An ensemble deep transfer-learning approach to identify COVID-19 cases from chest X-ray images

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***Abstract*—Novel coronavirus began in Wuhan, China back in December 2019. It has now outspread all over the world. Around 23 million people are currently affected by the novel coronavirus. It causes around 800,000 deaths globally. There are just about 300,000 people contaminated by COVID-19 in Bangladesh too. As it is an exceptional new pandemic infection, its diagnosis is challenging for the medical community. In regular cases, it is hard for developing countries to test cases frequently. The RT - PCR test is a generally utilized analysis framework for COVID-19 case detection. However, by utilizing X-ray image-based programs, recognition can diminish the expense and testing time. So it is important to program an effective recognition system to identify positive cases. In this paper, the author proposes an ensemble deep learning model, combining two state-of-art pre-trained models as ResNet-152 and DenseNet-121 to identify COVID-19 cases. The experimental validation result is immensely well with an accuracy of 98.43% on the proposed model. The author also compares the ensemble model's performance with ResNet-50 and DenseNet-121 separately.**

***Index Terms*—COVID-19, deep learning, ensemble, X-Ray, transfer learning.**

I. Introduction

A novel Coronavirus or COVID-19 is an infectious virus that has been transmitted through a set of all animals. Later, it has affected people too. Since December 2019, various examples of severe viral pneumonia identified in the seafood wholesale market in Wuhan City, China [2]. A Novel coronavirus affected people severely was officially affirmed on January 6, 2020 [1]. As indicated by Nature, the spread of coronavirus (COVID-19) is getting relentless and has just arrived at the important epidemiological measures for it is to be announced as a pandemic [18]. COVID-19 is an intense settled disease however it has around 3% death rate globally [6]. Like other viral pneumonia, for example, a serious intense respiratory disorder can be caused by the coronavirus. So that COVID-19 can prompt intense respiratory serious condition [1] [2].

There is an essential need for a viable treatment for COVID-19 affected people. The current spotlight has been on the improvement of novel therapeutics, including antivirals and antibodies, and developing vaccines. Gathering proof recommends that a subgroup of patients with serious COVID-19 may have a cytokine storm condition [7]. The most widely recognized test method for COVID-19 is the interpretation polymerase chain response (RT-PCR) [8]. COVID-19 can cause intense heart injury, in the vast majority of the cases, the patients who have co-morbidity like diabetes, circulatory strain, coronary illness [10].

The side effects of these sicknesses resemble ordinary influenza. The side effects can be discovered roughly in the middle of 14 days. As this COVID-19 is a new infection for the medical community, so explicit treatment for COVID-19 is still not viable. There are some recognized side effects in regards to COVID-19, declared by the World Health Organization (WHO). For example, high fever or mellow fever, hack, breathing problem, exhaustion, muscle or body throbs, migraine, loss of taste or smell, sore throat, clog or runny nose, spewing, diarrhea. It straightforwardly influences the lung in some cases. X-Ray based images can assist us with knowing the lung condition so we can discover more COVID-19 cases as per the lung report. CT scan reports also can be utilized in the same purpose [13]. Around 15-20% of the patients fall into a serious medical condition, which means they require oxygenation as a major aspect of treatment [19]. There are several vaccines currently in phase-3, so it is hoping that the end of this year an effective vaccine can be found.

While investigating images-based problems, Deep Convolutional Neural Network can comprehend more effectively by its state-of-art architecture. Deep neural-based frameworks can classify images or related problems more precisely and productively by its powerful algorithmic strength.

To tackle the classification problem more accurately, the author combines two pre-trained ResNet-152 and DenseNet-121 architectures to achieve the best possible result on the chest x-ray dataset.

II. Related Works

The novel coronavirus is a new virus in the medical community. Clinical researchers as well as deep learning specialists are attempting to detect COVID-19 cases. The fundamental objective is to distinguish COVID-19 cases in a less measure of time and minimal cost. So the AI researchers have handled this problem more efficiently by applying various state-of-art deep learning models. In this section, some related works have been presented.

