Classification of COVID-19 using Deep Convolutional Neural Network

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Abstract

The COVID-19 pandemic appears to have a devastating impact on the fitness and health of the world's population. Effective screening of infected patients is a critical step in the battle against COVID-19, with chest radiography being one of the main screening methods. In this paper, an Alexnet model based on a deep convolutional neural network with SVM is proposed to automatically detect COVID-19 disease using chest X-ray radiography, while optimizing detection accuracy using deep convolutional neural networks. Furthermore, large-scale experiments were performed with an Alexnet pre-trained deep learning model that was used to extract image patterns, and a Support Vector Machine (SVM) was used for the classification process. A support vector machine turned into used to update the higher layers of pre-trained models, trained the usage of off-the-shelf features from the bottom layers. The experimental results showed the validity and efficiency of our proposed model, where obtained an accuracy of 99.7% in classifying COVID-19 and non-COVID-19.

1. Introduction

In January 2020, the World Health Organization (WHO) declared the outbreak of the new coronavirus disease, COVID-19, a public health emergency. WHO says there may be a critical risk for the spread of COVID-19 to countries around the world. In March 2020, WHO estimated that COVID-19 was often classified as a pandemic [1]. COVID-19 has led to dangerous complications such as heart problems, acute respiratory disorder, and secondary infections in a comparatively high attribution of patients and thus high mortality.

Therefore, early detection and commencement of treatment in severe cases is key to reducing mortality [2]. It should be noted that one of the most reliable methods for diagnosing COVID-19 is the Reverse Transcription Polymerase Chain Reaction test (RT-PCR) [3]. Although the sputum real-time polymerase chain reaction test is the gold standard for coronavirus diagnosis, it takes a long time to validate COVID-19 in patients due to the high false-negative results [4]. Medical imaging methods such as Computed Tomography (CT) and Chest X-ray (CXR) may play a major role in confirming positive COVID-19 patients, especially in cases of infected pregnant women and children [5,6].

The major drawback of using CT imaging is the high dose of the patient, i.e., exposure to more radiation and cost scanning [13]. In contrast, one distinguished concept is the diagnosis of COVID-19 from radiographs. Most Italian hospitals are employing CXR as the first-line method, with faster results compared with those of RT-PCR, especially by using portable X-ray units which reduce the movement of patients and so minimize the risk of cross-infection [7,8]. An automated diagnostic system (CAD) has been developed so that clinicians can automatically recognize and measure suspected diseases of vital organs in X-ray images [9, 10].

In recent years, deep learning techniques have shown positive results in performing radiological tasks via automated processing of multimodal medical images [11, 12]. In fact, Deep Convolutional Neural Networks (DCNNs) are one of the important deep learning architectures and have been widely implemented in many practical applications such as pattern recognition and intuitive image classification [13].

This paper focuses on developing a framework to classify COVID-19 using a chest X-ray. To this end, a Convolutional Neural Network has been used to improve performance and accuracy. The rest of this paper is organized as follows: the next Section 2 presents related works. In Section 3, we provide the materials and methodology. Section 4, presents the main results and discussion. Finally, Section 5 concludes this paper.

2. Related Work

To detect lung-related diseases, medical imaging methods are required to diagnose pulmonary problems. Several experiments have been performed to detect pneumonia using chest X-rays, based on convolutional neural networks with different approaches. For example:

In [14], the authors proposed a framework for diagnosing COVID-19 automatically in X-ray images. They have validated 50 chest X-rays with 25 confirmed positive cases of COVID-19. In fact, the proposed framework consists of seven deep learning classifiers, which are: VGG19, DenseNet201, InceptionV3, ResNetV2, InceptionResNetV2, Xception, and MobileNetV2. They showed that they had an accuracy of 90%, 90%, 70%, 50%, 80%, 80%, 60%, respectively.

Apostolopoulos et al. [15], used a dataset of X-ray images from patients with common bacterial pneumonia, confirmed COVID-19 disease, and normal incidents to automatically detect coronavirus disease. The authors used five models of convolutional neural networks VGG19, MobileNetv2, Inception, Xception and Inception ResNetv2 with transfer learning. They obtained an accuracy of 96.78%, a sensitivity of 98.66%, and a specificity of 96.46%.

