TRANSFER LEARNING BASED CONVOLUTIONAL NEURAL NETWORK FOR COVID-19 DETECTION WITH X-RAY IMAGES

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ABSTRACT

Recently, all the world countries have focused on protecting human health and combatting the COVID-19 outbreak. It has caused a destructive effect on human health and daily life. Many people have been infected and have died in all around the world. It is critical to control and prevent the spread of COVID-19 disease by applying quick alternative diagnosis techniques. Although the laboratory test has been applied widely in the diagnostic tool, recent findings suggest that the application of X-ray and computed tomography (CT) images and pre-trained deep CNN models can help in the accurate detection of this disease. In this study, we propose a model for COVID-19 diagnosis, applying a deep CNN technique based on using raw chest X-ray images belonging to COVID-19 patients and can be accessed publicly on GitHub. 50 positive and 50 negative COVID-19 X-ray images for training and 20 positive and 20 negative images for testing phases are included. Since the classification of X-ray images need to deep architecture due to cope with the complicated structure of images, we apply the five different architectures of well-known pre-trained deep CNN models such as the VGG16, VGG19, ResNet, DenseNet, and InceptionV3. The pre-trained VGG16 model can detect COVID-19 from non-COVID-19 cases with the highest classification performance as 80% accuracy among the other four proposed models and can be used as a helping tool in the department of radiology. In the proposed model, a limited dataset of COVID19 X-ray images is used, and it can provide more accurate performance if the number of instances in the dataset increases.

Keywords: Coronavirus (COVID-19), transfer learning, pre-trained CNN model, Chest X-ray images, deep learning.

1. INTRODUCTION

The biggest pandemic we have experienced in this century has emerged with the COVID-19 outbreak. So far, more than 3 million people have been infected, and more than 200 thousand people have died in more than two hundred countries [1]. Even if the disease is diagnosed with the clinical findings by the physicians, the detection of this disease that spreads very quickly using data science methods at the early stage is critical for the improvement of the disease.

According to some studies, clinical findings of COVID-19 contain fever, cough, sore throat, radiographic images [2-3]. Clinical finding testing is accepted as the gold standard for diagnoses; however, it causes time-consuming with the important false negative diagnoses. Moreover, COVID-19 test kits number is limited in the hospitals. Therefore, quick alternative diagnosis techniques to combat COVID-19 spreading among people, treatment and care for the patient have a vital role and very critical issue to fight of the COVID-19. At this point, medical imaging such as X-ray and computed tomography (CT) images that are the one of the chest radiological imaging are familiar test techniques used for COVID-19 early and quick diagnosis and have an important role in the treatment of this disease [4]. In radiology, in recent days, much of the study has concentrated on the chest CT of COVID-19 [5-6]. According to a strong advice, the first step in detecting the COVID19 could be diagnostic with radiological images [7].

Specifically, Convolutional neural network (CNN) is used in computer vision to analyze images in deep learning significantly. Classification of X-ray images need to deep architecture due to cope with the complicated structure of images. We propose that pre-trained deep CNN models might be able to extract COVID-19's specific graphical features and provide a clinical diagnosis by using COVID-19 radiographical changes in CT images, by this way, the model provides to save critical time for disease diagnosis.

In this study, we use X-ray images belonging to patients undergoing COVID-19 scanning that can be accessed publicly on GitHub. We collect dataset from different hospitals; thus, we resized the pictures to be 256x22. Due to the insufficient number of examples, we enriched the data set by adding image augmentation methods. By this way, we tend to improve the performance of the classification model. Evaluation and experiment of the proposed model have been achieved in terms of 50 positive and 50 negative COVID-19 X-ray images for training and 20 positive and 20 negative images for testing phases. In this study, the five different architectures of well-known pre-trained deep CNN models such as the VGG16, VGG19, ResNet, DenseNet, and InceptionV3 are used for transfer learning by using x-ray images belonging to COVID-19 patients for our proposed method. Each pre-trained deep CNN models can analyze X-ray image to distinguish the COVID-19 case and health group due to their more in-depth structure. Our model achieves a classification accuracy of 80% for VGG16 that gives the best performance. We use an open public dataset of chest X-ray and CT images to build a COVID-19 detection. By showing our results in graphs and tables, we show the classification performance.

