Automatic Detection of Coronavirus (COVID-19) from Chest CT Images using VGG16-Based Deep-Learning

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***Abstract*—In recent months, coronavirus disease 2019 (COVID-19) has infected millions of people worldwide. In addition to the clinical tests like reverse transcription-polymerase chain reaction (RT-PCR), medical imaging techniques such as computed tomography (CT) can be used as a rapid technique to detect and evaluate patients infected by COVID-19. Conventionally, CT-based COVID-19 classification is done by a radiology expert. In this paper, we present a deep learning-based Convolutional Neural Network (CNN) model we developed for the classification of COVID-19 positive patients from healthy subjects using chest CT. We used 10979 chest CT images of 131 patients with COVID-19 and 150 healthy subjects for training, validating, and testing of the proposed model. Evaluation of the results showed the precision of 92%, sensitivity of 90%, specificity of 91%, F1-Score of 0.91, and accuracy of 90%. We have used the regions of infection segmented by a radiologist to increase the generalization and reliability of the results. The plotted heatmaps show that the developed model has focused only on the infected regions of the lungs by COVID-19 to make decisions.**

Keywords— Artificial Intelligence, Neural Networks, Image Processing, Rapid Identification, Infection Diagnosis

I. Introduction

A. Background

Coronavirus Disease 2019 (COVID-19) is a highly contagious disease that spreads from one person to another with the appearance of respiratory distress [1]. It has been spread all over the world since December 2019 and so far, it has infected more than millions of people. The clinical tests like reverse transcription-polymerase chain reaction (RT-PCR) are usually used for classifying the suspected patients, but medical imaging techniques such as computed tomography (CT) has also been used to detect and evaluate COVID-19. The chest CT-based COVID-19 classification of the suspected patients requires radiologists and considerable amounts of their times as the number of COVID-19 suspects increases at a rapid rate. Moreover, it has been found that the COVID-19-infected patients show some patterns on chest CT images that are not easily detectable by the human eye [2,3]. Therefore, an automatic detection tool is much needed to assist in screening COVID-19 pneumonia using chest CT imaging [3,4]. Like many other methodological innovations, artificial intelligence (AI) has been applied to the timely, rapid, and effective diagnosis of COVID-19 using chest CT images. AI-Driven tools may provide automated and fast approaches for the detection and classification of COVID-19 on chest CT.

In this study, we developed a deep learning-based Convolutional Neural Network (CNN) model to classify COVID-19 cases from healthy cases. We collected 10979 chest CT images of 131 COVID-19 positive patients, with the infection masks segmented by a radiologist, and 150 healthy subjects. For network training, 1936 CT slices involved by infection along with 1735 slices from healthy subjects, with slice locations similar to those of the COVID-19 positive group were used, to eliminate non-infection differences between the groups and make the model more generalized, reliable, and focused on the infected regions. The plotted heatmaps show the result of this meticulous data selection. The preprocessing steps consisted of transforming image intensities into the Hounsfield unit, extracting the lung part by image processing techniques, equalizing histograms with a transformation created by the intensities of the infection regions, and stretching the contrast of the images. Then, after training and evaluating several deep learning networks, such as ResNet, Inception, VGG16, DenseNet, and Xception by the images of 80% of the cases in each group, VGG16 was chosen as our base model, since it is less complicated compared to the other models. The two-class output was obtained using pooling, dropout, and dense layers. Finally, our model was tested by the CT images of 20% of the cases in each group. The results showed 89.78% precision, 91.50% sensitivity, 88.66% specificity, 0.9063 F1-Score, and 90.14% accuracy.

B. Related Works

Recently, several deep learning methods have been applied on chest x-ray images and CT scans for COVID-19 diagnosis as well as segmentation of lung infections [5]. In [6], N. Yang constructed a support vector machine (SVM) model for the classification of patients with COVID-19 and other types of pneumonia using CT chest images. This was done by extracting textural and histogram features of the infections and obtaining a radionics features vector from each sample. The method achieved a classification accuracy of 88.33%, a sensitivity of 83.56%, a specificity of 93.11%, and an area under the ROC curve of 0.947. This study showed that the SVM model using radionics features of CT chest images could effectively identify patients with COVID-19 compared with other types of pneumonia.

