AUTOMATIC DETECTION OF CORONA VIRUS DISEASE USING X-RAY IMAGING AND DEEP CONVOLUTIONAL NEURAL NETWORKS

L.Krishna, S.Aruna, Department of Electronics and Communication Engineering Andhra University College of Engineering,
K.Srinivasa Naik, Vignan's Institute of Information technology Visakhapatnam.

ABSTRACT

The 2019 novel coronavirus disease (COVID-19), which originated in China, has spread rapidly among people living in other countries and is approaching approximately 34,986,502 cases worldwide, according to statistics from the European Center for Disease Prevention and Control. Due to the daily increase in cases, a limited number of COVID-19 test kits are available in hospitals. Therefore, it is necessary to implement an automatic detection system as a rapid alternative diagnostic option to prevent the spread of COVID-19 among people. In this study, five pre-trained convolutional neural network-based models (ResNet50, ResNet101, ResNet152, InceptionV3, and Inception-ResNetV2) were designed to detect patients infected with coronavirus pneumonia using chest radiographs. Thus, three different binary classifications with four classes (COVID-19, normal (healthy), viral pneumonia, and bacterial pneumonia) were implemented using 5-fold cross-validation. Considering the performance results obtained, it was seen that the pre-trained ResNet50 model provides the highest classification performance (96.1% accuracy for dataset-1, 99.5% accuracy for dataset-2 and 99.7% accuracy for dataset-3) among the other four models used.

INTRODUCTION

The coronavirus disease (COVID-19) pandemic emerged in December 2019 in Wuhan, China and has become a serious public health concern worldwide. So far, no specific cure or vaccine for COVID-19 has been found. The virus that causes the epidemic disease COVID-19 is called severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2). Coronaviruses (CoV) are a large family of viruses that cause diseases such as Middle East respiratory syndrome (MERS-CoV) and severe acute respiratory syndrome (SARS-CoV). COVID-19 is a new species discovered in 2019 and has not yet been identified in humans. According to early data, COVID-19 causes milder symptoms in about 99% of cases, while the rest are severe or critical. As of October 4, 2020, the total number of people infected with the coronavirus worldwide is 35,248,330. Of these, 1,039,541 (4%) people have died and 26,225,235 (96%) have recovered. The number of active patients is 7,983,554. Of these, 7,917,287 (99%) had mild disease, while 66,267 (1%) had more severe disease. The world is currently dealing with the COVID-19 epidemic. Deaths from pneumonia caused by the SARS-CoV-2 virus are increasing day by day.

Chest X-ray (x-ray) is one of the most important methods used to diagnose pneumonia worldwide. Chest X-ray is a quick, cheap and common clinical method. A chest X-ray provides a lower radiation dose to the patient compared to computed tomography (CT) and magnetic resonance imaging (MRI). However, making the correct diagnosis from X-rays requires expertise and experience. It is much more difficult to diagnose with a chest X-ray than other imaging methods such as CT or MRI.

MATERIALS AND METHODS

DATASET

In this paper, chest X-ray images of 341 patients with COVID-19 were obtained from the open source Git Hub repository shared by Dr. by Joseph Cohenet al. . This repository consists of chest x-rays / computed tomography (CT) images of mostly patients with Acute Respiratory Distress Syndrome (ARDS), COVID-19, Middle East Respiratory Syndrome (MERS), Pneumonia, Severe Acute Respiratory Syndrome (SARS). 2800 normal (healthy) chest X-ray images were selected from the “ChestX-ray8” database. In addition, 2772 bacterial and 1493 viral chest X-rays from the Kaggle repository titled "Chest X-rays (Pneumonia)" were used.

ARCHITECTURE OF DEEP CONVOLUTION NEURAL LEARNING

Deep learning is a sub-branch of the field of machine learning, inspired by the structure of the brain. Deep learning techniques used in recent years continue to show impressive performance in the field of medical image processing, as well as in many fields. By applying deep learning techniques to medical data, we attempt to derive meaningful results from medical data.

Deep learning models have been successfully used in many areas such as classification, segmentation, and lesion detection of medical data. Analysis of image and signal data acquired by medical imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT) and X-ray with the help of deep learning models. The result of these analyzes is the comfortable detection and diagnosis of diseases such as diabetes mellitus, brain tumor, skin cancer and breast cancer.