We present a brief summary of the related research in relation to transfer learning-based diagnostic of the COVID-19 with using of the chest X-rays as inputs. Recently, X-rays and CT images have been extensively applied for the detection of COVID-19. Public datasets containing COVID-19 X-ray images of infected patients is provided by the studies. According to some studies, combining chest radiological imaging with clinical findings may assist for early detection of COVID-19 [8,9]. Ardakani et al. [10] propose a COVID-19 diagnosis method by applying artificial intelligence technique with 1020 CT from 180 infected patients as COVID-19 group and 86 other patients as the non-COVID-19 group. They used ten familiar convolutional neural networks to separate COVID-19 infection from nonCOVID-19 groups with the best performances of ResNet-101 and Xception methods that achieved 99.51% and 99.02% accuracy rates respectively. They prove that ResNet-101 indicates high sensitivity model to diagnose COVID-19 infections. Ucar and Korkmaz [11] present a SqueezeNet model network design a COVID-19 diagnosis with Bayesian optimization additive in X-rays images. Ozturk et al. [12] present a new model for COVID-19 detection using chest X-ray images by implementing diagnostics for binary classification multi-class classification with using DarkNet model that apply 17 convolutional layers with 1125 images (125 COVID-19). Their model can help radiologists by cloud system. Hemdan et al. [13] identify a new COVIDX-Net deep learning framework for helping radiologists to diagnose COVID-19 automatically in X-ray images. They apply seven well-known CNN models such as VGG19 and DenseNet by using 25 confirmed positive COVID-19 patients to classify COVID-19 in X-ray images. Wang et al. [14] present a deep convolutional neural network framework that is called as COVID-Net to detect COVID-19 cases in chest X-ray images. They provide CXR dataset including 13,800 chest radiography images across 13,725 patient open access data platform to assist clinicians. Ioannis et al. [15] provide the detection of Coronavirus by using Convolutional Neural Network architectures that apply transfer learning with 224 images with confirmed Covid-19 in a dataset of X-Ray images. They achieve an overall accuracy of 97.82%. Narin et al. [16] propose a convolutional neural network-based models such as pre-trained ResNet50, InceptionV3 and InceptionResNetV2 to detect COVID-19 cases in chest X-ray images with 98% accuracy that pre-trained ResNet50 model has the best one. Song et al. [17] introduce a CNN-based CT diagnosis system to classify COVID-19 patients by using chest CT scans of 88 patients diagnosed with the COVID-19 with AUC of 0.99. Wang et al. [18] present proof-of-principle for the modified Inception transfer learning CNN model to classify COVID-19 cases by using 325 CT images with 85.2%. Xiaowei at al. [19] present early screening three-dimensional deep learning model to separate COVID-19 pneumonia from Influenza-A viral pneumonia and irrelevant to infection groups by using CT images with 86.7 % accuracy. Xu et al. [20] provide pre-trained deep CNN ResNet model to detect COVID-19 patients by using CT images has an 86.7% accuracy performance rate. Sethy and Behera [21] propose a CNN model built on the pre-trained ResNet50 with

SVM classifier using X-ray images and demonstrate the best performance. Lastly, there are other studies in this field have been focused on using X-ray and CT datasets related to Covid-19 detection [22,23].

Organization of the chapter as follows: Section 1 contains the introduction part, information about Covid-19 disease, aims of this chapter and in addition a brief summary of related studies with X-ray and CT using neural networks methods is presented, Section 2 includes material and method, CNN, transfer learning methods, Section 3 provides material and methods, information about data preprocessing, number of data used for testing and training, evaluation model performance results and lastly Section 4 includes conclusion part.

2. CONVOLUTIONAL NEURAL NETWORK (CNN)

In this section, we will consider deep neural network analyzes and transfer learning methods. CNN is the most frequently used neural network class to analyze visual images in deep learning. CNN mainly contains many layers of neural networks, providing solutions especially for image and video recognition, classification, and analysis. A CNN architecture was designed with inspiration from the organization's visual cortex, similar to the connection model of neurons in the human brain [24]. Recently, learning from large scale datasets such as ImageNet has been effective in CNN's success. CNN basically consists of three main layers. These are the convolution layer, the pooling layer and the fully connected layer. Basically, convolutional and pooling layers provide the learning of the model, while the full connection layer provides the classification [25].

Convolutional layer is the main part of CNN architectures. In this layer, it is provided to learn the properties of the inputs. The feature map is created by applying high- and low-level filters in the input image. In general, in this layer, sigmoid, relu or tanh functions can be used as activation functions [25]. The mathematical equation of the convolution process is presented in Equation 1. While m and n in the equation indicate the dimensions of kernel$m \times n$, i and j indicate the matrix coordinate from which the convolution will be calculated.

$$S(i,j) = (I * K)(i,j) = \sum_{m}\sum_{n} I(m,n)K(i-m, j-n) \tag{1}$$

Pooling layer is generally applied between convoluted layers. Its main purpose is to reduce the computational power required to process the model by reducing the size of the feature map. In addition, it provides effective training of the model by removing the invariable and dominant features out of the model. Although there are many pooling processes, maximum and average pooling layers are most commonly applied.

In the full connection layer, all neurons from the previous layer are connected to each neuron in this layer. Depending on the structure of the CNN architecture, the full link layer can be one or more. The output layer comes after the last full link layer. In classification studies, at this stage, using softmax regression, output distributions are obtained by obtaining probability distributions for output classes [25].

2.1. Transfer Learning

Transfer learning (TL) is a strategy in machine learning in which the information extracted by a CNN from a given and related data is transported to solve a different but related problem [26]. Transfer Learning is based on the principle of developing learning by using the information obtained from a related task learned in a new task by transfer. Pre-trained deep learning networks are already well-trained using other datasets, which could be refined to obtain high accuracy with a much smaller dataset, thus, it is more preferred by researchers [27].