A. Mangla et al. [9] attempted to tackle COVID-19 case identification utilizing pre-prepared deep convolutional neural networks. Their model contains pre-prepared CheXNet, with a 121-layer Dense Convolutional Network (DenseNet) trailed by a completely associated layer. They supplant CheXNet classifier of 14 classes with the characterization layer of 4 classes, each with a sigmoid activation to the output layer. They wound up with a consequence of AUROC 0.9994 and an accuracy of 87.2% in 4 class classification. They named their model as CovidAID. El Asnaou et al. [11] attempted to discover image-based COVID-19 case recognition utilizing deep learning methods. They executed a few deep learning architectures, for example, VGG16, VGG19, MobileNet V2, Resnet50, DenseNet201, Inception ResNet V2 and Inception V3 in X-Ray and CT-Scan images. Where they infer that Inception ResNet V2 has performed better than architectures with a 92.18% accuracy. I. Apostolopoulos et al. [12] utilized pre-prepared deep learning models in their tests. They used a dataset that contains 1427 X-Ray images. Where 700 images are typical pneumonia, 224 images with affirmed Covid-19 cases and 504 images of normal conditions. They utilized MobileNet V2, VGG19, Inception, Xception, and Inception ResNet V2 designs. Where VGG 19 has given the best result of 98.75% accuracy in 2- class classification. H. Abiyev et al. [13] used the convolutional neural network to distinguish chest diseases. They initiated a correlation between the convolutional neural network, supervised back-propagation neural network, and competitive neural network by utilizing chest X-Ray images. Where the convolutional neural network has performed better than other models. A. Abbas et al. [14] actualized an altered deep neural network in X-ray images to distinguish COVID-19 cases all the more effectively. They remanufactured their model and named DeTraC which contains 3 internal layers. They built up this model by utilizing ResNet-18 in the backend and gets an accuracy of 95.12% in the X-Ray dataset. M. Rahimzadeh et al. [15] actualized an ensemble of the Xception V2 and ResNet50 model to distinguish COVID-19 cases. In their trial, they utilized an unbalanced X-Ray dataset. They experimented with various deep learning models to justify the best result in classification problems. The altered model which is a combination of Xception V2 and ResNet50 has accomplished 91.40% accuracy. Naurin et al. [16] have executed the convolutional neural network, for example, Inception V3, Inception ResNetV3, and ResNet50 for the identification of COVID-19 cases by X-Ray images. They achieved around 98% accuracy in the pre-trained ResNet50 model. Which is higher than Inception V3 model. T. Majeed et al. [22] proposed a new ensemble-based CNN-X model in their experiment. They achieved 93.15% sensitivity and 97.86% specificity respectively.

III. Methods

In this paper, the author applies various deep pre-trained models for classifying COVID-19 cases from normal, SARS, ARDS, and Streptococcus. To identify the COVID-19 class more accurately, two deep learning models are deployed such as ResNet152 and DenseNet121. The author has been ensemble these two models. This approach has been experimented and benchmarked against the latest publicly available dataset for COVID-19 X-ray images.

A. Dataset

In this experiment, the dataset has been retrieved from a Kaggle competition. The dataset is accessible publically [23]. The dataset consisted of a total of 5907 X-Ray grayscale images, where it has 5283 images for training and 624 images for test purposes. The input data are chest X-ray images in JPEG format. It additionally has two classes such as a normal class and a pneumonia class. Pneumonia class has four divisions, such as SARS, COVID-19, ARDS, and Streptococcus. Visual representation of normal and COVID-19 cases are shown in Fig. 1.

B. Visualization

The author has visualized and separated the classified images for better understanding. Therefore, the author has envisioned the data by utilizing an image histogram. Images histogram is a sort of histogram-based graphical representation of the tonal contrast of an image. However, it plots the number of pixels for each tonal side. It is also a gray-scale value-based representation that shows the frequency distribution of gray-scale value in the image. Here Fig. 2 shows the visualized histogram images of the normal case and COVID-19 case.