2 .CONVOLUTIONAL LAYER

Convolutional layer is the base layer of CNN. It is responsible for determining the properties of the pattern. In this layer, the input image passes through a filter. The values resulting from filtering consist of a map of objects. This layer applies some kernels that go through the pattern to extract low and high level elements from the pattern. The kernel is a 3x3 or 5x5 matrix that can be transformed using the input pattern matrix.

3. POOLING LAYER

The second layer after the convolutional layer is the pooling layer. A pooling layer is usually applied to the generated feature maps to reduce the number of feature maps and mesh. parameters using appropriate mathematical calculations. In this study, we used max-pooling and global average pooling. The max-pooling process selects only the maximum value using the matrix size specified in each feature map, resulting in a reduction in output neurons. There is also a global average pooling layer that is only used before the fully connected layer, reducing the data to a single dimension. It is connected to the fully connected layer after the global average pooling layer. Another intermediate layer used is the waste layer. The main purpose of this layer is to prevent network overfitting and divergence.

4 FULLY CONNECTED LAYER

The fully connected layer is the last and most important layer of the CNN. This layer acts as a multilayer perceptron. The Rectified Linear Unit (ReLU) activation function is commonly used on the fully connected layer, while the Softmax activation function is used to predict the output images in the last layer of the fully connected layer.

5 .PRE-TRAINED MODELS

When analyzing medical data, one of the biggest challenges researchers face is the limited number of data sets available. Deep learning models often need a lot of data. Labeling this data by experts is expensive and time-consuming. The biggest advantage of using the transfer learning method is that it allows training data with fewer datasets and requires less computational cost. Using the transfer learning method, which is widely used in the field of deep learning, the information obtained by a pre-trained model on a large dataset is transferred to the model to be trained.

6 .ResNet50

The Residual Neural Network (ResNet) model is an improved version of the Convolutional Neural Network (CNN). ResNet adds shortcuts between layers to solve the problem. This prevents the distortion that occurs as the network becomes deeper and more complex. In addition, bottleneck blocks are used to speed up training in the ResNet model. ResNet50 is a 50-layer network trained on the ImageNet dataset. ImageNet is an image database with more than 14 million images belonging to more than 20 thousand categories created for image recognition competitions.

7.BeginningV3

InceptionV3 is a kind of convolutional neural network model. It consists of many steps of convolution and maximum pooling. In the last stage, it contains a fully connected neural network. As with the ResNet50 model, the network is trained using the Image Net dataset.

8.Inception-ResNetV2

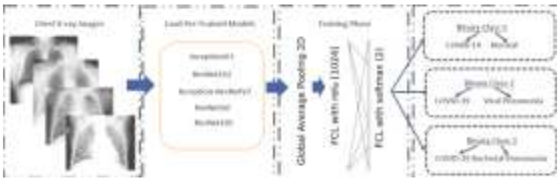
The model consists of a deep convolutional network using the Inception-ResNetV2 architecture, which was trained on the ImageNet-2012 dataset. The input to the model is a 299×299 image and the output is a list of estimated class probabilities.

9. ResNet101 and ResNet152

ResNet101 and ResNet152 consist of 101 and 152 layers thanks to stacked ResNet building blocks. You can load a pre-trained version of the network trained on over a million images from the ImageNet database. As a result, the network learned rich feature representations for a wide variety of images. The network has an input image size of 224x224.

10. Experimental Setup

The Python programming language was used to train the proposed deep transfer models. All experiments were performed on a Google Collaboratory (Colab) Linux server running Ubuntu 16.04 using an online cloud service with central processing unit (CPU), Tesla K80 graphics processing unit (GPU) or TPU (Tensor Processing Unit) hardware free of charge. The CNN models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) were pre-trained with random initialization weights by optimizing the cross-entropy function with the adaptive estimation of moment (ADAM) optimizer (β1 = 0.9 and β92 = 0). The batch size, learning rate, and number of epochs were experimentally set to 3, 1e-5, and 30, respectively, for all experiments. The dataset used was randomly split into two independent datasets with 80% and 20% for training and testing. The k-fold was chosen as the cross-validation method and the results were obtained according to 5 different k values (k=1-5)



Schematic representation of pre-trained model for the prediction of normal (healthy), COVID-19, bacterial and viral pneumonia patients.

