A Novel Deep Convolutional Neural Network Model for COVID-19 Disease Detection

Emrah Irmak
Electrical-Electronics Engineering Department
Alanya Alaaddin Keykubat University
Alanya, Antalya, Turkey
emrah.irmak@alanya.edu.tr

***Abstract*—The novel coronavirus, generally known as COVID-19, is a new type of coronavirus which first appeared in Wuhan Province of China in December 2019. The biggest impact of this new coronavirus is its very high contagious feature which brings the life to a halt. As soon as data about the nature of this dangerous virus are collected, the research on the diagnosis of COVID-19 has started to gain a lot of momentum. Today, the gold standard for COVID-19 disease diagnosis is typically based on swabs from the nose and throat, which is time-consuming and prone to manual errors. The sensitivity of these tests are not high enough for early detection. These disadvantages show how essential it is to perform a fully automated framework for COVID-19 disease diagnosis based on deep learning methods using widely available X-ray protocols. In this paper, a novel, powerful and robust Convolutional Neural Network (CNN) model is designed and proposed for the detection of COVID-19 disease using publicly available datasets. This model is used to decide whether a given chest X-ray image of a patient has COVID-19 or not with an accuracy of 99.20%. Experimental results on clinical datasets show the effectiveness of the proposed model. It is believed that study proposed in this research paper can be used in practice to help the physicians for diagnosing the COVID-19 disease.**

***Keywords*—coronovirus detection; deep learning; medical image processing; image classification**

I. INTRODUCTION

Coronavirus (COVID-19) is a type of flu that appeared in Wuhan, China in December 2019. It is observed that it is much more contagious and lethal than the known seasonal flu. Deaths occur when the disease turns into pneumonia [1]. People can be contagious before they develop symptoms, making it difficult to control the spread of the virus. Development of any vaccine can take twelve months according to the research conducted until the writing of this paper [2]. Covid-19 disease caused by coronavirus has been declared a pandemic by the World Health Organization as of March 11. The total number of confirmed cases worldwide is 10,173,722 whereas the total number of active cases is 4,510,716 and the number of death from COVID-19 is 502,517 according to Coronavirus Resource Center at Johns Hopkins University of Medicine on 29 of June 2020. These statistics reveal that this novel coronavirus can be deadly with a 4.94% case fatality rate.

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Early diagnosis of COVID-19 disease is of great importance for clinical treatment planning, patient monitoring and evaluation of treatment outcome. Looking at the current medical technological advances, COVID-19 disease diagnosis is typically based on swabs from the nose and throat [3]. The major disadvantages of this procedure are that it is time-consuming and susceptible to sampling error and therefore inefficient. These test are known as reverse-transcription polymerase chain reactions (RT-PCR) and are confirmed that the sensitivity of tests are not high enough for early detection [4]. It is possible to increase the diagnostic capabilities of physicians and reduce the time spent for accurate diagnosis with computer-assisted automatic detection and diagnosis systems. The purpose of these systems is to help experts make quick and accurate decisions. The motivation of this study is the early diagnosis of COVID-19 disease, the speed and high accuracy required for accurate detection and classification of COVID-19 disease. Automatic detection of COVID-19 disease from medical images is a critical component of the new generation of computer-assisted diagnostic (CAD) technologies and has emerged as an important area in recent years. X-rays is a widely used imaging method for the detection, classification and analysis of diseases caused by viruses.

Researchers who are always interested in artificial intelligence and sub-branches that aim to design more intelligent systems have modelled human thinking and decision making ability for the first time and presented a model that calculates the functioning of brain functions [5]. It was emphasized that the way to design better performing neural networks depends on the establishment of deeper networks, hence the use of the term Deep Learning (DL) has been expanded to draw attention to the theoretical significance of the depths [6]-[8]. Within this important research field, Convolutional Neural Networks (CNN) are considered the basic architectural models in deep learning. These models are designed to learn from input data without user-specified features [9]. CNNs are the developed and expanded versions of Artificial Neural Networks (ANN). The network deepening as a result of increasing the number of hidden layers in ANNs can be defined as CNN. This depth in the CNN was achieved by the use of 2-Dimensional filters. CNN has become a widely used method especially in researches such as medical image processing and disease diagnosis.