C. ResNet Architecture

Residual Network has been created and acquainted by Microsoft Research to handle image recognition tasks more accurately by its higher numbers of layers [5]. It has 8 times higher layers than VGGNet architecture. ResNet has different layer-based architectures, such as ResNet-50, ResNet-101 and ResNet-152. In this study, author has utilized the ResNet-152 model for combining with DenseNet model. The residual block has 3x3 convolutional layers. The formulation of residual nets can be underlying mapping $H(x)$. However, the mapping for non-linear layers is $F(x) : H(x) - x$. The original mapping can be followed by $F(x) - x$. Where $F(x) - x$ is inspired by the feed-forward neural network with an internal shortcut connection. Shortcut connections can reduce the layers of the model. It also can clarify the identity mapping by adding the output in the stacked layers. The residual block can be denoted as [5]:

$$y = F(x, W_i) + x \tag{1}$$

The input and output layer vectors are x and y respectively. $F(x, W_i)$ is the function that resembles the residual mapping to the layers. However, every 3x3 convolutional layers are followed by ReLU [20] activation function in this study. Fig. 3 shows an illustration of the residual block.

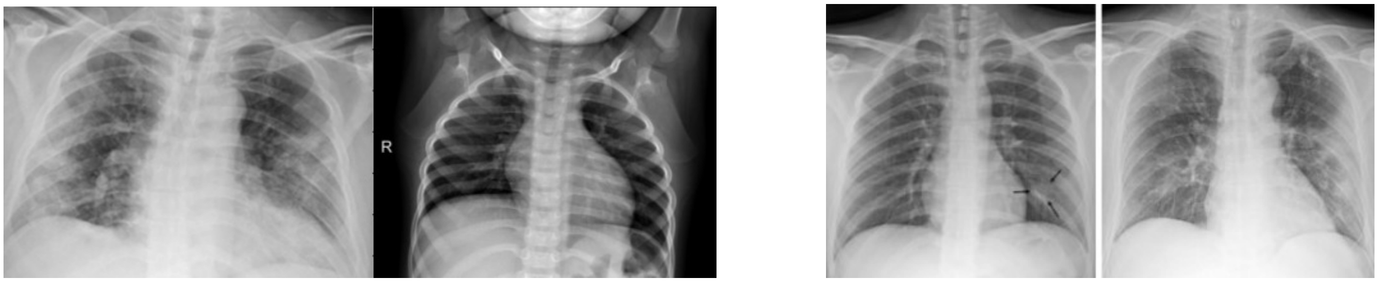

Fig. 1. From left side, (a) Samples of normal case X-Ray and (b) Samples of COVID-19 case X-Ray.

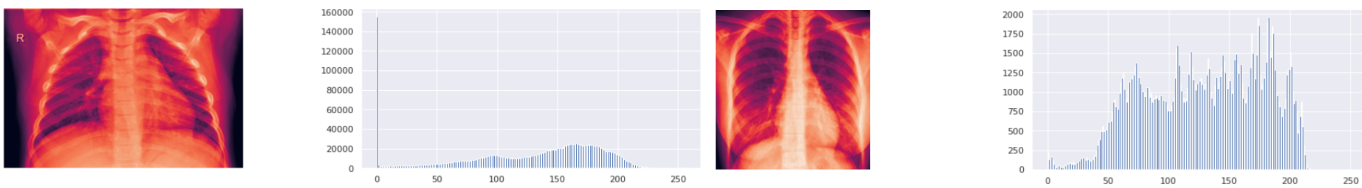

Fig. 2. From left side, (a) Histogram of normal case and (b) Histogram of COVID-19 case.

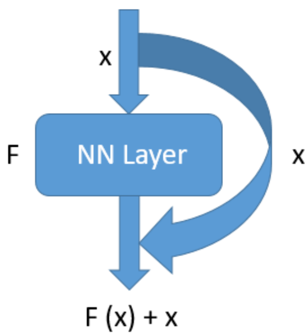

Fig. 3. An illustration of Residual Block.

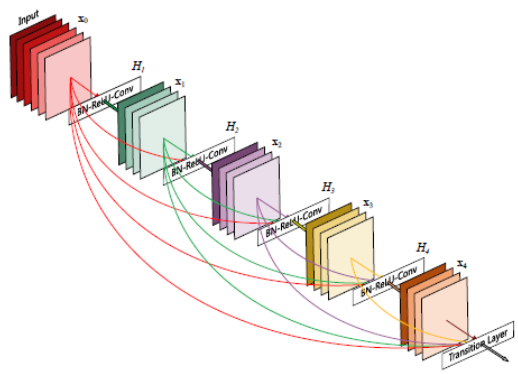

Fig. 4. DenseNet Architecture [17].