Chowdhury et al. [16] created a public database that combined numerous public databases and additionally by collecting images from recently published articles. It should be noted that the database created contains a combination of 423 COVID-19, 1485 viral cases of pneumonia and 1579 normal X-rays images. Hence, the transfer learning technique was used with the help of image augmentation to train and validate several pre-trained deep convolutional neural networks. The networks were trained to classify two different schemes: The first scheme is normal and COVID-19 pneumonia, and the second scheme is the normal, viral and COVID-19 pneumonia with and without image augmentation. The authors showed that the classification accuracy, precision, sensitivity, and specificity for both schemes were 99.7%, 99.7%, 99.7% and 99.55% and 97.9%, 97.95%, 97.9%, and 98.8%, respectively.

Also, in [17], five pre-trained convolutional neural network-based models (i.e., ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) have been proposed for detection of corona virus pneumonia infected patient using chest X-ray radiographs. The authors applied three binary classifications into four categories: COVID-19, viral pneumonia and bacterial pneumonia using 5-fold cross-validation. Considering the performance results obtained, they showed that the pre-trained ResNet50 model provides the highest classification performance (96.1% accuracy for Dataset-1, 99.5% accuracy for Dataset2 and 99.7% accuracy for Dataset-3) among the other four used models. In [19], the authors trained a deep convolutional neural network which has 60 million parameters and 650,000 neurons, to classify the data in the ImageNet LSVRC-2010 contest into 1000 different classes. They demonstrated the effectiveness of the results they obtained.

3. Methodology

3.1. Dataset

The dataset used in this paper contains covid-19 X-ray images to detect COVID-19 using chest X-ray images. Clearly, the dataset contains subfolders for each image category such as non-COVID-19 and COVID-19, The total number of images of each category is 912 [18], classified in Table 1 as training data and testing data. In Figure 1 we show a sample of X-ray images dataset for COVID-19 and non-COVID-19 patients.

Table 1. Shows the number of training and testing set

Category	Training Set	Testing Set
COVID-19	730	182
Non-COVID-19	730	182

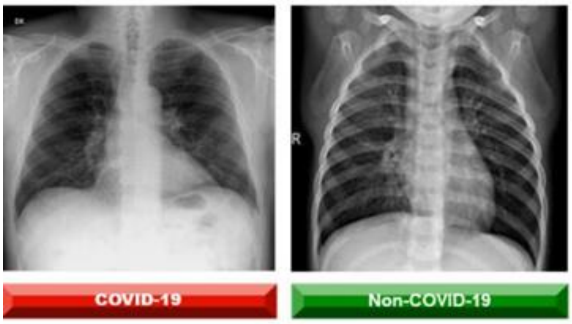

Figure 1. Sample dataset showing a COVID-19 and a non-COVID-19 case

3.2. Preprocessing

In the pre-processing step, All the images of dataset are resized with the input size of AlexNet network i.e. 227-by-227 and conversion of any grayscale image in dataset into RGB is performed.

3.3. Model

In Figure 2. we present the architecture of the proposed framework.

3.3.1 Feature Extraction

Feature extraction is a very important aspect of image classification task. In this paper, we use The pre-trained Convolutional Neural Network (Alexnet) model was designed by Alex - Krizhevesky and others [19]. used for feature extraction step .

There are two stages in the training process of the network, the forward and back propagation. Firstly, a number of training samples are extracted in a certain ratioand inputted into the initialized network. A convolution kernel was used to obtain the features of the convolutional layer. This network constructs a hierarchical representation of input images. The deeper layers contain higher-level features, which were constructed by the lower-level features of earlier layers. In order to get representations for the training and test images, we use activations on the fully-connected layer FC7. Fundamentally, we keep the parameters of AlexNet unchanged, and truncate the model. In particular, we take the input layer to the fully-connected layer of ALexNet as the FC7 feature transfer extraction module [20].

