Densely Connected Convolutional Networks (DenseNet) for Diagnosing Coronavirus Disease (COVID-19) from Chest X-ray Imaging

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***Abstract*—Since the beginning of the coronavirus disease (COVID-19) pandemic several machine learning and deep learning methods had been introduced to detect the infected patients using the X-Ray or CT scan images. Numerous sophisticated data-driven methods had been introduced to improve the performance and the accuracy of the diagnosis models. This paper proposes an improved densely connected convolutional networks (DenseNet) method based on transfer learning (TL) to enhance the model performance. The results show promising model accuracy.**

***Keywords*—COVID-19, DenseNet, chest X-ray, transfer learning, coronavirus disease, SARS-CoV-2, machine learning, deep learning, artificial intelligence**

I. Introduction

It is undeniable that using Convolutional neural networks (CNNs) have become a most well-known deep learning approach for medical image recognition problems. Many recent studies [1] have shown that convolutional networks are able to significantly become deeper, more accurate, and efficient to train. With the emergence of manually designed CNN (DenseNet [2], VGGNet [3] and ResNet [4]), large-scale practical image classification tasks witness a noticeable success. Using CNNs with a large kernel size leads to huge computational costs. To prevent this drawback, only small convolutional kernels (3-by-3 or 1-by-1) were applied, and this makes computing possible in very deep networks. Furthermore, these manually designed CNNs improve the training efficiency by using batch normalization in order to reshape the distribution of the input. The process of training of CNNS is usually done by using two common methods named gradient-based learning methods and backpropagation. By increasing the number of layers in CNN, in some cases, the gradient will be vanishingly small and this prevents the weight from changing its value [5]. To deal with this training difficulty, the Residual Network (ResNet) was proposed to reduce the total number of the parameters, which allowed the number of layers to be extended to over a hundred. ResNet allows a number of layers of the network to learn the difference between the input and the output rather than the input-to-output transformation for each layer. In DenseNet, Gao Huang et al. [2] present a dense connection strategy, to connect the outputs of all formal layers as the input of the following layer rather than sum all outputs in the ResNet. With this idea of dense connection strategy, the number of parameters was reduced to 1/3 of the original ResNet. DenseNet is a network architecture that connects each layer to every other layer in a feed-forward fashion. DenseNet insight into a simple connectivity pattern to ensure maximum information flow between layers in the network. This convolutional network connects all layers with each other in a direct way. Moreover, the preservation of the feed-forward nature is obtained by additional inputs from all preceding layers for each layer. This input passes on its own feature-maps to all subsequent layers. All of the mentioned innovations presented to perform image classification in an acceptable way. Image classification plays a pivotal role in the development of intelligent systems in the present age. Advances in computer hardware have led to the training of very deep CNNs with great number of parameters. For this reason, various deep CNN architecture have been presented in order to solve different problems (Image Classification, Segmentation, Object Detection) in real word applications. Using chest X-Ray or Computer Tomography (CT) scan images for COVID19 detection is one of the most pivotal research objects in the application of artificial intelligence medical assistant systems. The pandemic event called COVID19 has significantly affected the performance of centers such as small clinics, doctors' offices, emergency care centers and large hospitals with emergency rooms. [6,7]. The use of intelligent systems plays a considerable role in the process of treating the patient. Due to the fact that chest X-Ray or CT scan images of COVID19 reveal the complications the virus causes in the lungs, the development of intelligent image processing systems on these images can be an important step in the early diagnosis of this disease. This paper aims to present a DenseNet model, which detects COVID-19 suspected patients among pneumonia, normal patients regarding images were collected from front-line imaging systems like CT and mobile X-ray systems.

The main contributions of this work can be summarized as follows:

- This work aims to build an intelligent diagnosis system for COVID-19 patients by constructing the densely connected convolutional networks (DenseNet).
- The main objective of this study is to preventing the vanishing gradient problem and strengthening feature propagation by using a DenseNet for chest X-ray or CT scan images.

The rest of this paper is organized as follows. Section 2 reviews and summarizes previous studies in the field of detection of COVID-19 from chest X-ray imaging. Section 3 presents and discusses our proposed method. Section 4 analyzes and discusses the experimental results. Finally, the paper comes to a conclusion in Section 5. Table 1 specifies the acronyms applied in the rest of this article.