Pan and Yang [28] provided a comprehensive review of transfer learning. With the transfer learning, the learning process is not started from scratch. This process is started with the patterns learned while solving a different problem. In this way, both previous learning is used, and it is avoided to start the learning process from scratch. Besides, it prevents time-consuming and enables the creation of a correct model [29].

It can be said that Transfer Learning is a design methodology for machine learning, it not a machine learning model or technique. This design methodology commonly applies to pre-trained models. These pre-trained models are based on Deep Evolution Neural Networks. In deep learning, this method includes the initial training of a CNN for a classification problem using large-scale training datasets. Because a CNN model can learn to extract critical properties of the image, the availability of data for introductory training is an essential part of successful training. Depending on CNN's capacity to recognize and select the most outstanding display features, it is evaluated whether this model is fit for transfer learning.

2.1.1. VGG

VGG-Net model was developed by Simonyan et al. [30] with a very small convolution in the network. Although it is a simple model, its most significant difference compared to previous models is that it is widely applied CNN models because of more in-depth structured and followed by the layers of associating the double or triple convolution layers [30]. In previous models, the layers of sharing and convolution follow each other. Approximately 138 million parameters are calculated in this model [31]. VGG has a good representation of features for more than a million images (ImageNet dataset) from 1000 different categories, the model can function as a useful feature extractor for suitable new images. ImageNet dataset is able to extract related features from the images, even new images may never exist, or they may be in entirely different categories in the dataset. This provides the advantage of using pre-trained models as an effective feature remover [30].

Figure 1 indicates the architecture of the VGG-16.

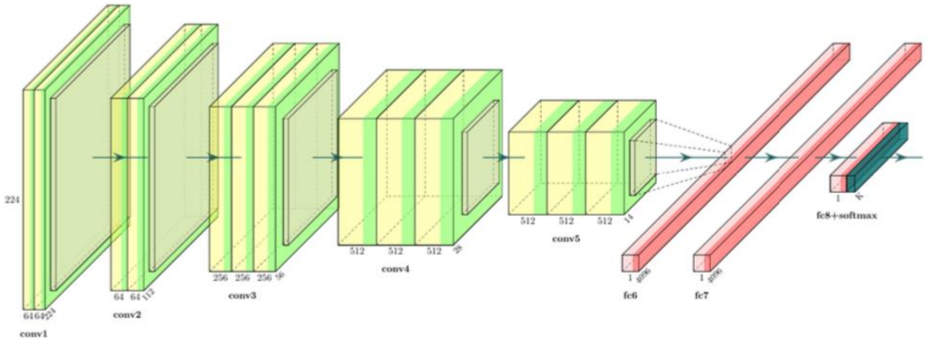


Figure 1. VGG16 architecture [30].

The VGG-16 architecture uses 3 convolution filters with 13 convolution layers for feature extraction, each convolution layer follows a ReLU layer and has maximum pooling layers for sampling. It has three layers that are fully linked for classification, two of which serve as hidden layers, while the final classification layer consists of 1000 units representing image categories in the ImageNet database [30]. This structure simulates a larger filter while preserving the benefits of smaller filter sizes. VggNet has been shown to perform better using fewer parameters, especially compared to previous models. In addition, two ReLU layers were used instead of a single ReLU layer for two convolution layers. Since the spatial size of the input volumes in each layer decreases (the result of the convolution and partnering layers), the depth of the volumes increases due to the increasing number of filters. It works well for both object classification and edge detection problems [31].

We use VGG16 network model in order to fine-tune our model duty. Suppose, we have a dataset with m samples $\{(x(1), y(1)), \dots, (x(m), y(m))\}$ for training. The network overall cost function can be defined as follow [30]:

$$J(W,b) = \left[\frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\ \| K_{w,b}\left(x^{(i)}\right) - y^{(i)}\ \|^2\right)\right] + \frac{\lambda}{2}\sum_{l=1}^{n_{l-1}}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}\left(W_{ji}^{(l)}\right)^2 \quad (2)$$

Where $K_{w,b}\left(x^{(i)}\right)$ is the neural network model, $W_{ji}^{(l)}$ is the connection weight between the *j* th element of layer 1 and the *i* th element of layer $l+1$, and b is the bias term of the hidden layer neuron. Equation 2 is a regulation item on the right side, which can prevent overfitting, reduces the weight greatly and adjusts the relative importance of the two terms before and after the cost function λ. Solving the minimum values of (2), solving the minimum value of $J\ (W, b)$, adopts the recognized batch gradient descent optimization algorithm and calculating the partial derivative of W and b, for the reverse conduction algorithm.

2.1.2. ResNet

ResNet is an architecture designed as more depth structured than all the previous architectures. It consists of 152 layers. ResNet was developed in 2015 [32]. It ranked first in the ImageNet competition held in 2015, with an error rate of 3.6% [32]. Figure 2 demonstrates the architecture of the residual mapping of the model.

The most significant feature that distinguishes it from other architectures is that the blocks that feed the values to the next layers are added to the model. This value, added every two layers between the Linear and ReLu activation codes, changes the system value as stated. The value of $a^{[\int\ ]}$ from the previous layer is added to value $a^{[\int\ +2]}$[33].

