained on a different domain's data is fine tuned for use in another domain. Figure 2 illustrates the overview of the transfer learning approach.

In general, the initial CNN layers encode some low level features. The higher convolutional layers prior to the final layer learn some complex features. In transfer learning, those layers are retained to solve a particular task and adjusted as per requirement.

In the proposed method, instead of the pre-trained model's fully connected layer we use a new fully connected layer specific to our problem. The last layer consists of four neurons which is same as the number of target classes in the application, i.e., COVID–19, normal, Lung opacity, and pneumonia. This newly added layer has random weights and it is necessary that they be assigned suitable weights. The optimizer of the network updates the weights of the newly added layer by freezing the previous layers so that the layer weights of the pre-trained network are retained.

In our case, the chest X-Ray image dataset comprising of COVID-19 and non COVID-19 images are not adequate to train a CNN model from scratch that involves a large of trainable parameters. Therefore, transfer learning is used to train our models more accurately with limited number of data and more quickly with limited resources. DLCC consists basically of training a CNN model using transfer learning for effective classification of COVID-19 X-ray images. Before training, we also find suitable learning rate using a learning rate finder called cyclical learning rates which help us to obtain the best global learning rate range without exhaustive complicated experimentation. Next, since the newly added layer has random weights, so we train the randomly added layer for one epoch, with all other layers frozen. After that, unfreezes all the layers, and trains them for the number of epochs requested.

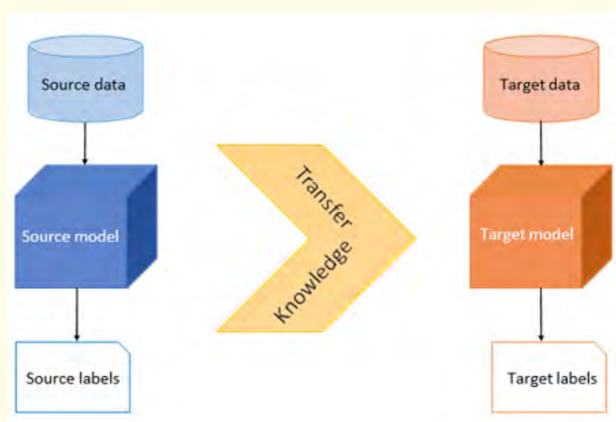

Figure 2: Illustration of transfer learning.

DLCC includes eight CNN architectures belonging broadly to four categories namely ResNet, DenseNet, AlexNet, and VGG. These architectures are ResNet (18, 34, 50), AlexNet, VGG, DenseNet (121, 161, 169). All the models are fine tuned using transfer learning [17] in order to distinguish COVID-19 CXR images from non COVID-19 instances.

Data source

In this study, we consider a study population comprising of four classes of Chest X-Ray (CXR) images, namely COVID-19, non-COVID-19, Lung opacity and Viral pneumonia. While there are 3616 images of COVID-19 collected from [3,6,10,19], there are 10,192 normal images collected from [4,12]. On the other hand, there are 6012 and 1345 CXR images of Lung opacity and Viral pneumonia collected from Radiological Society of North America (RSNA) CXR dataset [2] and Chest X-Ray Images (pneumonia) database [4] respectively. All the collected images are quality checked to ensure they are suitable for model training. The training and testing sets are randomly populated with collected CXR images using random sampling without replacement in a 80:20 ratio.

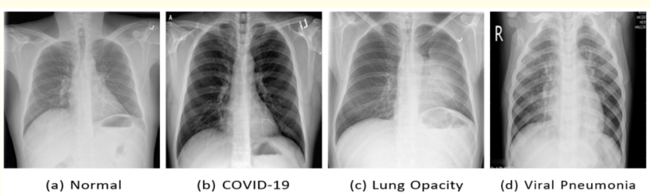

Figure 3

It is important here to note that, each data sample from all the four categories has an equal opportunity for selection. Table 1 shows the summary of the dataset. Figure 3a, 3b, 3c and 3d shows the sample images of the dataset.

Dataset			
Normal	COVID-19	Lung Opacity	Viral Pneumonia
10192	3616	6012	1345

Table 1: Dataset information.