TABLE I. ABBREVIATIONS AND ACRONYMS

Abbreviation	**Description**
CNN	Convolutional neural network
COVID-19	Coronavirus disease
CT	Computer Tomography
DenseNet	Densely connected convolutional networks
MCC	Matthews correlation coefficient
ResNet	Residual Network
TL	Transfer learning
VGGNet	Visual Geometry Group Network
WHO	World Health Organization
X-ray	Energetic High-Frequency Electromagnetic Radiation

II. SATE-OF-THE-ART

A. Selecting a Template (Heading 2)

The CNN and several hybrid variations of it have been the dominant methods used for the detection of COVID-19 from chest X-ray imaging. The accuracy of the method has been improved in several different implementations and also through new preprocessing techniques. TABLE II represents a state-of-the-art of deep learning methods been used.

TABLE II. STATE OF THE ART

References	**Year**	**Method**	**Journal**
Abbas et al. [8]	2021	Classification with DeTraC deep CNN	Applied Intelligence
Afifi et al. [9]	2021	Ensemble CNN	Symmetry
Gupta et al. [10]	2021	InstaCovNet-19: DL classification	Applied Soft Computing
Hussain al. [11]	2021	CoroDet: CNN	Chaos, Solitons and Fractals
Ibrahim et al. [12]	2021	Pneumonia Classification CNN	Cognitive Computation
Joshiet et al.[13]	2021	CNN	Biocybernetics
Karakanis et al. [14]	2021	Lightweight DL	Computers in Biology and Medicine
Singh Punn and Agarwal [15]	2020	Transfer learning in various DL methods	Applied Intelligence
Nayaket al. [16]	2021	Hybrid CNN	Biomedical Signal Processing and Control
Shervin Minaee et al. [17]	2020	Deep transfer learning	Medical Image Analysis
Singh et al. [18]	2021	COVID Screen: explainable DL	Neural Computing
Umer et al. [19]	2021	COVINet: CNN	Journal of Ambient Intelligence and Humanized Computing

III. THE PROPOSED DIAGNOSIS SYSTEM BASED ON DENSENET

In standard version of CNN, an input image goes through multiple convolution and obtain high-level features. But in DenseNet, each layer obtains additional inputs from all preceding layers and passes on its own feature-maps to all subsequent layers. Each layer receives a collective knowledge from all preceding layers. Due to the fact that each layer receives feature maps from all preceding layers, network can be compact in term of number of channels. The proposed method uses the DenseNet with 169 layers. First, the pre-trained DenseNet model is loaded for feature extraction. Loading pre-trained model makes use of the TL method. In fact, TL utilizes knowledge (features, weights) from previously learned patterns and applies them to related ones. Using this method shows its superiority when the number of data is highly imbalanced and the knowledge obtained by another task (pneumonia or non-pneumonia classification) may lead to better utilization. Second, the last layer of the pre-trained DenseNet model is changed to a fully connected layer with a three neurons classifier for a three-class (COVID-19, Pneumonia, and Normal) classification task. The modified DenseNet model is trained with datasets that include 6432 unique x-ray images. In the testing stage, the trained DenseNet model is used to detect the x-ray images.

The workflow of the DenseNet-based proposed method is shown in Figure 1.

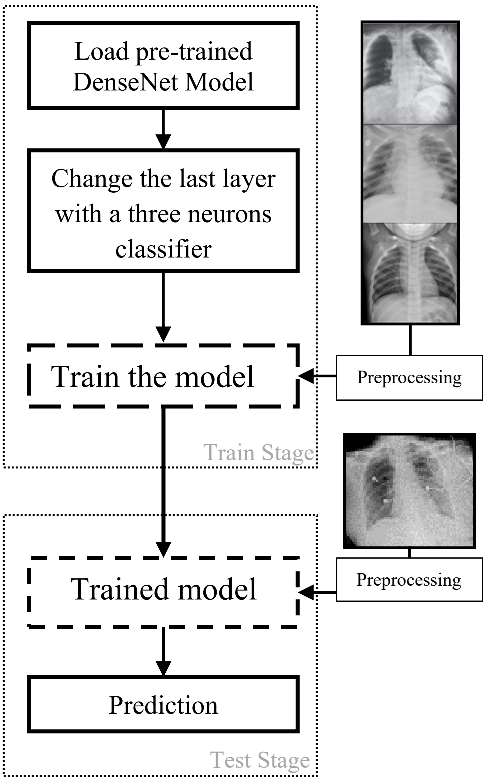

Fig. 1. Schematic diagram of the proposed diagnosis system

In a nutshell, the proposed model be made up of two parts, feature extractor (Densenet-169), and classifier (a fully connected layer with sigmoid activation function) part.