Besides, in [7], a SVM model has been used for the classification of patients with COVID-19 using the features extracted by Gray Level Co-occurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM), Gray-Level Size Zone Matrix (GLSZM), Local Directional Pattern (LDP), and Discrete Wavelet Transform (DWT) algorithms. The feature extraction process has been applied to the patches of 150 CT images from four different datasets with the sizes of 16×16, 32×32, 48×48, and 64×64, and 2-fold, 5-fold, and 10-fold cross-validations have been implemented. Considering accuracy, sensitivity, specificity, precision, and F-score metrics, the best classification accuracy has been obtained as 99.68% with 10-fold cross-validation and GLSZM feature extraction method.

In another study, S. Hu et al. [1] proposed a weakly supervised deep learning method for the classification of COVID-19 and nonCOVID-19 cases from chest CT images. In this study, 450 chest CT images of COVID-19, community-acquired pneumonia (CAP), and non-pneumonia (NP) patients, acquired from two participating hospitals between September 2016 and March 2020, were used for analysis. The classification of COVID-19 from NP cases achieved a mean accuracy of 96.2%, precision of 97.3%, sensitivity of 94.5%, specificity of 95.3%, and area under the ROC curve of 0.970.

In [8], a multitask deep learning model was developed for jointly identifying COVID-19 patients and segmenting infections from chest CT images. The method is composed of an encoder, two decoders for reconstruction and segmentation, and a multi-layer perceptron neural network for classification. This study used a dataset of 449 COVID-19 patients, 98 cases with lung cancer, 100 healthy subjects, and 397 patients with other kinds of pathology. The dice coefficient and area under the ROC curve were used for evaluating the performance of the method, which were higher than 0.78 and 0.93, respectively.

Singh, et al. [2] used a CNN model for the classification of COVID-19 patients as two groups of infected or not-infected. A multi-objective differential evolution (MODE) model was used for tuning the initial parameters of CNN. Extensive experiments were performed by considering the proposed and the competitive machine learning techniques on the chest CT images. The results showed an accuracy of 93.3%. The method outperformed competitive models, i.e., ANN, ANFIS, and CNN in terms of accuracy, F score, sensitivity, specificity, and Kappa statistics by 1.98%, 2.09%, 1.83%, 1.68%, and 1.93%, respectively.

In another study, Hasan, et al. [9] applied a combination of deep learning methods on Q-deformed entropy handcrafted features to discriminate CT scans of COVID-19, pneumonia, and healthy subjects. After pre-processing and histogram thresholding, each of the CT lung scans underwent a feature extraction process that involved deep learning and a Q-deformed entropy algorithm. Then, a long short-term memory (LSTM) neural network classifier was used to classify the features. Performance of this network was significantly improved by combining all extracted features to precisely discriminate COVID-19, pneumonia, and healthy cases. The maximum accuracy achieved for classifying the collected dataset comprising 321 patients was 99.68%.

In [10], Sun, et al. proposed an adaptive feature selection guided deep forest (AFSDF) algorithm for the classification of COVID-19 from chest CT images using a dataset with 1495 patients of COVID-19 and 1027 patients of CAP. This model was learned from a high-level representation of the features. A feature selection method was used to reduce the redundancy of the features based on the trained deep forest model. This feature selection method was adaptively incorporated into the COVID-19 classification model. The accuracy, sensitivity, specificity, and area under the ROC curve were 91.79%, 93.05%, 89.95%, and 96.35%, respectively.

Wang, et al. [11] developed a weakly-supervised deep learning framework for the classification of COIVID-19 and localization of the infected regions from 3D CT volumes. Lung segmentation was done using a pre-trained UNet. Segmented lungs were fed into a 3D deep neural network for predicting the probability of COVID-19. Lesions were localized by combining the activation regions in the classification network and the unsupervised connected components. An area under the ROC curve of 0.959 and an accuracy of 0.976 were achieved when 499 CT volumes were used for training and 131 CT volumes were used for testing. Using a probability threshold of 0.5 for classifying COVID-positive and COVID-negative cases, the algorithm obtained an accuracy of 0.901, a positive predictive value of 0.840, and a very high negative predictive value of 0.982. The algorithm took only 1.93 seconds to process a single patient's CT volume using a dedicated GPU.