Increasing the number of layers in a model normally means that performance will increase, but in practice, the situation is changing. Thus, if w [l + 2] = 0, then according to the new theory, a [l + 2] = b [l + 2]. This causes the problem that the derivative produces zero value. It is undesirable [32]. However, now the value feed optimizes the learning error even if the value a [l] from the two previous layers is 0, and the network is trained faster.

ResNet50 architecture consists of replacing both layer blocks in a 34-layer network with a 3-layer bottleneck layer. This 50-layer network contains 3.8 billion FLOPs.

ResNet101 and ResNet152 architectures more layers than 3-layer blocks use. ResNet152 contains 11.3 billion FLOPs. It currently has a lower complexity than VGG16 / 19 networks [32].

ResNet architecture was the winner in a study on the CIFAR10 dataset with 10 classes, 50000 educational images and 10000 test images [34].

As the depth of CNN models increases, the problem of increasing gradients that vanish and explode affect the convergence of CNN models.

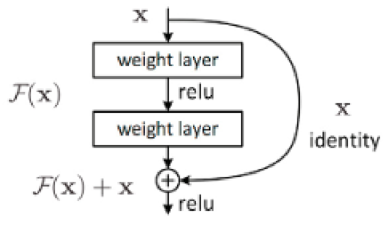


Figure 2. Residual mapping structure [32].

This architecture consists of the residual blocks shown in Figure 2. In the residual block, the convolution of input x yields an F (x) result after the ReLu-convolution series. This result is then added to the original x entry and expressed as H (x) = F (x) + x.

ResNet50 model provides easy training and significant advantage of use due to learning residuals from image instead of features [32].

2.1.3. DenseNet

While neural networks are being trained, feature maps decrease due to convolution and sub-sampling processes. At the same time, there are losses in the image feature in transitions between layers. In order to use image information more effectively, Huang et al. [35] developed the DenseNet system.

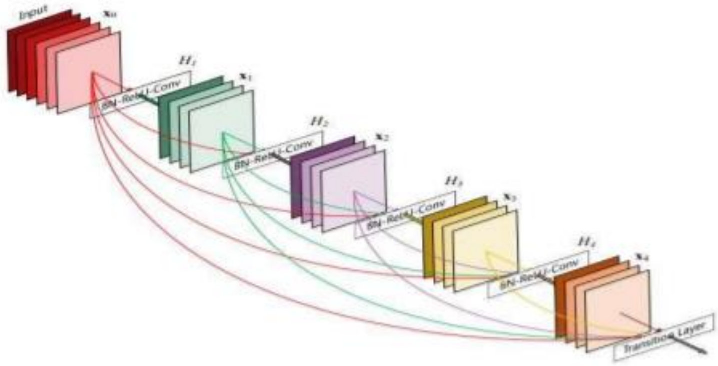


Figure 3. DenseNet Architecture.[35]

In the system, each layer is fed forward to the other layers. In this way, any layer *l* can access the property information of all layers before it. It is possible to see the general network architecture of densely connected neural networks in Figure 3 [35].

$$X_l = H_l(X_0, X_1, X_2, \dots, X_{l-1}) \tag{3}$$

Layers $[X_1, X_2, X_3, \dots, X_{l-1}]$ are a combination of property information. H_l is the transfer function used to process property information. In this way, the rate of propagation of the features increases, it becomes easier to use again and the number of parameters decreases significantly.

2.1.4. InceptionV3

In 2013, Lin et al. [36] proposed an innovative solution to the calculation complexities of previous models with the 1x1 convolution process. The idea behind Inception to provide an optimal local sparse structure in a convolutional vision network can be approximated and covered by readily available dense components [37]. The basic idea of 1x1 convolution is to reduce the number of channels in the image. Thus, the number of parameters is also reduced. Normally 1x1 convolution does not affect the size of the matrix; however, if the input matrix is multi-channel, the channel number of the output matrix of the 1x1 convolution process is equal to the number of channels of the 1x1 convolution filter applied.
The network model named as inception consists of several modules. In each of these modules, different sizes of convolution and maximum partnering are applied. In the literature, GoogLeNet is also known

as inception-v1. Versions later called inception-v2, inceptionv3 [38] and inception-v4 [39] have also been developed. In Inception-v3 architecture, there two parts such as feature extraction and classification.

The feature extraction section includes the convolutional neural network. Inception-v3 is a well-known architecture, and the input of the network should be an image of 299x299 pixels. On the other hand, the classification section is fully connected and includes Softmax layers.