Data Preprocessing

A crucial step before data is fed into a CNN model is the step of Data Preprocessing, which helps improve the model accuracy. Because the overall process demands the images to be of same dimension, a significant step in preprocessing is image resizing. The images in our dataset are resized into 242x242 pixels and then randomly cropped to full height or width in each epoch. For image resizing, an image interpolation technique called bilinear non adaptive interpolation is applied in our case. In bilinear interpolation [11], two linear interpolations are used one in horizontal and other in vertical direction. The non-adaptive technique does not use the content based features of the image instead it directly acts on the pixel values of the image. Subsequently, we apply data augmentation techniques to create transformed versions of the original data while preserving its class labels. Data augmentation techniques like rotation, flipping, perspective warping, brightness changes, contrast changes, noise addition and resolution adjustment are applied. Figure 4 shows the original image and its transformed versions after applying data augmentation. It is worth noting here that data augmentation comes in handy when data is scarcely available to build the model as it can create a number of varied images from the original image [15,18]. It is carried out in the following ways (all the values taken are decided through experimentation process).

- The images are randomly rotated by 10 degrees with a probability of 0.75.
- The images are flipped in a horizontal manner with a probability of 0.5.
- The colours of the images are adjusted by changing the brightness and contrast. The brightness is changed by 20% and contrast by 20% with a probability of 0.75.
- Images are zoomed randomly to a maximum of 100% with a probability of 0.5
- Perspective warping is applied with magnitude 0.2 to all the images with probability 0.5.

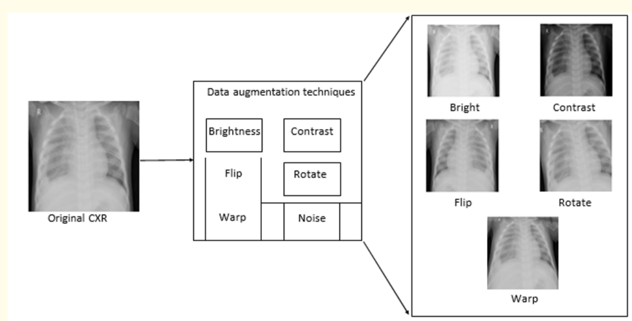

Figure 4: Illustration of data augmentation techniques.

Results

We implement all deep learning models using PyTorch 1.9.0. The experimental works are conducted on a workstation consisting of Intel Xeon (R) W-2145 processor with 8 cores, 64GB RAM, and NVIDIA Tesla K80 GPU with 12GB VRAM. For updating weights of the network, especially the newly added layers (head) during the training period, adam optimizer [9] with parameter settings $\beta1$ = 0.9, $\beta2$ = 0.999, and ϵ = 1e-5 and cross entropy loss function is used. A learning rate finder called cyclical learning rate is utilized to obtain a learning rate of 3e-3 during training phase. Throughout all the conducted experiments, a batch size of 64 is used. For training and validation purpose, we divide the data into 80-20 proportion. The models are trained precisely for 20 epochs and the weights achieving the highest validation accuracy is retained. Table 2 lists the validation accuracy, sensitivity, and specificity of each model used in the experiment. It can be noted that DenseNet 161 gives the best performance with 96.4% accuracy.

Comparison with other methods

Here we compare our method with other methods in the literature.

In [13], the authors unlike us have used full chest CT scans to detect COVID-19 infection. Transfer learning and other preprocessing techniques are also used and an accuracy of 94.9% is achieved. Comparison with other methods section.

	Accuracy	Sensitivity	Specificity
ResNet18	95.6	93.8	96.5
ResNet34	95.6	93.2	97.3
ResNet50	96.0	95.4	97.0
DenseNet121	95.8	95.10	97.0
DenseNet161	96.4	95.7	97.10
DenseNet169	96.2	96.0	97.3
AlexNet	94.2	93.4	95.5
VGG	95.4	94.8	96.7

Table 2: Accuracy, sensitivity, and specificity of CNN models.

In [8], the authors have used Resnet and VGG models in COVID-19 detection. The resnet 50 model gives the highest accuracy of 92.6%. In addition, they also used SVM classifier with features extracted from CNN model. Highest accuracy of 94.7% is obtained with the SVM classifer with linear kernel function.

In [1], the authors unlike us have used a study population consisting of 5644 patients where they have considered 111 laboratory findings. Of all the six different deep learning models used Long-Short Term Memory (LSTM) achieves the highest accuracy of 86.6%.

In [20], the authors used four CNN models namely, ResNet34, ResNet50, VGG16, and Inceptionv3 along with mask attention mechanism. The resnet 50 with mask attention mechanism gives the highest accuracy of 96.32%.