He, et al. [12] developed a multi-task multi-instance deep network (M2UNet) to assess severity of COVID-19 and segment the lung lobes. This algorithm included a patch-level encoder, a segmentation subnetwork for segmentation, and a classification subnetwork for severity assessment. It was applied to a dataset of 666 COVID-19 CT images. The algorithm achieved an accuracy of 0.985 for the classification, and a Dice Similarity Coefficient (DSC) of 0.785, a Positive Predict Value (PPV) of 0.799, and a Sensitivity (SEN) of 0.783 for the segmentation.

Yu, et al. [13] used four pre-trained deep network models (ResNet-50, ResNet-101, Inception-V3, and DenseNet-201) with multiple classifiers (linear discriminant, linear SVM, cubic SVM, KNN, and Adaboost decision tree) to discriminate between severe and non-severe COVID-19 cases. The methods were applied on a dataset of 729 2D axial CT images (246 severe and 483 non-severe cases). For validation of the methods, holdout validation, 10-fold cross-validation, and leave-one-out validation were employed. The DenseNet-201 with cubic SVM model achieved the best performance. They achieved a classification accuracy of 95.20% and 95.34% for 10-fold and leave-one-out cross-validation methods, respectively.

II. MATERIALS AND METHODS

A. Patients and Data

In this study, we used a total of 10979 CT images from 131 COVID-19 patients and 150 healthy cases, acquired in the Alinasab Hospital of Tabriz, Tabriz, Iran. In each of the CT slices, our expert co-investigator segmented regions of infection. We used these slices and their segmentation masks in preprocessing and training of the model to increase the performance and generalization of the resulting model. Besides, for the healthy cases, we used images that were similar to the images of the COVID-19 group in terms of their anatomical locations, to eliminate non-infection differences between the groups and force the model to focus on the infections. This meticulous selection has made our model reliable and concentrated on detecting COVID-19 infections in CT images. Specifically, 1966 CT slices with COVID-19 infections, along with 1735 similar slices from healthy subjects were used for the training of the model.

B. Image Preprocessing

The following preprocessing steps were applied to each of the images:

- A transformation was applied to the intensities for mapping them into the Hounsfield unit.
- The lung part of images was extracted by image processing techniques to eliminate the irrelevant features in the training of the model and increase the focus on the infections.
- Histogram equalization was applied to the images using a transformation created by the histogram of the infected regions segmented by the radiologist, to highlight the infection intensities.
- Finally, another intensity transformation was applied for stretching the contrast of images to be more informative for the model.

Sample preprocessed CT images of the COVID-19 cases and nonCOVID-19 cases are shown in Fig. 1 and Fig. 2, respectively.

C. Deep Transfer Learning

The necessity of using a very large training dataset makes it extremely time and memory-consuming to train the CNN models. This difficulty can be overcome by using a pre-trained network (i.e., deep transfer learning) and update the model with our dataset. We reviewed multiple pre-trained deep learning networks such as ResNet [14], Inception V3 [15], VGG16 [16], DenseNet [17], and Xception [18]. Most of them have a complicated network with several layers and need a large dataset to train even when we use transfer learning. Because of this limitation, VGG16 was chosen as our base model since it is less complicated compared to other models. Then, we added some layers such as pooling layers, dropout layers, and dense layers to generate the two-class output and get a reasonable accuracy. In detail, after the last pooling layer of VGG16, we used a flatten layer to transform our feature map to a vector, then we used 3 dense layers: (1) layer 1 has 512 neurons and ReLU is used as the activation function, (2) layer 2 has 64 neurons and ReLU is used as the activation function, and (3) layer 3 as the output layer has 2 neurons and softmax is used as the activation function,. Furthermore, we utilized 50% drop out in all 3 layers. In addition, Adam algorithm was chosen for optimization with an initial learning rate equal to 0.001 and 5×1e-5 decay. Also, the batch size was set to 64 and the number of training epochs was set to 20. The model architecture is shown in Fig. 3.

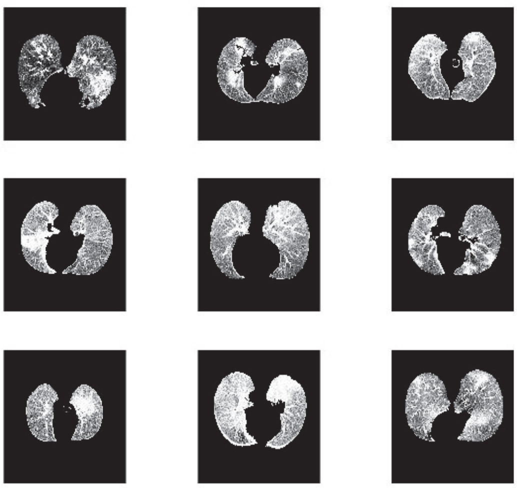

Fig. 1. Sample lung images of COVID-19 patients after preprocessing.