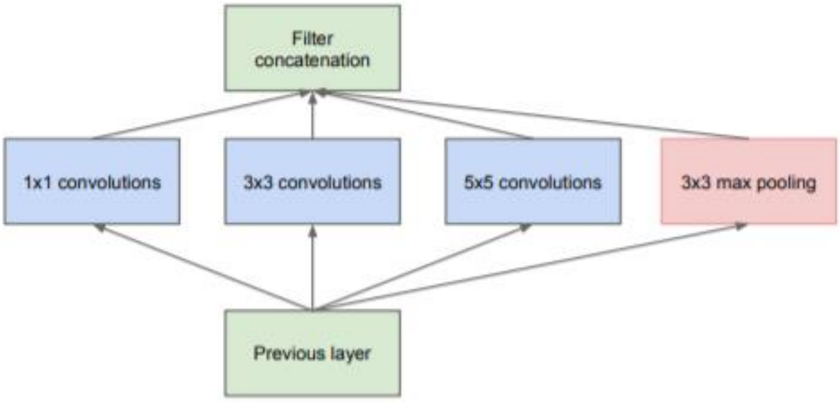


Figure 4. Inception module, naive version [37]

The start modules consist of a 3x3 maximum joint and 1x1, 3x3, 5x5 convolution layers as indicated in Figure 4. After applying this inception layer on the data from the previous layer, the network collects the filters at the output and transfers them to the next layer. By the contribution of this module, both general and specific properties of an object are tried to be discovered. In Figure 4 the lower green box is the Inlet and the top one is the output of the model.

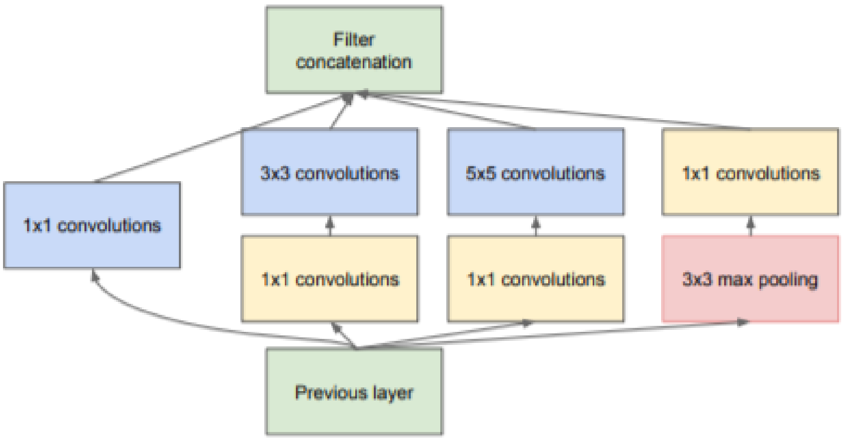


Figure 5. Inception module with dimension reductions [37]

The calculation cost increases as there will be too many parameters during the convolution process in the Inception structure in Figure 4. To overcome this problem, as shown in Figure 5, 1x1 convolution was applied to dimension reduction.

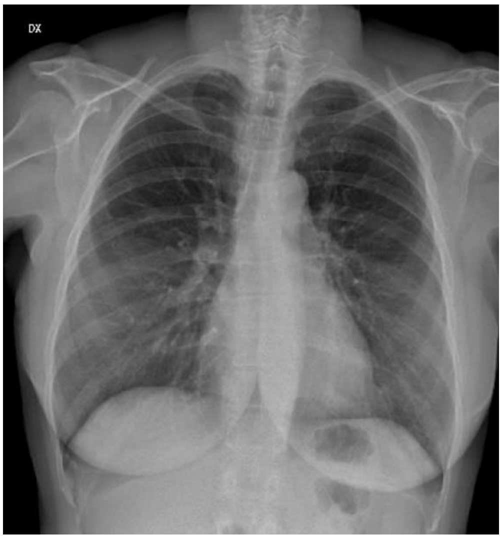
3. MATERIALS AND METHOD

3.1. Dataset

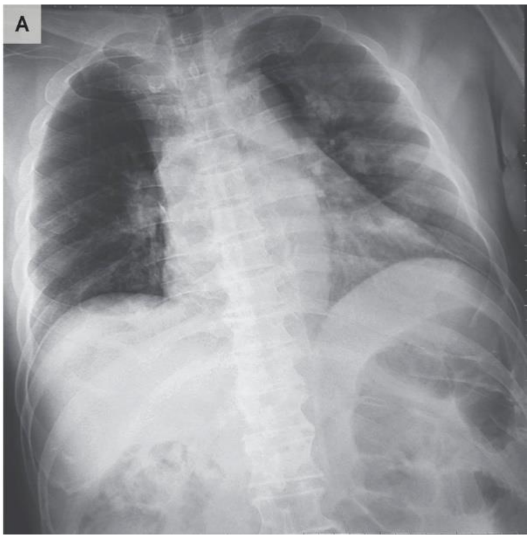
In this work, we used an open public dataset of chest X-ray and CT images of COVID-19 patients, which are positive or suspected of COVID-19 or other viral and bacterial types of disease (MERS, SARS, and ARDS.). The dataset is collected from public sources as well as through indirect collection from hospitals and physicians. All images and data are published openly in the GitHub repository. The original dataset contains both X-ray images and CT scans. In this application, we chose the X-ray scan images to build a COVID-19 detection model. 50 positive 50 negative COVID-19 posteroanterior X-ray scan images are used to create a training dataset while another 20 positive and 20 negative scans are used for testing the model.