In [5], unlike our approach, the authors used lung ultrasound imagery for the detection of COVID-19 infection. Of all the Deep Learning models used, InceptionV3 network achieved the best average accuracy of 89.1%.

In [7], unlike us the authors have used four CNN architectures namely, VGG19-CNN, ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), and ResNet152V2 + Bidirectional GRU (Bi-GRU) for detecting COVID-19 by classifying both CT scan and X-ray images. Highest accuracy of 98.05% is achieved by VGG19+CNN model.

Discussion

This paper presents an effective deep learning approach called DLCC based on Convolutional Neural Network (CNN) to automate the process of discrimination between covid-19 and non-covid19 (lung opacity, viral pneumonia, normal) CXR images. This model offers fast, automated, precise and effective results to classify and screen COVID-19. As input, we provide Chest X-Ray (CXR) images to the model which uses raw pixel values from them instead of extracting some selected features. Since, medical datasets are not abundantly available due to several reasons, a CNN model is difficult to train from scratch. Therefore, we use transfer learning approach to fine tune pre-trained CNN models to map to our problem. Of all the eight architectures used in our study, we observe that Densenet 169 gives better performance than others in terms of validation accuracy. Additionally, the performance of the models can be improved especially by cleaning the data along with correctly labeling the images in the dataset with the help of a domain expert. Out of all the misclassified images, we consider two sample images as shown in Figure 5 as example where the ground truth available is normal but the model predicts it to be COVID-19 with a high probability of 0.98. In such scenarios, consulting a domain expert is inevitable.

Figure 5: Misclassified image.

Figure 6: Misclassified image.

In figure 7, it is shown that the gradient class activation map [14] of a CNN model where important input regions are highlighted, is given most importance by the model for prediction. Similarly, in figure 8, the gradient class activation map of second last resnet group is shown. Here, we can see that the model gives importance to the highlighted portion of the input region in the second last layer of the resnet 18 model. Bright input regions correspond to high activations and other correspond to low activations. So this class activation map can be used to analyze the false positives and also to improve the quality of the training data. Also, with the help of domain expert, appropriate localization of the input region can be done so that the model can give more importance to the localized area. So, using domain expert localization, it is possible to improve the performance of the model.

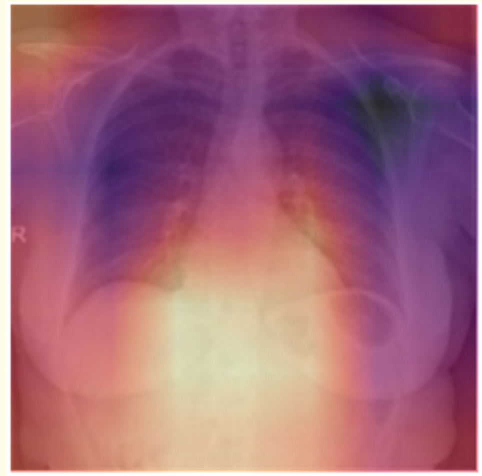

Figure 7: Gradient Class activation map of Resnet18 model.

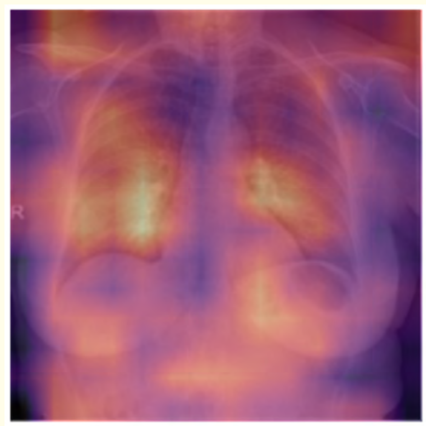

Figure 8: Gradient Class activation map of second last layer of Resnet18 model.

Conclusion

COVID-19 pandemic has created havoc in and around the globe. Adequate testing and treatment seem to be the only answer to tackle the pandemic. Although, medical infrastructure facilitates testing, many a times these testing procedures are very time consuming. Hence, an appropriate approach is needed which can not only fasten up the testing procedure but is also reliable. Our approach DLCC is successful in detecting whether a given sample belongs to the COVID-19 category or not in a fast and efficient manner. To this end, four categories of CNN architectures are used for automated detection of COVID-19. All the eight CNN architectures show good results however, Densenet has been found superior in terms of accuracy.

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