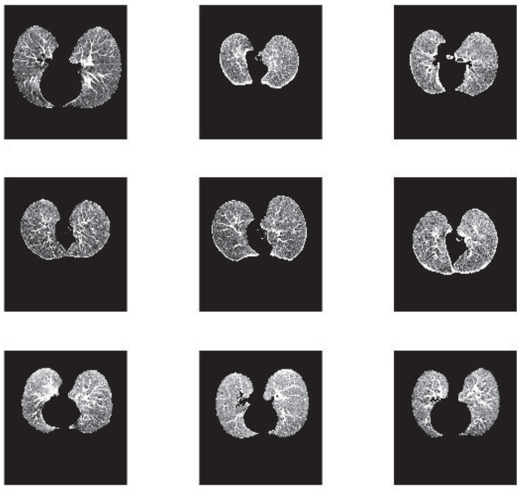

Fig. 2. Sample lung images of nonCOVID-19 cases after preprocessing.

Our dataset was divided into 3 groups: training data, validation data, and test data. We trained our model with the training data, then we set the model's hyperparameters with

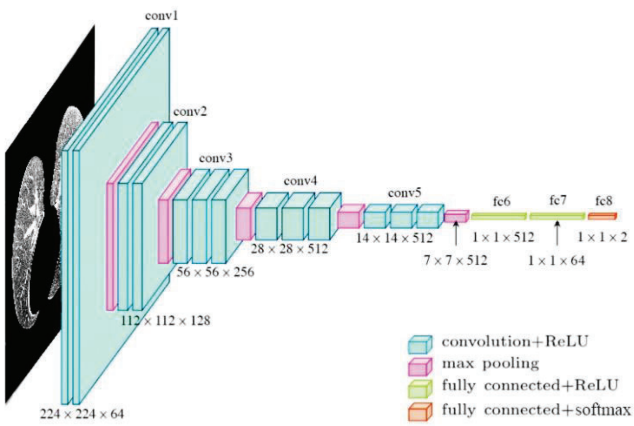

Fig. 3. The deep model architecture with VGG16 as the base model.

the validation data, and finally, we tested the performance of our model with the test data, which was not fed to the model before. CT images of 20% of the subjects were separated as test data, then for training and validating the model, as explained in Subsection A of this section, the selected slices of 20% of the remaining data, i.e., 16% of the entire data, were used for validation, and the remaining data, i.e., 64% of the entire data, used for training. TABLE I shows the number of images in each group.

III. Results

After training the model, we used the standard statistical analysis to estimate the performance of the model. To do so, the test data were fed into our model using a five-fold cross-validation procedure to determine the performance, i.e., the accuracy of the model to classifying the images of each group correctly. First, the confusion matrix was constructed and then some primary metrics such as positive predictive value, false discovery rate, true positive rate, and false negative rate were calculated. We also calculated the following metrics: precision, sensitivity, F1 score, specificity, and accuracy. These quantities are defined in Eqs. (1)-(5), where, TP, TN, FP, and FN are true positive, true negative, false positive, and false negative rates, respectively.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Sensitivity = Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$F1\ score = 2 \times \frac{recall \times precision}{recall + precision} \tag{4}$$

$$Accuracy = \frac{TP + TN}{Total\ samples} \tag{5}$$

The resulting confusion matrix and the calculated performance measures are shown in Fig. 4. Note that the accuracy of 90.14% is achieved by the VGG16 network for classifying COVID-19 from healthy cases. In examining the confusion matrix, note that 1765 COVID-19 images of the total of 1966 images (89.78%) are classified correctly. The resulting 0.9150 positive predictive value means that in all positive predicted images, 91.50% were recognized correctly. The detailed results are shown in TABLE II. Besides, we have plotted the heatmap to identify the regions that had critical information for the network. For simulating a practical situation, we also repeated our testing with the whole 3D CT scans of the test subjects and obtained the same accuracy. In addition, we investigated the effect of image augmentation, as a method to increase the number of samples for the training of the CNN model, but the performance did