D. DenseNet Architecture

Densely Connected Convolutional Network (DenseNet) interfaces each layer to each other layer in a feed-forward design [17]. DenseNet is a combination of dense layers. However, it has a convolutional and pooling in every dense layer. DenseNet has some convincing points of interest such as it can overcome the vanishing gradient problem, it also can reuse the feature so that it makes the dense-net with fewer parameters than other models. To enhance the information flow in the dense layers, it follows a particular connectivity pattern. It creates a significant connection between feature map and connection layers. Each convolutional block obtains the output for reusing as the input of the next layer as illustrated in Fig. 4. The connection output can be expressed as [17]:

$$x_l = H_l([x_0, x_1, x_2, x_3, ..., x_{l-1}]) \tag{2}$$

In the equation (2), x_l, H_l and $[x_0, x_1, x_2, x_3, ..., x_{l-1}]$ represent the output layer-1, excitation function and $1, 2, 3, ..., l-1$ layer feature map, which is associated with the channel dimension respectively. By its dense layer-based architecture and dense connectivity, it is called as Dense Convolutional Network (DenseNet). Author has utilized the DenseNet-121 architecture to ensemble with ResNet-152.

E. Ensemble Architecture

Ensemble of two different architectures is very rare due to its significant computational power and complexity [4]. To enhance the performance of deep learning networks, it is needed to ensemble architectures. Ensemble models can achieve better results in a single constructed network. The proposed ensemble model optimized over the utilized models via softmax activation function. The loss function is Cross-Entropy Loss (CEL), here the cross-entropy for the dataset D of size n is [4]

$$CEL = -\frac{1}{n}\sum_{j=1}^{n} log(f(x_j, y_j)) \tag{3}$$

Where f, x_j and y_j are the softmax function, input and label taken by the function. The final loss can be expressed as

$$Loss = CEL + \sum_{l} \alpha_l ||w_i|| \quad (4)$$

Where l and α are the network layer and the regularization parameter respectively. Fig. 5 shows the illustration of ResNet and DenseNet ensemble.

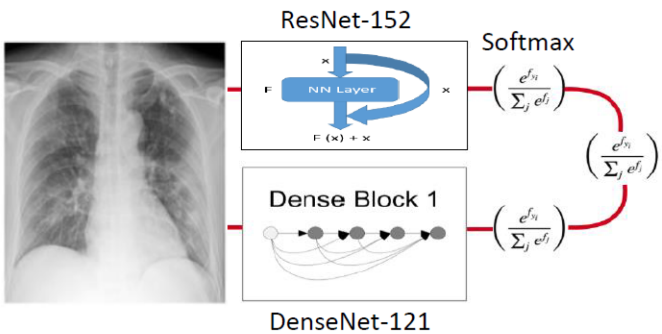

Fig. 5. An illustration of Residual Network and Densely Connected Network Ensemble (Reproduced from [4]).

F. Training

For training purposes, the PyTorch framework has been utilized in this experiment. Adam [21] optimizer has been used for better optimization. The author also has used 24 batch sizes to train the ResNet-152 and DenseNet-121 models for better and optimized memory usage. The author trains each model over 30 epochs and the ensemble model over 20 epochs. An initial values of each model are $1x10^-5$ and $3x10^-4$. Pre-trained weights are utilized to ensure faster concurrence.

IV. Experimental Results and Discussions

In this experiment, the author splits the dataset 70% and 30% for training and testing purposes. Since the dataset has 5907 images in various classes. But the author has used only 1409 images, where 987 images are used for training and 422 images for the test, considering two individual classes such as normal and COVID-19. The test set is utilized to get the best epoch for validation. The validation results are for ResNet-152, DenseNet-121 and ensemble of ResNet-152 DenseNet-121 architectures. To evaluate the validation result, the author has utilized there extensively used matrices such as accuracy, specificity, and sensitivity. Table 1 shows the validation results and Table 2 shows the comparison between the proposed model with other models. Fig. 6 separately shows the proposed model accuracy and loss respectively.

$$Accuracy = \frac{XP + XN}{XP + XN + YP + YN} \quad (5)$$

$$Specificity = \frac{XP}{XP + YP} \quad (6)$$

$$Sensitivity = \frac{XP}{XP + YN} \quad (7)$$

TABLE I
Validation Results of Every Algorithm (%)