The X-ray scan images were rescaled to a size of 256×222. We implemented different image augmentation methods to produce more enhanced input instances such as: flipping right/left and up/down, rotation, and translation utilizing random five various angles.

The data set used in the study can be said not to contain sufficient X-ray scanning results at the moment. This dataset is the publicly accessible one, contains the most data, and is tagged when this book chapter is written. In the future, both the number of data sets and the number of samples they contain will increase. Another issue is labeling. This data set contains X-ray scan images containing the disease. There are only 3 records in the dataset with COVID-19 negative samples, and the "finding" field was chosen as No finding. Therefore, X-ray pictures with ARDS and Streptococcus results are tagged to select COVID-19 negative samples. In the future, we believe that samples of COVID-19 negative patients will increase in this type of data collection.



(a)



(b)

Figure 6. An example of a X-ray scan image taken from the dataset (a) with a label of COVID-19 negative, (b) COVID-19 positive.

We used image augmentation techniques to increase the samples in the data set and to improve the performance of the classification model. Our image augmentation parameters are rotation range 20, zoom range 15, width shift range 0.2, height shift range 0.2, shear range 0.15, horizontal flipping. An example image augmentation technique is shown in Figure 7.

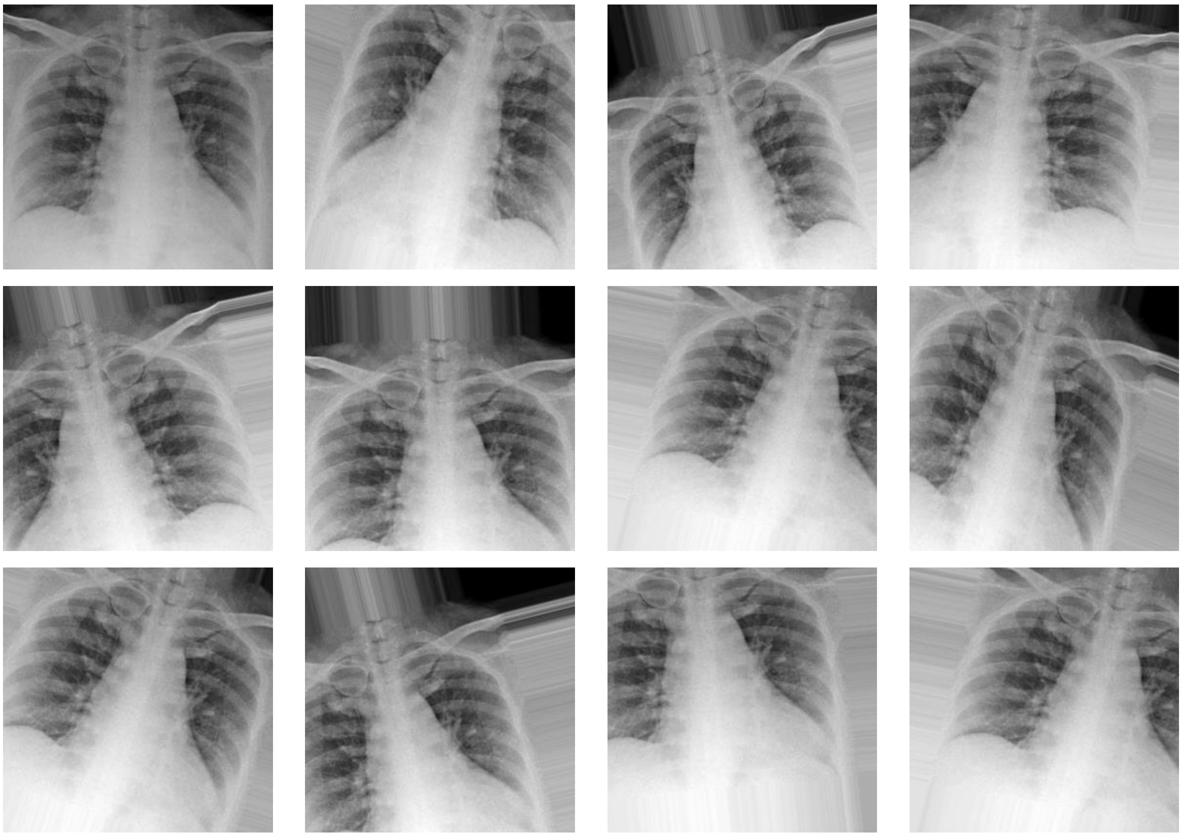


Figure 7. Data augmentation example. The first image is the original image, and the rest are augmented images.

3.2. Evaluation

Although the dataset that is used in our experiments is almost balanced, traditional accuracy-based performance evaluation is not enough to find out an optimal classifier. We used four different metrics, the overall prediction accuracy, average recall, average precision and F1-score, to evaluate the classification accuracy which are common measurement metrics in machine learning [40-42].

Precision is defined as the fraction of retrieved samples that are relevant.

$$Precision = \frac{Correct}{Correct + False} \tag{4}$$

Recall is defined as the fraction of relevant samples that is retrieved.

$$Recall = \frac{Correct}{Correct + Missed} \tag{5}$$

F1-score is defined as the harmonic mean of precision and recall.