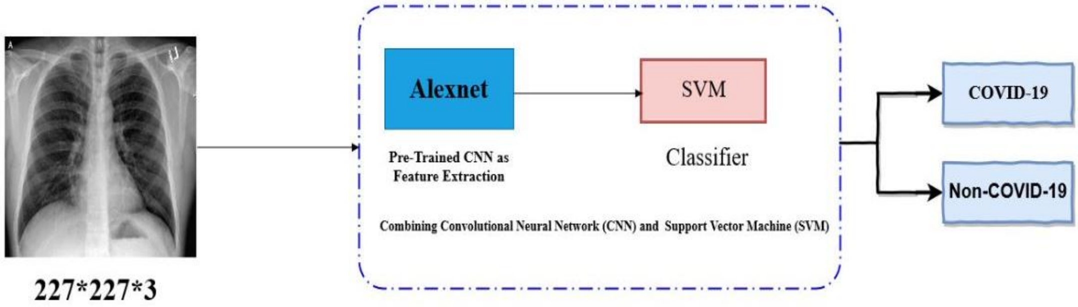

Figure 2. Illustrates the architecture of the proposed framework

3.3.2 Classification

In this step, we Loaded the pretrained network (Alexnet) and extract the image features from specified layers and Train the SVM classifier using features extracted from layers, test the SVM model using the features extracted from the test images.

3.4. Performance measures

The performance of different pre-trained models to test the dataset is evaluated after completion of the training phase and compared using four performance measures (such as accuracy, sensitivity and specificity) through different class labels computed as follows:

Accuracy: The accuracy was the fraction of the predicted labels which was correctly calculated as follows:

$$Accouracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Sensitivity: The proportion of actual positive samples that correctly is given by sensitivity measures and calculated as follows:

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Specificity: Also, in this study, we will focus on specificity as measures of the proportion of specific negative samples, where the percentage of Non-COVID-19 images is correctly classified as Non-COVID-19 and is calculated as:

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

In the previous equations, while classifying Non-COVID-19 and COVID-19 patients, TP, TN, FN, FP represents the number of true positive, true negative, false negative, false positive respectively.

4. Results and Discussion

The main goal of our proposed framework is the adequate diagnosis of pneumonia from chest X-ray images. Therefore, all the models that we explained above were prepared and trained separately. Then, we conducted training and testing using a Windows platform computer with an Intel Core i5- CPU @ 2.7 GHz configuration with 8 GB of RAM. The aim of this study is to correctly diagnose COVID-19 from chest X-ray images. Therefore, we prepared a model (as we have seen previously) and train it. In fact, we performed training and testing using a computer on the platform of Windows with the configuration of Intel Core i5- CPU @ 2.7 GHz with 8GB of RAM.

In the remainder of this section, we will present the results obtained by our classification model and compare the results with those obtained in [21] since we used the same dataset. In Table 2, we present the results of CNN performance to those obtained by Alqudah et al. [21]. Also, in Figure 3, we show the confusion matrix for two classes. It is clear from Table 2 that the results of Resnet50 + SVM outperform the result in [21], where we obtained an accuracy of 99.7%.

Table 1. Results of CNN performance compared to the results of Alqudah et al. [21]

	Sensitivity	Specificity	Accuracy
Alexnet + SVM	100%	99.5%	99.7%
Alqudah et al. [21]	100%	93.3%	95.2%

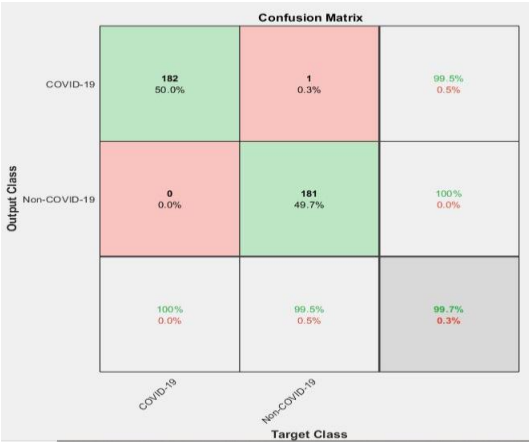

Figure 3. Show the confusion matrix

5. Conclusion

In this paper, we proposed an Alexnet model based on a deep convolutional neural network with SVM for the detection of COVID-19 from the chest X-ray of patients. The pre-trained model (Alexnet) was used to extract features from X-ray images and SVM in the classification process using the features extracted via the pre-trained CNN model. Furthermore, we compared our results with ones obtained in [21] since we used the same dataset. The experimental results showed the efficiency of our proposed model, where obtained an accuracy of 99.7%.

6. References

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