Algorithms	Accuracy	Specificity	Sensitivity
DenseNet-121	87.50	83.96	91.29
ResNet-152	94.33	95.72	94.92
ResNet-152 + DenseNet-121	**98.43**	**99.23**	**98.71**

TABLE II
Comparative Performance Analysis of Proposed Model with Others

Algorithms	Accuracy (%)	Dataset
Inception+ResNet V2 [11]	92.18%	Same-Open Source
VGG-19 [12]	98.75%	Same-Open Source
DeTrac [14]	95.12%	Same-Open Source
Xception+ResNet50 [15]	91.40%	Same-Open Source
ResNet50 [16]	98.00%	Same-Open Source
Proposed	**98.43%**	**Same-Open Source**

Here, XP and XN denote as true positive and true negative, YP and YN denote as false positive and false negative respectively.

Automatic COVID-19 patient detection is an important task for deep learning researchers. However, in contrast to this, the author also tries to solve this problem in a different model approach. An ensemble of two state-of-art deep learning architectures has ensured a dominant result in COVID-19 patient detection. Pre-trained models such as ResNet-152 and DenseNet-121 also have performed well. No other literature has utilized this architecture that the author has used in this experiment. It is a novel approach, but due to time and computational power limitations, the author could not run the k-fold validation in this experiment. This research has some limitations, because of the significant changes in symptoms to the patients. Some patients have not been affected by severe pneumonia, even after they have affected by COVID-19. So this measure should be in mind.

But the proposed method can also be utilized for further use such as pneumonia, SARS, ARDS, and Streptococcus disease detection. There are some other new architectures such as EfficientNet, HR-Net can also be utilized for future research.

V. Conclusion

The main objective of this study is to identify COVID-19 affected individuals and limit the transmission as it is a viral disease. RT-PCR method is costly and needs more time than our proposed method to detect COVID-19 cases. In this work, the author introduces a deep ensemble model for COVID-19 case detection, the ensemble model is a combination of ResNet-152 and DenseNet-121 architectures. However, the proposed model has performed enormously well than other architectures with an accuracy, specificity, and sensitivity of 98.43%, 99.23%, and 98.71% respectively. Although, this work still has some limitations and not properly convenient in some cases, because the symptoms of COVID-19 infected patients are changing day by day, as it is not limited to severe pneumonia.

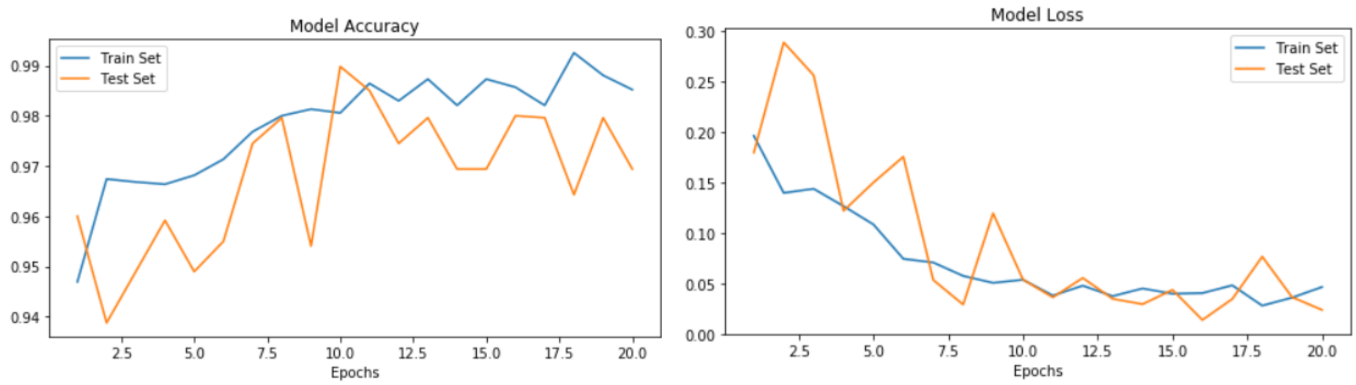

Fig. 6. From left side, (a) Model accuracy of proposed ensemble model and (b) Model loss of proposed ensemble model.

ACKNOWLEDGMENT

The author has dedicated this research to his mother Rahima Khatun for her unconditional sacrifice, love and support.

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