The rest of this paper is organized as follows. Section II presents materials and methods. All the steps about the proposed architecture can be found in this section. In section III, experimental results are discussed and these results are compared with the state-of-arts methods. Finally, section IV concludes the paper.

II. Materials and Methods

A. Architecture of the Proposed CNN Model

In this paper, a novel, powerful and robust CNN architecture is designed and proposed for COVID-19 disease detection. This CNN model is used to decide whether a given chest X-ray image of a patient has COVID-19 or not. The proposed CNN architecture consists of 12 weighted layers, in which there are 2 convolutional layers and 1 fully connected layer as shown in Fig. 1. The convolutional layers are followed by ReLU and max pooling layers. In the proposed architecture ReLU is used as an activation function since it is already standard activation function in image classification tasks. The fully connected layer, resulting in 2-dimensional feature vector is fed as an input to Softmax classifier, which makes the final prediction whether there is a coronavirus or not. There are 2 neurons in the output layer as this model tries to classifies an image into 2 classes: COVID-19 (+) or COVID-19 (-). The first convolutional layer has 96 kernels of size 7x7 with stride 4 and padded with [0 0 0 0] whereas the second convolutional layer has 2 groups of 128 kernels of size 5x5 with stride 1 and padded with [2 2 2 2]. Size of the input images that are forwarded into the all architectures are 227x227x3. Stochastic Gradient Descent Momentum (SGDM) is used as the optimization method.

B. Performance Evaluation Matrix

After the classification algorithm is performed, the performance of the classification must be evaluated. To check the performance of the classification algorithm the confusion matrix is used in this paper. Confusion matrix provides helpful information regarding to the actual image labels and predicted image labels proposed by the classification method. Different aspects of the classification performance can be assessed using this valuable information. Confusion matrix has diagonal values which show true positives (TP). TP is the number of samples that is classified as true when it is actually true. True Negative (TN) is the number of samples that is classified as false when it is actually false. False Positives (FP) is the number of samples that is classified as true when it is actually false. False Negatives (FN) is the number of samples that is classified as negatives when it is actually true. The most used performance evaluation metrics are Accuracy, Specifity, Sensitivity and Area of ROC Curve (AUC). The corresponding formulas regarding these metrics is shown in (1) through (4).

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

$$Specifity = \frac{TN}{TN+FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

III. Experimental Results and Discussion

A. Dataset

Since COVID-19 is a very new type of coronavirus, it is very difficult to find images and data about this disease. This research study is important for the literature because as much as possible number of X-ray images is used for the disease detection. The first dataset used in this study is collected by Joseph Paul et al. and contains 542 frontal chest X-ray images from 262 people from 26 countries [10]. The second dataset used in this study is called COVID-19 Radiography Database created by a researcher team from Qatar University [11]. The last dataset is by Kermany et al. [12]. In summary, a total of 625 COVID-19 images and 625 normal images are prepared to train and test the proposed CNN model. All the datasets used in this study are publicly available and corresponding websites are given in this paper.

B. Experiment Platform and Time Consumption

The hardware and software environment used in this study is as follows:

- Software environment: Windows 10 (64-bit) operating system, Matlab R2019a.
- Hardware environment: NVIDIA GeForce GTX-850M GM107 GPU, Intel Core i7 5400 GPU 2.60 Ghz, 16.0 GB RAM.
- Elapsed time for training the deep learning model (500 images) was 7 minutes.