TABLE I. Random Division of The Dataset

Type	*Training*	*Validation*	*Test*	*Total*
COVID-19	1262	316	388	1966
Normal	1112	278	345	1735
Total	2374	594	733	3701

		Prediction			
Ground Truth	COVID-19	1765	201	**0.8978**	**0.1022**
Ground Truth	Normal	164	1571	**0.9055**	**0.0945**
TPR: True Positive Rate **TNR: True Negative Rate** **FPR: False Positive Rate** **FNR: False Negative Rate**		COVID-19	Normal	**TPR / TNR**	**FPR / FNR**
	PPV / NPV	**0.9150**	**0.8866**	**PPV: Positive Predictive Value** **NPV: Negative Predictive Value** **FDR: False Discovery Rate**	
	FDR	**0.0850**			

Fig. 4. The confusion matrix and related indices obtained using 5-fold cross-validation.

not improve. In Fig. 5, the left side shows sample results of COVID-19 cases and the right side of those of healthy cases. We observed that our proposed network provides reasonable accuracy for detecting the infection of COVID-19 in CT images. So, this network can be used to distinguish COVID-19 cases from healthy subjects. Also, since the heatmaps showed that our proposed network decides based on the pixels infected by the virus, this network can be used for detecting the regions of infection from chest CT images.

IV. Discussion

COVID-19 is a new coronavirus pandemic that affects the daily life of people around the world and screening is an approach to prevent the disease spread. When screening is done in the first phases of the disease, the patient can prevent the outbreak using health recommendations. However, this approach has some difficulties. For instance, there are not sufficient automated toolkits available, and also using these toolkits are time and cost consuming. In this study, we proposed to use a convolutional neural network to identify an infected person using CT images quickly and automatically. By using the recommendations of a specialist, we used the infected regions in the chest CT images of COVID-19 patients to classify infected people from non-infected. We developed a CNN model based on the popular VGG16 network for detecting the virus. Experimental results show that our model has 90% accuracy. Also, according to the heatmaps, our model focuses on the infected regions in the lung CT image, and this is an important element that makes our results reliable.

V. Limitations And Future Works

Considering the novelty of COVID-19, there are several limitations in the studies of automatic detection. An important limitation is the lack of a large dataset to increase the generalization of the methods for practical applications.

TABLE II. The Performance of The Developed Model

Metric	*Precision*	*Recall*	*Specificity*	*F1 Score*	*Accuracy*
Value	0.9150	0.8978	0.9055	0.9063	0.9014

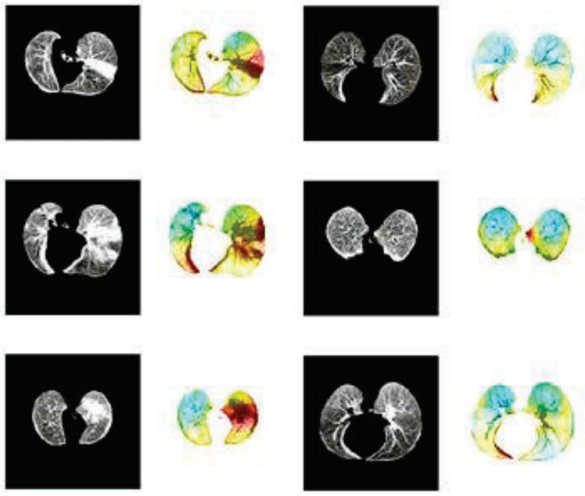

Fig. 5. COVID-19 lung images (left) and normal lung images (right) with their heatmaps.

Also, using a considerable change in the size of the dataset, the networks should be changed so that they work appropriately. For future works, a more advanced backbone architecture of deep learning networks can be employed, handcrafted features can be extracted based on the prior knowledge, generative adversarial networks (GANs) can be developed to increase the number of proper images for training the network and increase the performance of the model, attention-based multiple instances learning can be used instead of training on individual slices, putting the patient-specific slices into a bag and train on bags so the network will learn to assign weights to individual slices in a COVID-19 bag and automatically sample those high weighted slices for detecting the infection [1,10]. Also, deep learning methods can be used not only for classifying and segmenting infections of the images but also for predicting the disease progression or the outcome of treatment [19].

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