IV. EXPERIMENTAL RESULTS

We use a personal computer (Intel Core i5-2.20 GHz with 16 GB RAM) for training and testing, respectively. All experimental results are provided by using Keras (a high-level API built on TensorFlow 2.0) and Scikit-Learn that are facilitated under Python. The dataset used in this experiment contains 6432 x-ray images (normal patients or patients suspected of COVID-19, or pneumonia).

A. Data description

In this section, we use the dataset contains 6432 x-ray images that divided into three class (COVID19, PNEUMONIA, NORMAL). All images are collected from various publicly available resources. According to the data collected from [20,21,22], the number of training and testing samples (x-ray images) is described in the Table 2.

TABLE III DESCRIPTION OF DATASET

Class	**Train set**	**Test set**
COVID19	460	116
PNEUMONIA	3418	855
NORMAL	1266	317

In Figure 2, a number of x-ray images belonging to the three mentioned classes are illustrated.

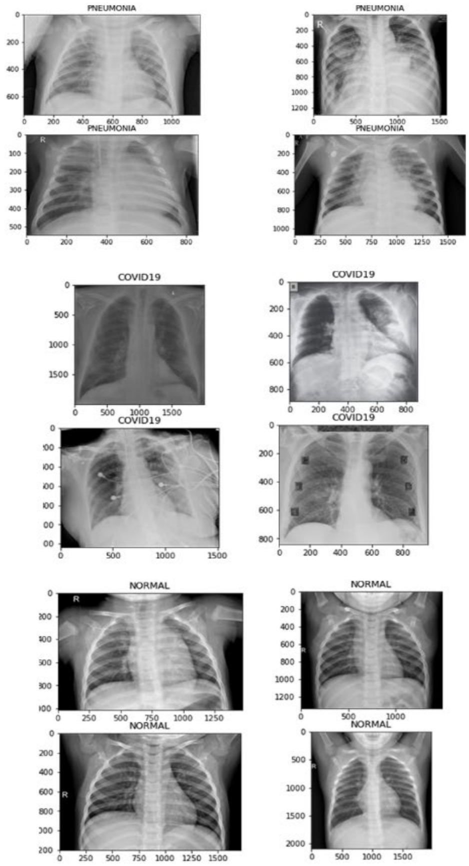

Fig. 2. X-ray images belonging to the three class (COVID19, PNEUMONIA, NORMAL)

B. Performance evaluation measures

In the presented study, we use 80% of the data as the training data for training the model, the next 20% remaining data were used as testing data. The performance of the presented method is evaluated by using the confusion matrix. The following criteria employed for evaluation are accuracy, specificity, sensitivity, precision, recall, F–measure, G–mean and the Matthews correlation coefficient (MCC) [23,24].

$$Accuracy = \frac{T_P+T_N}{T_P+F_N+F_P+T_N} \tag{1}$$

$$Sensitivity = \frac{T_P}{T_P+F_N} \tag{2}$$

$$Specificity = \frac{T_N}{F_P+T_N} \tag{3}$$

$$Precision\,(P) = \frac{T_P}{T_P+F_P} \tag{4}$$

$$Recall\,(R) = \frac{T_P}{T_P+F_N} \tag{5}$$

$$F1-score = \frac{2\times P\times R}{P+R} \tag{6}$$

$$G-Mean = \sqrt{Sensitivity \times Specificit} \tag{7}$$

$$MCC = \frac{T_P\times T_N-F_P\times F_N}{\sqrt{(T_P+F_P)(T_P+F_N)(T_N+F_P)(T_N+F_N)}} \tag{8}$$

C. Results and Discussion

Due to the excellent performance of DenseNet architecture with fewer parameters to train, this paper considered this architecture among the other CNNs existed architectures. Table 3 illustrates the configuration of the training process of the model with the following parameters.

Table III. The configuration of the model

Parameter	Value
Batch size	256
Classes	3
Dropout	0.4
Epochs	10
Loss	Categorical cross-entropy
Optimizer	Adam optimization

Figure 3 plots the graph of the training loss vs. validation loss over the number of epochs.