C. Results

The CNN model is trained by splitting the data into training, validation and test set. Training set is used to train the network and then the test set is used for validation and parameter optimization processes. A total of 625 images, with a training subset of 375, validation subset of 125 images and test subset of 125 images (60%-20%-20%) are used for the study. The X-ray images are rescaled to a size of 227x227 at the pre-processing stage. Accuracy and Loss plots for the task of COVID-19 (+) image vs COVID-19 (-) image are shown in Figure 2. The proposed CNN model achieves an overall classification accuracy of 99.20% after 90 iterations. This result indicates the

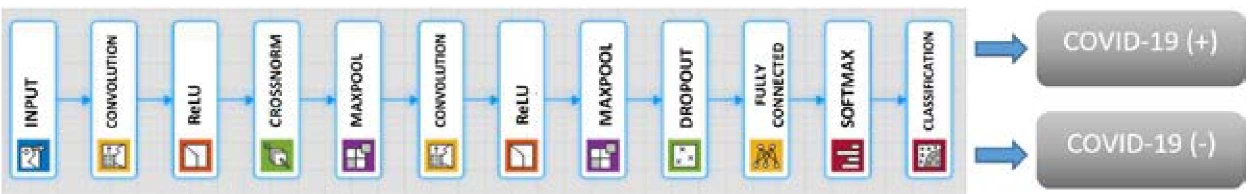

Fig. 1. Proposed CNN architecture for COVID-19 disease detection

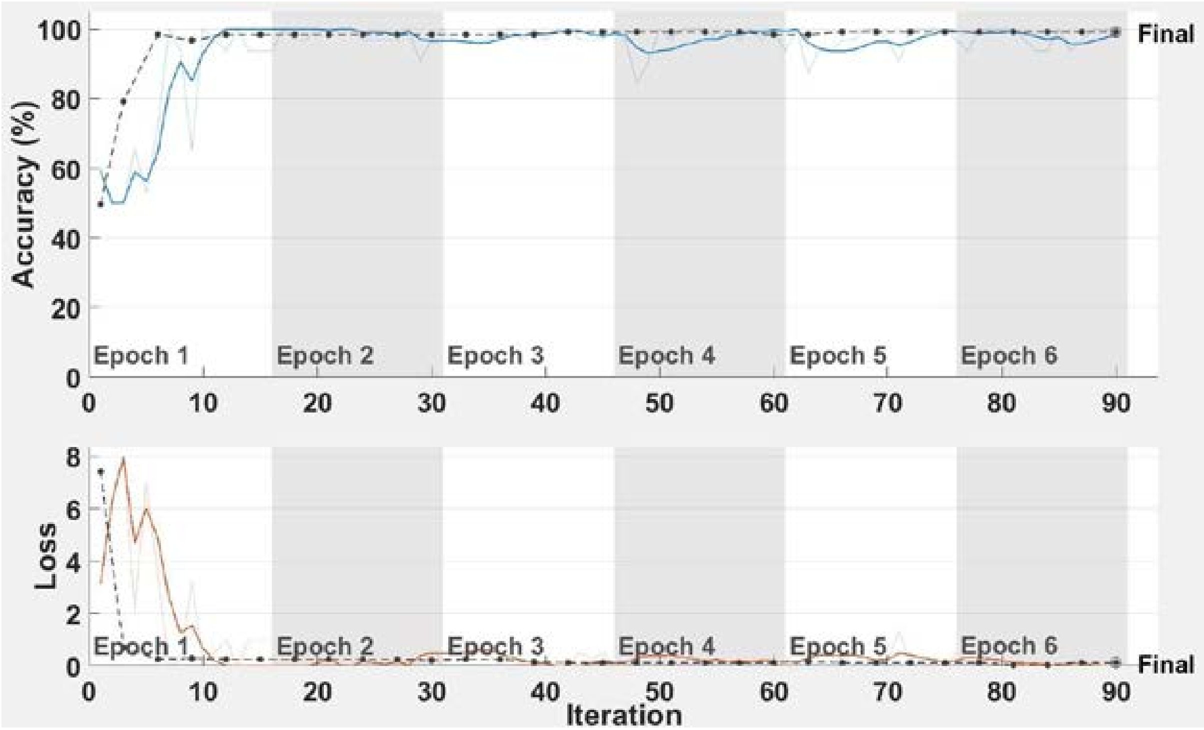

Fig.2. Accuracy and Loss results for the proposed CNN model

ability of the architecture for COVID-19 detection.