OUTPUT AND SCREENS

4.1 Negative image of covid-19 X-RAY IMAGE

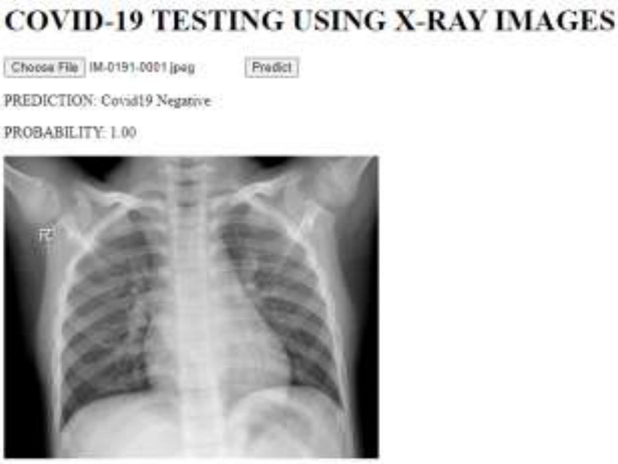


Fig 4.1,Negative image of covid-19 X-RAY IMAGE

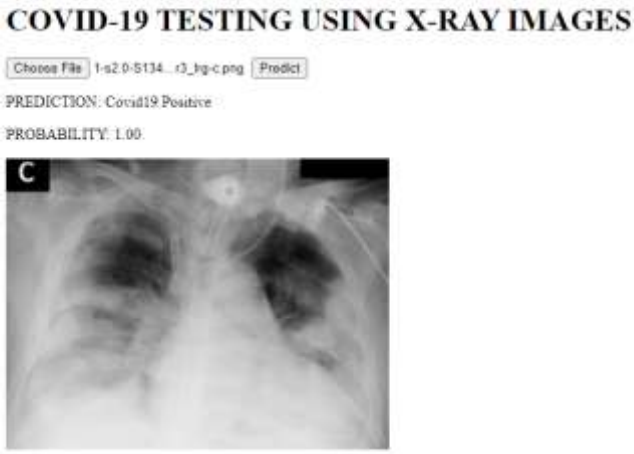
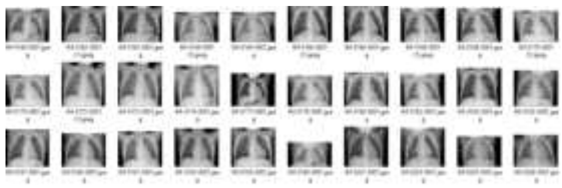
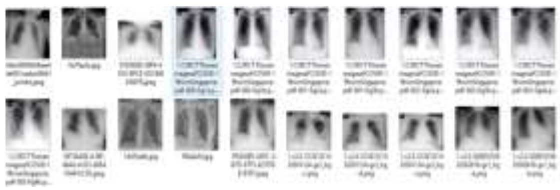


Fig 4.2.Positive image of covid-19 X-RAY IMAGE


Negative images of covid-19 X-RAY IMAGES


Positive image of covid-19 X-RAY IMAGES

Experimental results

In this paper , 3 different binary classifications with 4 different classes (COVID-19, normal, viral pneumonia and bacterial pneumonia) were performed. 5-fold cross-validation method. It was used to obtain a robust result in this study conducted with 5 different pre-trained models which are InceptionV3, ResNet50, ResNet101, ResNet152 and Inception-ResNetV2. While 80% of the data is reserved for training, the remaining 20% is reserved for testing. This entire process continued until every 20% part was tested. First, the values of accuracy and loss in the training process obtained for the models applied to dataset-1, which includes binary class-1 (COVID-19 / normal classes) . It is clear that the performance of the ResNet50 model is better than other models. It can be said that the ResNet50 model achieves lower values among the loss values of other models. The detection performance on the test data is shown in Figure 6. While a large amount of oscillation is observed for some models, some models are more stable. The ResNet50 model appears to have less oscillation after the 15th epoch. The comprehensive performance values for each multiple of the value of each model . As can be seen from Table 2, the detection of the ResNet50 model in the COVID-19 class is significantly higher than that of the other models. ResNet50 and ResNet101 have the highest overall performance with 96.1%. Obviously, the excess of common data results in higher performance for all models.