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

The dataset was divided into two groups; 80% for training the model and 20% for evaluation of the classification performance.

3.3. Proposed Model

In this study, we used the data set containing X-ray images belonging to patients undergoing COVID-19 scanning, which can be accessed publicly on GitHub [43]. Since these data were obtained from different hospitals, the picture resolutions differ from each other. In order to overcome this problem, we resized the pictures to be 256x22. Due to the use of a CNN-based method, it is not affected by the adverse effects of this type of data compression. Due to the insufficient number of examples, we enriched the data set by adding image augmentation methods such as flipping and different angle. In this way, we aimed to improve the performance of the classification model.

In the last part of the transfer models we have used, we have added a heading model designed by ourselves. In this way, we transformed the transfer learning models to detect our COVID-19 patients from X-ray scanning images. The output of the classification model in this problem is in the form of binary classification such that it is positive and negative. We canceled the optimization by training the layers belonging to the transfer models. The model we created is trained only by making parameter optimization to the heading model part. Figure 8 shows the overall architecture.

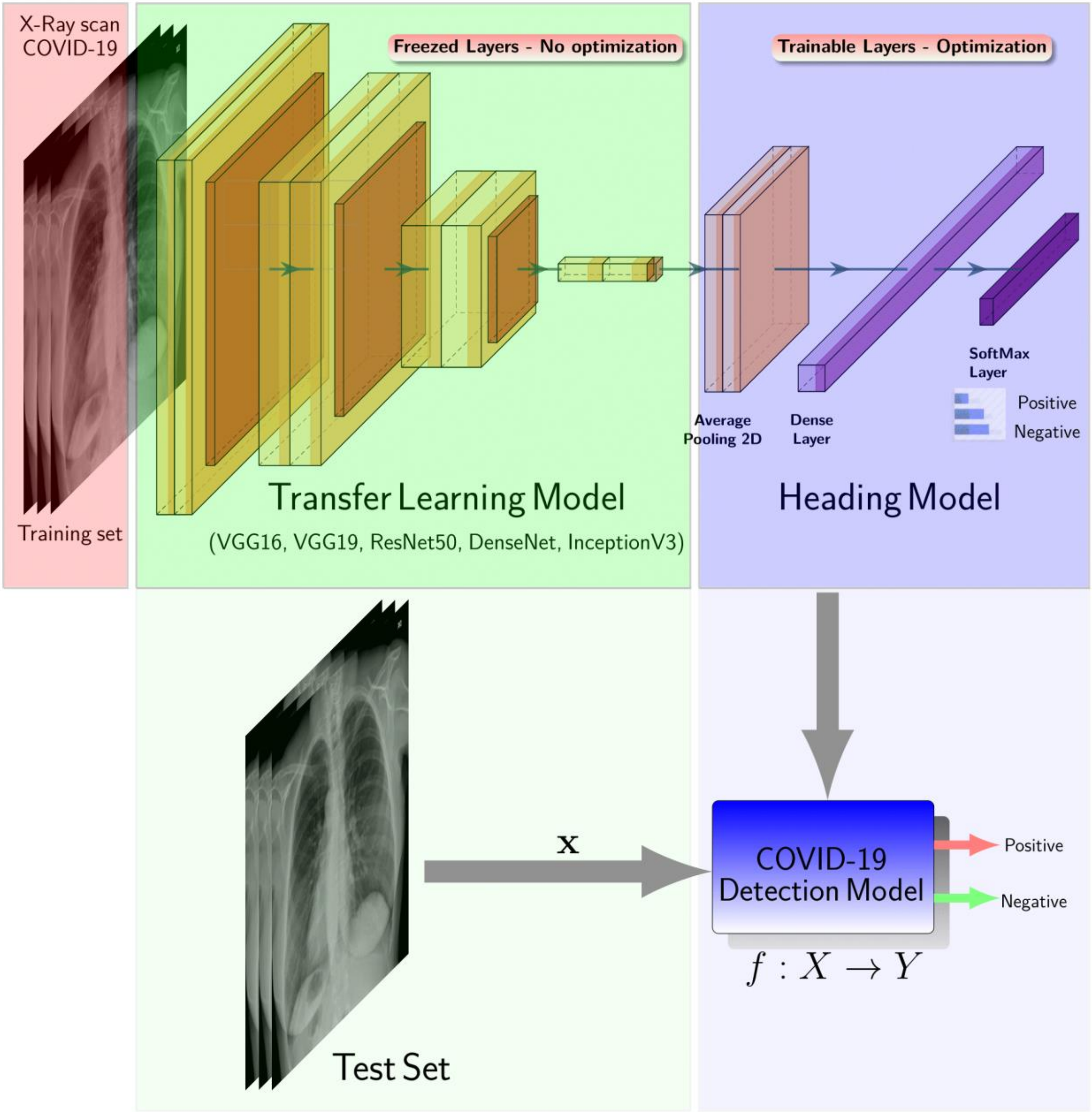


Figure 8. The proposed system models.

Figure 9 shows the confusion matrix of each transfer learning model. VGG16 model has the best classification performance.