The confusion matrix which proves the performance of the system is shown in Figure 3. The vertical axis (Y-axis) stands for the predicted values which are actually the system output and the horizontal axis (X-axis) stands for the true labels which are ground truth values. Performance of the architecture is evaluated using Accuracy, Specifity, Sensitivity and Precision metrics. These metrics are calculated using the results from the confusion matrix and are show in Table I. Accuracy of 99.20%

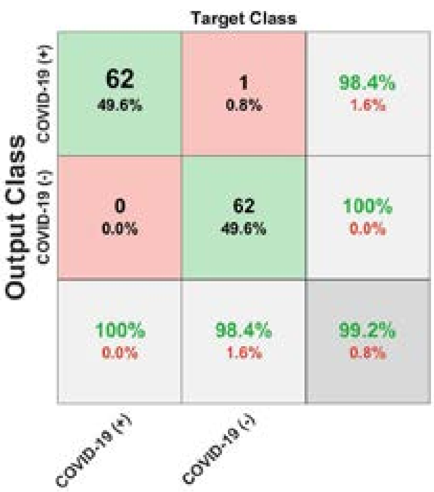

Fig.3. Confusion matrix

is obtained to classify COVID-19 (+) and COVID-19 (-). The Receiver Operation Characteristic Curve (ROC) curve is used as another method to quantify the performance of the architectures. The area under the curve (AUC) of the ROC curve is found to be 0.9998. Fig. 4 shows four sample validation images with predicted labels and the predicted probabilities of the images having those labels.

D. Comparison with State-of-the Art Methods

There are quite a few studies in the literature about COVID-19 disease detection using DL because of lack of data and images. For instance, Ozturk et al. [3] used DarkCovidnet deep learning model to classify X-ray images as COVID-19 and healthy image. They obtained an overall accuracy of 98.08%. Lin et al. [4] proposed a three-dimensional deep learning model for COVID-19 detection. They called their model COVID-19 detection model neural network (COVNet) which actually consists of ResNet50 as the backbone. They obtained a classification accuracy of 96%. Apostolopoulos et al. [13] adopted a procedure based on Transfer Learning for detection of COVID-19 from X-ray images. They obtained a classification accuracy of 96.78%. However, the classification accuracy that is obtained using the proposed model in this study is 99.20% which is higher than the above results.

TABLE I. ACCURACY METRICS IN TERMS OF TP, TN, FP, FN, ACCURACY, SPECIFITY, SENSITIVITY AND PRECISION

Classes	**TP**	**TN**	**FP**	**FN**	**Accuracy**	**Specifity**	**Sensitivity**	**Precision**	**Total**
COVID-19 (-)	62	63	0	1	**99.20%**	**1**	0.9841	**1**	63
COVID-19 (+)	62	62	1	0	**99.20%**	0.9841	**1**	0.9841	62

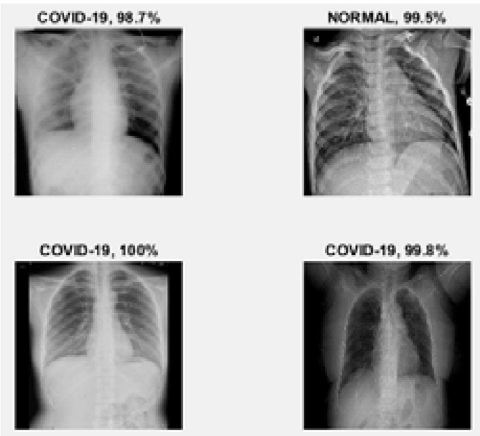

Fig.4. Four sample validation images with predicted labels and the predicted probabilities of the images having those labels

IV. CONCLUSION

In this paper, a novel and fully automatic study using deep convolutional neural networks is presented for COVID-19 disease detection. In this paper, a novel, powerful and robust CNN architecture is designed and proposed for COVID-19 disease detection using publicly available datasets. Detection of COVID-19 (i.e. classification of chest X-ray images into COVID-19 (+) and COVID-19 (-) images) is achieved with a high accuracy such as 99.20%. It is believed that thanks to its simplicity and flexibility, the model proposed in this paper can be readily used in practice to help the physicians for diagnosing the COVID-19 disease.

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