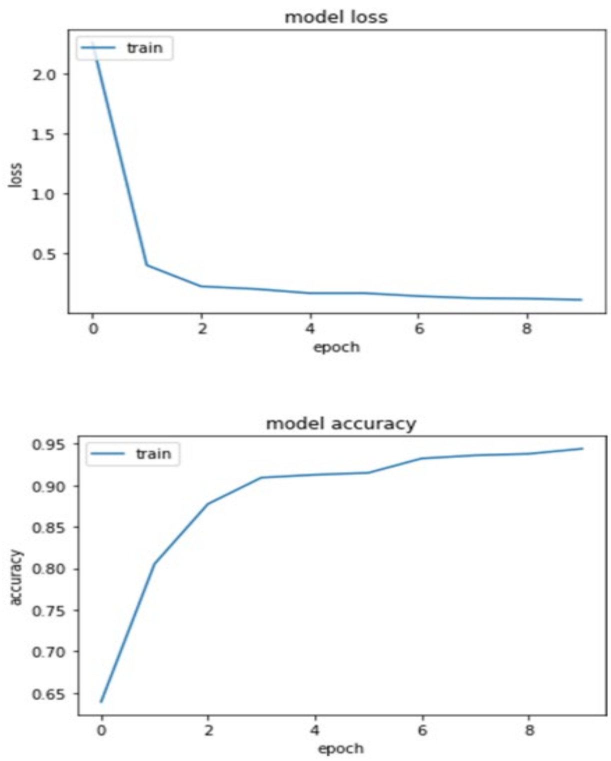

Fig. 3. The accuracy versus epoch and loss versus epoch for train set

To analyse the performance of the proposed method, we calculated the test accuracy, specificity, sensitivity, precision, recall, F–measure, G–mean and MCC. As mentioned in Table II, presented method have to deal with an imbalanced class distribution. For this reason, accuracy cannot provide a proper performance metric and the other metrics mentioned above assess our presented model.

TABLE IV CLASSIFICATION RESULTS (TEST SET)

Class	Accuracy	Sensitivity	Specificity	F-score	G-Mean	MCC
Overall	0.957	0.874	0.957	0.877	0.911	0.854
COVID-19	0.948	0.676	0.982	0.720	0.981	0.7441
Pneumonia	0.945	0.962	0.913	0.958	0.937	0.8786
Normal	0.978	0.986	0.975	0.954	0.815	0.941

In Table III, the results indicate that using the pre-trained model by taking the advantage of TL can provide acceptable performance for the a DenseNet TL-based model. Furthermore, the confusion matrix for the DenseNet TL-based diagnosis model is constructed in Table IV.

TABLE V CONFUSION MATRIX OF DENSENET-169 (TEST SET)

Confusion matrix		Predicted		
		Normal	Pneumonia	COVID-19
Actual	Normal	**293**	13	11
	Pneumonia	3	**817**	35
	COVID-19	1	19	**96**

Table VI compares Densenet-169 trained model with other well-known computer vision models. In this table, ResNet 50 and VGG 16 are compared with the same setup as three-class classification.

TABLE VII COMPARISON OF ACCURACY, F-SCORE AND G-MEAN WITH OTHER COMPUTER VISION MODELS (TEST SET)

Models	Densenet-169			Resnet50			VGG16		
	Accuracy	F-score	G-Mean	Accuracy	F-score	G-Mean	Accuracy	F-score	G-Mean
Overall	0.957	0.877	0.911	0.933	0.853	0.889	0.918	0.828	0.865
COVID-19	0.948	0.720	0.981	0.901	0.698	0.959	0.889	0.678	0.935
Pneumonia	0.945	0.958	0.937	0.938	0.914	0.901	0.924	0.894	0.872
Normal	0.978	0.954	0.815	0.961	0.947	0.809	0.943	0.914	0.789

Given the critical role that CT imaging has played in diagnosis and management in the context of COVID-19, many research groups began to explore the benefits of deep learning algorithms to assist with the detection of COVID-19. Early literature has faced two important challenges called data set imbalance and lack of sufficient data. When sufficient data is not available, the process of training in classification algorithms becomes more difficult due to the unequal distribution between classes. The presented TL-based method aims to provide a robust classifier to tackle both mentioned important challenges. In fact, the proposed method uses the weight obtained for convolutional layers to extract the features in images related to the three diseases. During the process of training, all fully connected layers try to obtain the most appropriate weights for classification based on the extracted features.

V. CONCLUSION

This work presents a DenseNet TL-based method to detect COVID-19. The presented model can classify COVID-19 radiology images from healthy persons and pneumonia patients. In fact, this paper aims to address the problem of lack of data (small number of radiology images of COVID-19 patients) by taking the advantage of TL. The extensive experiments that are performed 3-class classifications revealed the fact that DenseNet is able to detect COVID-19 radiology images from chest radiology images in an effective way. For the future research, integration of the diagnosis methods with outbreak prediction, e.g., [24-33] technologies are highly recommended.

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