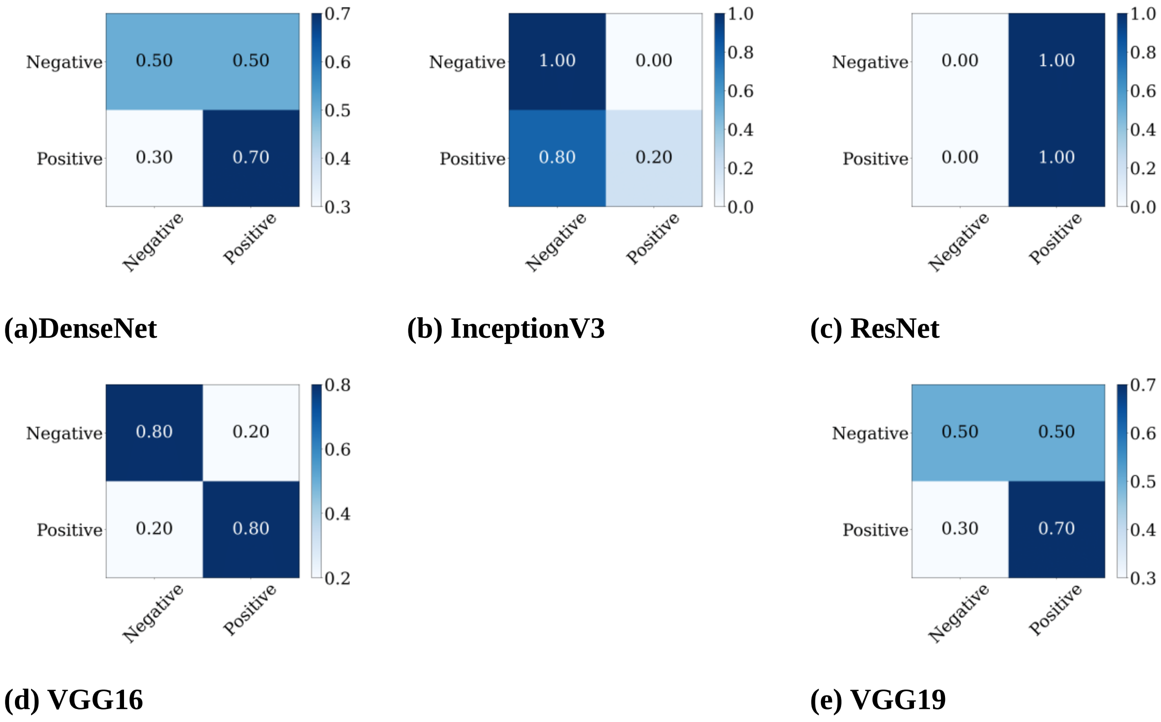


Figure 9. The confusion matrix of each transfer model.

Table 1. Performance results for each CNN pre-trained model for COVID-1 of the proposed model.

Model	Accuracy	Precision	Recall	F-Score
VGG16	0.80	0.80	0.80	0.80
VGG19	0.60	0.50	0.625	0.55
ResNet	0.50	0.0	nan	nan
DenseNet	0.60	0.50	0.625	0.55
InceptionV3	0.60	1.0	0.55	0.71

Findings in Table 1 indicate that the pre-trained VGG16 model provides the highest classification performance of automated COVID-19 classification with 80% accuracy among the other four proposed models. The VGG19, DenseNet and InceptionV3 models indicate the same performance of classification with accuracy of 0.60 and the ResNet shows the lowest classification performance with 0.50 accuracy.

The VGG19, DenseNet and InceptionV3 models show the same performance of COVID-19 classification with f1-scores of 0.55. VGG16 model presents the highest classification performance with 80% f1-score.

4. CONCLUSION

In recent days, medical imaging such as X-ray and computed tomography (CT) images as a rapid diagnosis technique have a key role in the treatment of COVID-19.

In this study, we first introduced the reason behind using X-rays images in COVID-19 detection. We then described a few related studies about pre-trained CNN methods by using X-ray images. We used an open public dataset of chest X-ray and CT images to build a COVID-19 detection. Because of the insufficient number of public COVID-19 datasets, we collected 50 positive and 50 negative COVID-19 X-ray images for training and 20 positive and 20 negative images for testing phases. We resized the pictures to be 256x22. We enriched the data set by adding image augmentation methods such as flipping and different angle. We proposed five pre-trained deep CNN models such as the VGG16, VGG19, ResNet, DenseNet, and InceptionV3 are used for transfer learning by using x-ray images belonging to COVID-19 patients. The pre-trained VGG16 model provided the highest classification performance of automated COVID-19 classification with 80% accuracy among the other four proposed models. By showing our results in graphs and tables, we indicated the classification performance. The VGG19, DenseNet and InceptionV3 models presented the same performance of classification with accuracy of 0.60 and the ResNet showed the lowest classification performance with 0.50 accuracy.

The data set used in the study contains an insufficient number of examples. Therefore, the limited dataset of COVID19 X-ray images is used. By increasing the number of instances in the dataset, the model can present more accurate performance.

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