Discussion

The use of artificial intelligence-based systems is very common in detecting people caught in the COVID-19 epidemic. there are many studies on this topic in the literature. In a binary classification, it is common to distinguish between COVID-19 positive and COVID-19 negative. In addition, it is very important to differentiate patients with viral and bacterial pneumonia, which are other types of lung diseases, from patients who are positive for COVID-19. There are a limited number of studies in the literature that work with multiple classes. Das et al. performed studies for 3 different classes (positive for COVID-19, pneumonia and other infections). The researchers used 70% of the data for training, the remaining 10% for validation, and 20% for testing. As a result, they obtained 94.40% accuracy over the test data with the CNN model they designed. Singh et al. designed a two-class study using limited data. They reported their performance by splitting the dataset at different training and testing rates. They achieved the highest accuracy of 94.65 ± 2.1 with 70% training - 30% testing. In their study, they set the CNN hyperparameters using multi-objective adaptive differential evolution (MADE). Afshar et al. conducted their studies using a method called COVID-CAPS with multiclass studies (normal, bacterial pneumonia, non-COVID viral pneumonia, and COVID-19). They achieved 95.7% accuracy with the no-pre-training approach and 98.3% accuracy with the pre-trained COVID-CAPS. However, although their sensitivity values are not as high as the general accuracy, they detected without pretraining and 98.3% accuracy with pretrained COVID-CAPS as 90% and 80%, respectively.

Ucar and Korkmaz performed a multiclass (normal cases, pneumonia cases, and COVID-19) with a Bayes-SqueezeNet deep network. They obtained an average accuracy value of 98.26%. They worked with 76 COVID-19 dates. Sahinbas and Catak worked with 5 different pre-trained models (VGG16, VGG19, ResNet, DenseNet and InceptionV3). With the performance of the VGG16 binary classifier, they achieved 80% accuracy. They worked with a total of 70 COVID positive and 70 COVID negative. Khan et al. worked with normal, pneumonia-bacterial, pneumonia-viral and COVID-19 chest radiographs. As a result, they achieved 89.6% overall performance with a model they named CoroNet. They used 290 COVID-19 data. They worked with more COVID-19 data than many studies. Medhi et al. achieved a 93% overall performance value in their study using a deep CNN. 150 pieces of COVID-19 data were worked on. In another study, Zhang and colleagues performed binary and multi-class classifications on 106 pieces of COVID-19 data. They found a detection accuracy of 95.18% using the Confidence Aware Anomaly Detection (CAAD) model. Apostopolus et al. obtained an accuracy of 93.48% using a total of 224 COVID-19 data with the VGG-19 CNN model for their 3-class (COVID-19 – Bacterial – Normal) study [26]. Narin et al. used 50 COVID-19 / 50 Normal data in their study where they achieved 98% accuracy with ResNet50. In many studies in the literature, researchers have studied a limited number of data on COVID-19. In this study, the ability to differentiate 341 COVID-19 data from each other was investigated using 3 different studies. In the study, 5 different CNN models were compared. The most important points in the study can be expressed as follows:

• There is no manual feature extraction, selection and classification in this method. It was implemented end-to-end directly with raw data.
• The performance of the COVID-19 data across the Normal, Viral Pneumonia and Bacterial Pneumonia classes was significantly higher.
• Has been studied with more data than many studies in the literature.
• It has been studied and compared with 5 different CNN models.
• A highly accurate decision support system was designed for radiologists to automatically diagnose and detect patients with suspected COVID-19 and follow-up.

From another point of view, if we consider that this period of the pandemic affects the whole world, there is a serious increase in the work density of radiologists. For these manual diagnoses and determinations, expert fatigue can increase the error rate. Clearly, decision support systems will be needed to overcome this problem. A more effective diagnosis can thus be made.
The most important issue limiting this study is working with limited data. Increasing the data and testing it with data from many different centers will allow more stable systems to be created.

Classification algorithms. In addition, the results will be compared with deep learning models. In addition, the results of the study will be tested with data from many different centers. In a future study, studies will be conducted to determine patient demographics and the capabilities of COVID-19 with AI-based systems.

Conclusion

Early prediction of patients with COVID-19 is essential to prevent the spread of the disease to other people. In this study, we proposed a deep transmission approach using chest X-ray images obtained from normal patients with COVID-19, bacterial and viral pneumonia to automatically predict patients with COVID-19. The performance results show that the pretrained ResNet50 model yielded the highest accuracy among the five models for the three different datasets used (Dataset-1: 96.1%, Dataset-2: 99.5%, and Dataset-3: 99.7%). In light of our findings, it is predicted that the higher performance will help radiologists make decisions in clinical practice. In order to detect COVID-19 at an early stage, this study provides an overview of how deep transfer learning methods can be used. In subsequent studies, the classification performance of different CNN models can be tested by increasing the number of chest X-rays of COVID-19 in the dataset.

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